NMED
EXHIBIT
139

Revised Regulatory Analysis for New Mexico's Clean Transportation Fuel Program

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List of Abbreviations

ACC II	Advanced Clean Cars II
ACT	Advanced Clean Trucks
AR5	Fifth Assessment Report (of the Intergovernmental Panel on Climate Change)
AVFT	alternative vehicle fuel and technology
AW	animal waste (i.e., manure)
bbl	barrel
B0	fossil diesel (0 percent biodiesel)
B5	5 percent biodiesel blend
BD	biodiesel
BCA	benefit-cost analysis
BenMAP	Benefits Mapping and Analysis Program
BRG	Berkeley Research Group
CARB	California Air Resources Board
CA-GREET	California-modified GREET model
CDB	county database (MOVES)
$C.H_2$	compressed gaseous hydrogen
CI	carbon intensity
CIDI	compression-ignition direct-injection
CLCA	consequential lifecycle analysis
CNG	compressed natural gas
CO	carbon monoxide
CO_2e	carbon dioxide equivalent
COBRA	CO-Benefits Risk Assessment
CTFP	Clean Transportation Fuel Program
DPF	diesel particulate filter
EFs	emission factors
EIA	economic impact analysis
EPA	U.S. Environmental Protection Agency
ERG	Eastern Research Group, Inc.
FCEV	fuel cell electric vehicle
FCMM	Fuel and Credit Markets Model
FHWA	Federal Highway Administration
FSE	fueling supply equipment
GHG	greenhouse gas
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Technologies model
GTAP	Global Trade Analysis Project Model
GWP	global warming potential
H_2	hydrogen
ICCT	International Council on Clean Transportation
ICEV	internal combustion engine vehicle
ILUC	indirect land use change
IMPLAN	Impact Analysis for Planning
I-O	input-output (modeling)
IPCC	Intergovernmental Panel on Climate Change
LCA	lifecycle analysis

LF	landfill
LFG	landfill gas
L.H_2	liquefied hydrogen
LNG	liquefied natural gas
LPG	liquefied petroleum gas
LUC	land use change
MHDV	medium- and heavy-duty vehicle
MJ	megajoule
mmBtu	million British thermal units
MOVES	Motor Vehicle Emission Simulator
NEI	National Emissions Inventory
NG	natural gas
NMED	New Mexico Environment Department
NM-GREET	New Mexico–specific version of GREET for the CTFP
NMVES	New Motor Vehicle Emission Standards
NO_x	nitrogen oxides
OPGEE	Oil Production Greenhouse gas Emissions Estimator
PADD	Petroleum Administration for Defense Districts
PEM	proton exchange membrane
$PM_{2.5}$	particulate matter with diameter of 2.5 microns or smaller
RD	renewable diesel
R100	100 percent renewable diesel
REC	renewable energy credit
RNG	renewable natural gas or biomethane
scf	standard cubic foot
SMR	steam methane reforming
SO_2	sulfur dioxide
UNM	University of New Mexico
VOC	volatile organic compound
VMT	vehicle miles traveled
WTW	well-to-wheel
ZEV	zero emission vehicle

Acknowledgements

Eastern Research Group, Inc. (ERG) enlisted a multidisciplinary team of subject matter experts and project management professionals across several service areas—Lifecycle Analysis, Clean Transportation, Economics, and Strategic Communications—to assist the New Mexico Environment Department with establishing its Clean Transportation Fuel Program. Collectively, ERG brings over 132 years of experience to this analysis.

Lifecycle Analysis (LCA)

- Andrew Beck has six years of experience working with LCA models of fossil and biological transportation fuels and chemicals, with a focus on improving reproducibility and scalability via open-source tools and data.
- Kyle McGaughy has four years of experience in fuel cycle assessments, with a focus on using the Oil Production Greenhouse gas Emissions Estimator (OPGEE) to assess unconventional extraction in North American fuel production pathways.
- James Santa Ana has two years of experience performing lifecycle assessments and data analysis support for the energy sector using the Greenhouse gases, Regulated Emissions, and Energy use in Technologies model (GREET) and other LCA models.
- Ben Young has nine years of experience in fuel cycle assessments for fossil fuels and other energy pathways, specializing in the use of publicly available datasets to develop tools for assessing emissions from the transportation sector.

Clean Transportation

- Andrew Eilbert has 13 years of experience in regulatory support and emissions modeling, which includes time spent on the U.S. Environmental Protection Agency's (EPA's) Motor Vehicle Emission Simulator (MOVES) development team, as well as implementing federal vehicle greenhouse gas and fuel economy standards.
- Alex Dumont has two years of experience providing alternative fuel vehicle technical assistance and research to private fleets, government entities, and policymakers.
- Audrey Njo has two years of experience supporting government communications, including circular economy and battery recycling initiatives, and supporting charging station infrastructure incentives through the Massachusetts Electric Vehicle Incentive Program.
- John Koupal has 35 years of experience modeling and helping to regulate vehicle emissions, including a breadth of expertise in characterizing fleets, vehicle activity, and emission fuel effects for EPA and other federal agencies along with many states and international nongovernmental organizations.

Economics

- Owen Stokes-Cawley has seven years of experience conducting economic and public health analyses, including modeling impacts in input-output models such as Impact Analysis for Planning (IMPLAN) and interpreting health outcomes with tools such as EPA's CO-Benefits Risk Assessment (COBRA) model for recent policies, including New Mexico's New Motor Vehicle Emission Standards (NMVES).
- Paige McKibben has four years of experience supporting benefit and cost analyses for government agencies, including regularly modeling macroeconomic impacts of policy changes and other market shocks using IMPLAN.
- Natalie Rodman has three years of experience analyzing economic and health impacts from clean transportation policies, including a COBRA analysis of New Mexico's NMVES.
- Janet Carpenter has over 25 years of experience analyzing benefits and costs of technological innovations and policy changes in a variety of contexts, including recent support applying economic impact analysis and health impact analysis for NMVES.

Project Management

- Joanna Kind has 20 years of experience as an environmental scientist and contract manager, and leads ERG's Santa Fe office, which involves coordinating with New Mexico public agencies—in particular, the New Mexico Environment Department.
- John Koupal, in addition to his clean transportation subject matter expertise, leads ERG's Clean Transportation Group and has extensive experience managing contracts and ERG personnel for federal and state clients, including for New Mexico's NMVES policy.

1. Executive Summary

In this uncertain regulatory landscape for federal emission programs, New Mexico has sought more predictability by recently adopting the Advanced Clean Cars II (ACC II), Advanced Clean Trucks (ACT), and Heavy-Duty Low NOx Omnibus rules, modeled off California's clean vehicle programs and collectively referred to as New Mexico's Motor Vehicle Emission Standards (NMVES). Ongoing legal challenges to California's emissions preemption waiver aside, until a final decision is reached, the NMVES will presumably meet these goals through vehicle electrification; however, there is a growing interest in alternative fuels to help reach the state's climate goals, including biofuels, natural gas, and hydrogen. Like California, Oregon, and Washington, New Mexico is seeking to adopt a Clean Transportation Fuel Program (CTFP), which would create a credit market for low-carbon fuels either produced in state or imported for consumption within the state. Conversely, fossil fuels sold in New Mexico for transportation use would generate deficits that must be offset by purchasing and retiring credits.

Beyond the credit market, New Mexico's CTFP is expected to lead to other benefits and costs, such as avoided health damages from criteria pollutant reductions, improved productivity for alternative fuel producers, credits for eligible fuel supply equipment (FSE), and added program revenue from the social cost of carbon and other greenhouse gas (GHG) externalities. These cumulative CTFP benefits and costs have been summarized in Table 1-1, along with the net benefits of a combined CTFP and NMVES policy suite. The combined policy suite is anticipated to deliver more than $1.8 billion in net benefits, with over $1.6 billion coming from the CTFP alone.

Table 1-1 Summary of total CTFP and NMVES benefits and costs through 2040 (in 2024 USD)[1]

NMVES Total	$188,043,999		$188,043,999
CTFP	**Benefits (average)**	**Costs**	**Net**
Fuel Markets	$0	-$959,423,181	-$959,423,181
Direct Fuel Markets		*-$577,919,646*	
Indirect and Induced		*-$381,503,535*	
Health Effects	$15,712,160		$15,712,160
GHG Emissions	$2,435,963,386		$2,435,963,386
Direct Jobs from FSE	$161,894,181		$161,894,181
CTFP Total	$2,613,569,726	-$959,423,181	$1,654,146,545
NMVES + CTFP suite	$2,801,613,725	-$959,423,181	$1,842,190,544

Eastern Research Group, Inc. (ERG) has been involved in nearly all facets of New Mexico's CTFP development, particularly fuel carbon intensities, emission projections, public health effects, and macroeconomic input-output modeling of the program. This executive summary highlights findings from ERG's CTFP analysis among these four focus areas.

[1]See Table 6-22 for further description and notes on the program's full benefit-cost analysis.

1.1 Fuel Carbon Intensities

As with low-carbon fuel programs in other states, the ERG team has built a custom version of Argonne National Laboratory's Greenhouse gases, Regulated Emissions and Energy use in Transportation (GREET) model for New Mexico's CTFP—referred to as NM-GREET—based on the best available state data. A menu of fuel pathways in NM-GREET have been tailored to represent New Mexico–specific carbon intensity (CI) values in grams of carbon dioxide per megajoule of energy (g CO2/MJ).

Several key assumptions differentiate NM-GREET CIs from default values and those in other states' programs; namely, indirect land use change (ILUC), use of well-to-refinery emissions from a crude oil production model called Oil Production Greenhouse gas Emissions Estimator (OPGEE) rather than GREET, and process credits for biogas from manure. While New Mexico's ILUC values are in line with other states' low-carbon fuel programs, OPGEE assumptions have been parameterized for Petroleum Administration for Defense District 3 (PADD3) and animal waste pathways yield additional credit when using biomethane as a process fuel, particularly for natural gas and hydrogen.

Table 1-2 summarizes all possible CTFP conventional and alternative fuel pathways available in NM-GREET. Upon development and thorough review, ERG passed NM-GREET CI values to another CTFP contractor, Berkeley Research Group (BRG), for credit market forecasting under varying policy scenarios: CTFP, NMVES, and the federal baseline.

Table 1-2. Carbon intensities for the full list of CTFP pathways prior to the margin-of-safety adjustments[2]

Pathway ID	Alias	Fuel	CI ($g\ CO_2/MJ$)
NMGAS001	Gasoline, clear	Gasoline	96.7
NMETOH001	Corn ethanol	Ethanol	68.9
NMETOH002	Sorghum Ethanol	Ethanol	60.2
NMULSD001	Diesel, clear	Diesel	95.0
NMBD001	B100 soy	Biodiesel	56.6
NMRD001	R100 soy	Renewable diesel	59.0
NMRN001	Naphtha Virgin Plant Oil	Naphtha	59.0
NMBD002	B100 Waste Oil	Diesel	19.9
NMRD002	R100 Waste Oil	Diesel	18.3
NMRN002	Naphtha Waste Oil	Naphtha	18.3
NMLPG001	LPG	Liquefied petroleum gas	78.4
NMCNG001	CNG fossil	Compressed natural gas	74.3
NMRCNG001	CNG AW	Compressed natural gas	62.7
NMRCNG002	CNG AW	Compressed natural gas	-27.4
NMRCNG003	CNG LF	Compressed natural gas	21.4
NMLNG001	LNG fossil	Liquified natural gas	87.1
NMRLNG001	LNG AW	Liquified natural gas	72.1

[2] In the interest of time, ERG did not attempt to rerun the CTFP analysis from an NMVES baseline using the following CI corrections made since docketing for the September 2nd Notice of Intent.

Pathway ID	Alias	Fuel	CI ($g\ CO_2/MJ$)
NMRLNG002	LNG AW, alt.	Liquified natural gas	-18.5
NMLNG003	LNG LF	Liquified natural gas	31.0
NMELEC001	Elec. net-zero	Electricity	0.0
NMHYG001	C.H_2 fossil	Gaseous compressed hydrogen	94.4
NMHYG002	C.H_2 AW	Gaseous compressed hydrogen	88.3
NMHYG003	C.H_2 AW, alt.	Gaseous compressed hydrogen	-1.8
NMHYG004	C.H_2 LF	Gaseous compressed hydrogen	46.1
NMHYG005	C.H_2 avg.-grid	Gaseous compressed hydrogen	217.8
NMHYG006	C.H_2 net-zero	Gaseous compressed hydrogen	14.3
NMHYL001	L.H_2 fossil	Liquid hydrogen	135.7
NMHYL002	L.H_2 AW	Liquid hydrogen	127.0
NMHYL003	L.H_2 AW, alt.	Liquid hydrogen	37
NMHYL004	L.H_2 LF	Liquid hydrogen	89.8
NMHYL005	L.H_2 avg.-grid	Liquid hydrogen	266.7
NMHYL006	L.H_2 net-zero	Liquid hydrogen	46.9

For more information on CI development, please review Chapter 3, which provides detailed descriptions of each pathway, as well as further discussion of how NM-GREET differs from the default model and how New Mexico's CI values differ from those of other states.

1.2 Projected Emission Reductions from Fuel Changes

Using fuel volume projections from BRG based on credit market forecasts for the CTFP and NMVES scenarios, ERG was able to estimate expected emission reductions in tailpipe exhaust. Switching from fossil fuels to low-carbon alternatives—namely, from diesel to biodiesel (BD) and renewable diesel (RD) blends—is anticipated to reduce both adverse air quality and climate impacts. While BRG determined GHG reductions directly from NM-GREET CI values and fuel volume changes with a few notable exceptions discussed further in Section 6.4. ERG calculated onroad and nonroad reductions in criteria air pollutants using New Mexico–specific emission factors derived from the latest release of the Motor Vehicle Emission Simulator (MOVES5) and BRG's fuel volume changes between scenarios.

Most of the emission benefits that reduce nitrogen oxides (NOx), fine particulate matter (PM2.5), sulfur dioxide (SO2), and volatile organic compounds (VOCs) are a result of increased renewable diesel (R100) adoption to offset decreased fossil diesel consumption in New Mexico over time, as shown in Table 1-3. To a lesser degree, increases in biodiesel blends (5 percent biodiesel, or B5, in this case) also offset fossil diesel and result in emission benefits—though there is a slight NOx disbenefit for legacy diesel engines running on B5. Emission benefits for the final rule are somewhat greater than for the draft rule due to dampened electrification curves in the NMVES scenario, leading to more RD and BD consumption in the CTFP scenario.[3]

[3] New Mexico Environment Department, "Clean Transportation Fuel Program," accessed July 3, 2025, https://www.env.nm.gov/climate-change-bureau/clean-fuel-program/.

Table 1-3. Summary of annual emission reductions through 2050 by pollutant and policy scenario (negative values equate to reductions in tons)

	NO_x		VOC		$PM_{2.5}$		SO_2	
Year	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**
2026	-9.12	-9.12	-38.39	-38.39	-26.76	-26.76	0.09	0.09
2027	-88.30	-22.54	-64.53	-38.56	-27.73	-26.65	-1.97	0.08
2028	-115.16	-37.73	-73.92	-40.01	-28.93	-27.56	-2.34	0.06
2029	-140.75	-52.08	-88.02	-45.30	-35.26	-33.59	-2.75	0.05
2030	-147.49	-47.73	-86.10	-37.70	-31.52	-29.64	-3.02	0.03
2031	-179.24	-41.20	-109.55	-32.55	-27.89	-25.79	-3.71	0.03
2032	-209.47	-34.48	-130.46	-27.32	-24.17	-21.87	-4.34	0.03
2033	-228.22	-16.78	-146.48	-15.95	-15.70	-13.17	-5.01	0.05
2034	-251.79	-4.43	-166.81	-7.54	-9.43	-6.66	-5.72	0.06
2035	-278.77	2.26	-184.36	-2.29	-5.46	-2.51	-6.26	0.08
2036	-294.77	0.00	-211.00	0.00	-2.96	0.00	-6.75	0.00
2037	-308.30	0.00	-239.11	0.00	-2.98	0.00	-7.14	0.00
2038	-321.36	0.00	-265.15	0.00	-2.99	0.00	-7.50	0.00
2039	-333.89	0.00	-288.71	0.00	-2.99	0.00	-7.80	0.00
2040	-345.19	0.00	-306.37	0.00	-2.96	0.00	-7.99	0.00
2041	-348.39	0.00	-319.06	0.00	-2.97	0.00	-8.12	0.00
2042	-351.75	0.00	-332.32	0.00	-3.00	0.00	-8.27	0.00
2043	-355.95	0.00	-349.74	0.00	-3.04	0.00	-8.51	0.00
2044	-360.97	0.00	-371.28	0.00	-3.10	0.00	-8.83	0.00
2045	-366.45	0.00	-395.23	0.00	-3.17	0.00	-9.20	0.00
2046	-372.57	0.00	-422.62	0.00	-3.26	0.00	-9.63	0.00
2047	-378.82	0.00	-450.82	0.00	-3.34	0.00	-10.08	0.00
2048	-384.62	0.00	-476.72	0.00	-3.42	0.00	-10.47	0.00
2049	-388.34	0.00	-491.54	0.00	-3.45	0.00	-10.66	0.00
2050	-392.09	0.00	-506.55	0.00	-3.49	0.00	-10.86	0.00

Chapter 4 has a full discussion of MOVES emissions modeling, fuel effects from recent literature, and ERG's projections of criteria pollutant reductions for the combined NMVES and CTFP policies and the CTFP policy itself.

1.3 Avoided Health Damages

Even though GHG emissions and FSE credits contribute a larger proportion of the benefits in this rule, improved air quality and health outcomes from emission reductions should be acknowledged. Based on the projected reductions to criteria air pollutants in tailpipe exhaust from onroad vehicles and nonroad equipment, ERG was able to model health benefits with the U.S. Environmental Protection Agency's (EPA's) Co-Benefits Risk Assessment (COBRA) tool as avoided health damages. These damages include acute respiratory symptoms and respiratory disease that lead to hospitalizations and lost productivity, as shown in Table 1-4.

Table 1-4. Cumulative avoided incidence for CTFP-only and CTFP and NMVES scenarios

Health Outcome Category	Cumulative Avoided Incidence for CTFP-Only Scenario	Cumulative Avoided Incidence for CTFP and NMVES Scenario
Total mortality (low estimate)	0.6	2.0
Total mortality (high estimate)	1.2	2.8
Total asthma symptoms	336.7	1,462.8
Total asthma onset	1.9	8.9
Total emergency room visits	0.7	3.0
Total hospital admittance	0.4	0.6
Total onset	12.6	59.4
Minor restricted activity days	353.0	466.4
Work loss days	59.9	79.0
School loss days	58.6	712.9

In addition to these avoided health incidence values, COBRA monetizes damages to calculate health benefits. As in ERG's emissions analysis, Table 1-5 compares health benefits over time for the combined NMVES and CTFP policies and the CTFP alone. In early CTFP years, the CTFP constitutes a majority of health benefits, but the NMVES contribute more benefits cumulatively to the combined policies, especially after 2030.

Table 1-5. Annual health benefits by policy scenario through 2040 (in million 2024 USD)

Calendar Year	**$ Total CTFP-Only Health Benefits** (lower-upper bound)	**$ Total Combined NMVES + CTFP Health Benefits** (lower-upper bound)
2026	$1.1–$2.1	$1.1-$2.1
2027	$1.2–$2.3	$1.7-$2.9
2028	$1.4–$2.5	$2.0-$3.3
2029	$1.8–$3.4	$2.5-$4.2
2030	$1.6–$3.1	$2.5-$4.0
2031	$1.5–$2.7	$2.6-$4.0
2032	$1.3–$2.4	$2.8-$4.0
2033	$0.8–$1.4	$2.6-$3.5
2034	$0.4–$0.7	$2.5-$3.1
2035	$0.1–$0.2	$2.7-$3.1
2036	—	$2.7-$3.1
2037	—	$2.9-$3.2
2038	—	$3.1-$3.4
2039	—	$3.2-$3.6
2040	—	$3.5-$3.9
Cumulative	**$11.0–$20.8**	**$38.2-$51.5**

For further information on health effects, please refer to Chapter 5, which describes ERG's COBRA modeling for both policy scenarios in greater detail and elaborates on COBRA's derivation of health outcomes and their monetization.

1.4 Macroeconomic Impacts

Beyond emission reductions and health benefits, New Mexico's CTFP is expected to impact fuel markets in the state and regionally. To model the program's macroeconomic impacts, ERG employed the Impact Analysis for Planning (IMPLAN) model for input-output (I-O) analysis. Within this I-O analysis, ERG evaluated two cases: one case assuming 0 percent passthrough, where industry absorbs any increased cost of fuel production due to the CTFP, and another case assuming 100 percent passthrough, where consumers bear any fuel price increases related to the program. These represent edge cases, and they have been averaged to create a 50 percent passthrough for the final CTFP benefit-cost analysis (BCA).

IMPLAN accounts for various economic effects to fuel producers and adjacent industries: direct, indirect, and induced. There are a number of direct CTFP effects each year, particularly fuel credits and deficits generated, FSE credits and renewable energy credit (REC) retirements, banking impacts of reduced fossil fuel activities, import costs for biofuels (renewable diesel and biodiesel blends especially), and health and productivity effects. Based on these IMPLAN inputs for direct program effects, the model can estimate any indirect and induced effects. All aforementioned model inputs—including jobs stemming from FSE credits—have been supplied through BRG's separate market analysis, aside from the health effects as previously discussed.

ERG summarized annual direct, indirect, and induced costs related to credit and deficit generation in New Mexico's clean fuels market in Table 1-6 and Table 1-7, respectively.

Table 1-6. Direct and secondary impacts annually for 0 percent passthrough (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$8,993,861	-$5,485,195	$124,823
2027	-$17,326,704	-$9,790,960	-$214,940
2028	-$30,092,303	-$16,500,201	-$682,904
2029	-$71,471,707	-$38,608,656	-$3,274,056
2030	-$155,628,931	-$81,800,091	-$10,969,552
2031	-$112,096,241	-$59,197,574	-$7,112,908
2032	-$76,949,450	-$40,904,457	-$4,104,839
2033	-$53,221,357	-$28,498,766	-$2,215,072
2034	-$45,057,933	-$24,351,255	-$1,206,016
2035	-$38,389,883	-$20,974,485	-$348,094

Table 1-7. Direct and secondary impacts annually for 100 percent passthrough (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$11,585,837	-$4,090,019	-$3,143,083
2027	-$25,335,412	-$10,107,821	-$7,319,490
2028	-$46,187,213	-$19,087,533	-$13,596,993
2029	-$106,126,311	-$41,538,844	-$30,352,982
2030	-$191,666,349	-$73,203,716	-$54,121,634

Year	Direct	Indirect	Induced
2031	-$135,586,427	-$54,802,606	-$39,443,278
2032	-$90,561,617	-$39,631,864	-$27,506,225
2033	-$60,628,172	-$29,092,864	-$19,396,445
2034	-$55,156,721	-$28,054,230	-$18,293,829
2035	-$39,763,688	-$24,453,206	-$14,781,475

Similarly, ERG summarized CTFP benefits modeled through IMPLAN, namely from direct jobs from FSE credits and improved health outcomes, in Table 1-8 and Table 1-9, respectively.

Table 1-8. Annual CTFP results from job creation through FSE credits (in 2024 USD)

Year	Direct	Indirect	Induced
2027	$12,436,042	$2,757,102	$2,587,195
2028	$17,729,622	$3,959,808	$3,702,316
2029	$21,338,555	$4,800,605	$4,472,471
2030	$8,005,849	$1,892,714	$1,721,567
2031	$12,144,437	$2,825,715	$2,589,915
2032	$12,398,228	$2,906,704	$2,654,473
2033	$12,649,566	$2,987,056	$2,718,477
2034	$12,898,514	$3,066,782	$2,781,938
2035	$9,996,850	$2,447,912	$2,189,898
2036–2040	$2,949,311	$902,421	$731,797

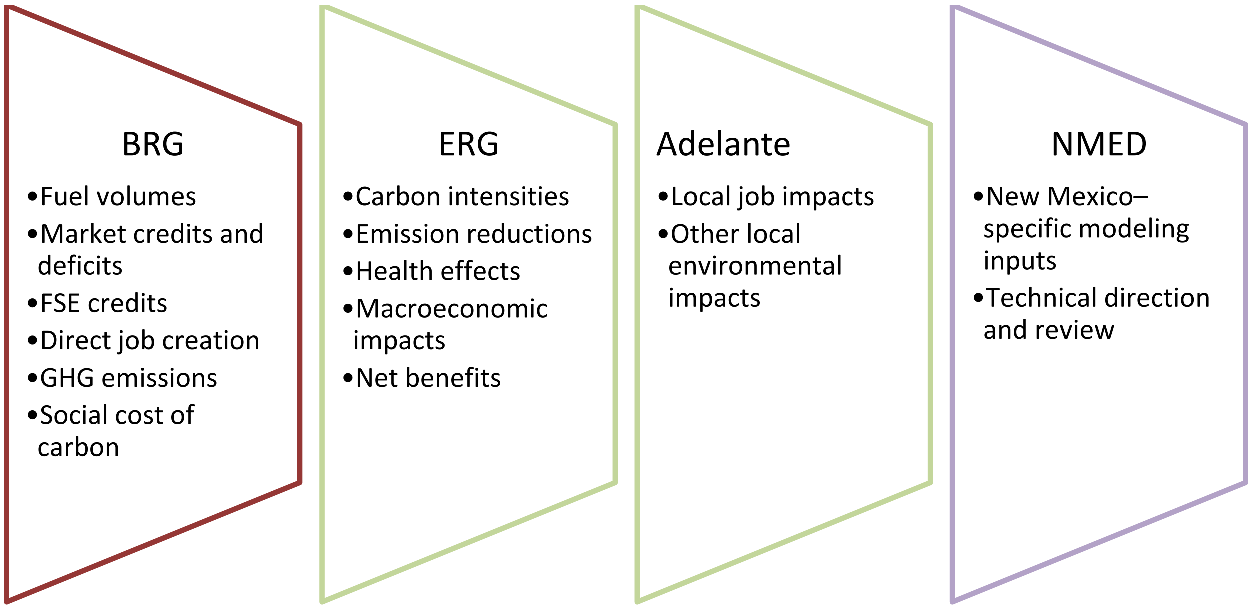
Table 1-9. Annual direct and secondary CTFP health impacts (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$16,070	-$4,940	-$4,057
2027	-$19,859	-$6,105	-$5,391
2028	-$24,795	-$7,622	-$7,069
2029	-$33,474	-$10,290	-$9,621
2030	-$30,702	-$9,438	-$8,854
2031	-$27,176	-$8,354	-$7,830
2032	-$23,399	-$7,193	-$6,732
2033	-$13,216	-$4,063	-$3,719
2034	-$5,614	-$1,726	-$1,485
2035	-$1,048	-$322	-$157

Importantly, the only BCA component that ERG did not model explicitly was GHG benefits, which BRG supplied from its calculation of GHG emissions and the social cost of carbon. Most of the rule's net benefits come from these GHG reductions. Please refer to Chapter 5 for a detailed discussion of IMPLAN I-O modeling and the CTFP's macroeconomic impacts.

To better visualize the full delegation of CTFP analysis responsibilities between BRG, ERG, and the New Mexico Environment Department (NMED), see Figure 1-1 below.

Figure 1-1. Delegation of CTFP analysis responsibilities between BRG, ERG, and NMED



The first chapter in this report provides the regulatory context for New Mexico's clean fuels program, introductions to similar programs in other states, and an overview of ERG's CTFP modeling and analysis across the four focus areas highlighted in this executive summary.

2. Introduction

2.1 Overview of New Mexico's Clean Transportation Fuel Program

In 2024, the passage of the New Mexico Clean Transportation Fuel Standard (CTFS) codified the creation of its Clean Transportation Fuel Program (CTFP) under New Mexico Statutes Annotated (NMSA) 1978, Sections 74-1-3, 7(A)(15), 8(A)(16), and 18.[4] The CTFP as proposed would curtail greenhouse gas (GHG) emissions from the transportation sector, which is currently the state's second-largest GHG source, behind only the oil and gas industry.[5] The CTFP will lower the overall carbon intensity (CI) of the state's transportation fuel supply by setting a target CI each year for gasoline and gasoline substitutes, diesel and diesel substitutes, and alternative jet fuel. These annual targets establish the schedule for annually decreasing CI for transportation fuel produced, imported, or dispensed in New Mexico, and constitute the CTFS also referred to as "the standard." The CTFP establishes rules, measures, and procedures to enforce and achieve the CI reduction targets of 20 percent and 30 percent below a 2018 baseline by 2030 and 2040, respectively. These targets are statutorily mandated under Section 75-1-18(C)(1) NMSA 1978. The CTFP will also stimulate economic growth, improve health outcomes, create jobs, and promote more fueling options within the state.[6]

The CTFP establishes methods to determine the CI of each transportation fuel on a "well-to-wheel" (WTW) basis using lifecycle analysis (LCA) methods detailed in Chapter 3. Each transportation fuel's "well to wheel" CI represents emissions produced through the full path of a transportation fuel, including the production and processing of the fuel and its feedstocks, as well as fuel and feedstock transportation, storage, and consumption or use. The CTFP objectively determines CIs for each transportation fuel pathway solely from its lifecycle GHG emissions per energy unit, based on observable data, with no inherent preference given to one transportation fuel over another. In this way, New Mexico's CTFP implementation mechanisms are technologically neutral (i.e., fuel agnostic), as required under Section 75-1-18(C)NMSA 1978. Under the CTFP, regulated parties that produce, import, or dispense transportation fuel for use in New Mexico receive credits and deficits based on each fuel pathway's CI compared to the annual standard. Regulated parties will receive credits or deficits for transportation fuel pathways with CIs that are, respectively, below or above the standard each year. Regulated parties may buy and sell CTFP credits each year to ensure that they meet their "compliance obligation" of fully offsetting all deficits with credits each compliance period.

New Mexico would be the fourth U.S. state to adopt a clean fuels program. Similar policies exist in three West Coast states: California, Oregon, and Washington. California became the first state to enact a clean fuel program, approving its Low Carbon Fuel Standard in 2009 and opening its credit

[4]"New Mexico Statutes Annotated (NMSA) 1978," § 74-1-3, 7(A)(15), 8(A)(16), 18 (1978), https://nmonesource.com/nmos/nmsa/en/item/4415/index.do#a1.

[5] New Mexico Environment Department, "NMED Releases Draft Rule for Clean Fuel Program," News Release, December 19, 2024, https://www.env.nm.gov/wp-content/uploads/2024/12/2024-11-19-COMMS-NMED-releases-draft-rule-for-clean-fuel-program-FINAL.pdf.

[6] New Mexico Environment Department, "Clean Transportation Fuel Program," accessed July 3, 2025, https://www.env.nm.gov/climate-change-bureau/clean-fuel-program/.

market in 2011.[7] Oregon's legislature also authorized its Clean Transportation Fuel Program in 2009 but did not fully implement its regulation until 2016.[8] Most recently, Washington adopted legislation to create its own Clean Fuel Standard in 2021 and began implementation in 2023.[9]

In developing the proposed rule, the New Mexico Environment Department (NMED) contracted Eastern Research Group, Inc. (ERG) to develop CI values for different fuels and pathways. As highlighted in Figure 1-1. NMED assisted ERG with state-specific CI assumptions, as well as technical direction and review. With guidance and input from NMED, ERG calculated fuel pathway CI values using a custom version of Argonne National Laboratory's Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) for research and development (R&D). In model development, ERG adjusted parameters and methods within the default GREET R&D's use for evaluating transportation fuels in New Mexico's CTFP—this customized model will subsequently be referred to as NM-GREET. In particular, NM-GREET incorporates fuel parameter adjustments to better reflect local conditions, and methodological adjustments to align calculations with New Mexico's more conservative approach to determining certain fuel pathway CIs relative to defaults.

New Mexico engaged many experts in crafting the CTFP, including its own staff, staff from other states, and contractors across multiple disciplines: LCA, clean fuels, emissions, and economics.

2.2 Overview of Report Contents

This report discusses how the ERG team developed transportation fuel CIs, emission reductions, avoided health damages, and macroeconomic impacts for New Mexico's CTFP. Each CTFP analysis area is addressed in a subsequent chapter of the report, laying out the ERG team's application of the latest research and modeling tools for this rule. An overview of chapters and analysis methods can be found below.

2.2.1 Fuel Carbon Intensities

To determine the CI of transportation fuels produced and imported into the state, ERG defined parameters for a New Mexico–specific version of GREET for the CTFP, which included crude oil adjustments from the Oil Production Greenhouse gas Emissions Estimator (OPGEE), and performed a lifecycle analyses. This NM-GREET tool assesses the environmental impacts of New Mexico transportation fuels on a WTW basis.[10] The CI values from NM-GREET were incorporated into a key lookup table in the rule.

[7] California Air Resources Board, "Low Carbon Fuel Standard 2023 Amendments: Standardized Regulatory Impact Assessment (SRIA)," September 8, 2023, https://ww2.arb.ca.gov/sites/default/files/2023-09/lcfs_sria_2023_0.pdf.

[8] U.S. Department of Energy, "Clean Transportation Fuel Standards," Alternative Fuels Data Center, accessed May 20, 2025, https://afdc.energy.gov/laws/6606.

[9] Clean Fuels Alliance America, "Washington Clean Fuel Standard Achieves Impressive First Quarter Results," October 4, 2023, https://cleanfuels.org/washington-clean-fuel-standard-achieves-impressive-first-quarter-results/.

[10] U.S. Department of Energy, "GREET," accessed May 20, 2025, https://www.energy.gov/eere/greet.

2.2.2 Projected Emission Reductions

ERG performed mobile source emission modeling to quantify the CTFP's impact on harmful criteria air pollutants from onroad vehicles and nonroad equipment. To estimate onroad and nonroad emissions, ERG ran the Motor Vehicle Emission Simulator (MOVES), the regulatory emissions inventory model developed by the U.S. Environmental Protection Agency.[11] For the CTFP, ERG utilized MOVES results to derive New Mexico–specific emission factors (EFs). Both EFs and fuel volume projections (estimated instead by BRG) were paired to calculate onroad and nonroad emission reductions for following criteria air pollutants known to contribute to adverse human health impacts:

- Volatile organic compounds (VOCs)
- Nitrogen oxides (NO_x)
- Particulate matter (PM)
- Sulfur dioxide (SO_2)

Projected emission reductions from switching to lower-carbon fuels were then employed to determine avoided health damages and monetized to estimate benefits. Modified versions of the MOVES outputs helped inform CTFP vehicle population, vehicle miles traveled (VMT), and fuel economy data being developed by BRG for its fuel projections.

2.2.3 Avoided Health Damages

Avoided health damages modeling was performed to estimate the health outcomes and monetized benefits associated with criteria air pollutants and precursor emission reductions from New Mexico's CTFP. The earlier projected emission reductions were input into the U.S. Environmental Protection Agency's (EPA's) CO-Benefits Risk Assessment (COBRA) screening model to estimate the change in ambient pollutant concentrations from various fuels on statewide human health impacts.[12] COBRA provides estimations for the monetary value of a wide range of health outcomes. Some COBRA inputs, such as projected human populations, were tailored to New Mexico.

2.2.4 Macroeconomic Impacts

Both direct and second-order economic effects from New Mexico's CTFP were calculated using the Impact Analysis for Planning (IMPLAN) economic analysis platform for input-output (I-O) modeling.[13] To determine the macroeconomic effects of this program, ERG ran a series of economic impact analyses (EIAs) in IMPLAN. The credit market and direct job projections from BRG, along with avoided health damages from COBRA, were used as inputs to the I-O model to calculate statewide impacts for the benefit-cost analysis of New Mexico's program.

[11] U.S. Environmental Protection Agency, "MOVES and Mobile Source Emissions Research," accessed May 20, 2025, https://www.epa.gov/moves.

[12] U.S. Environmental Protection Agency, "What Is COBRA?," accessed May 20, 2025, https://www.epa.gov/cobra/what-cobra.

[13] IMPLAN, "IMPLAN," accessed May 20, 2025, https://implan.com/.

3. Fuel Carbon Intensities

This chapter details how the NM-GREET v1.0 model was derived from R&D GREET version 2023-rev1 in order to best reflect the expected characteristics, supply chains, and resulting CIs of transportation fuels sold in the state of New Mexico.

3.1 Background

The CTFP—much like programs in other jurisdictions—relies on WTW LCA modeling of transportation fuels to calculate their lifecycle CIs. For each fuel pathway, GHG species emitted during each stage of the fuel's lifecycle are normalized to their carbon dioxide equivalent (CO_2e) mass via IPCC AR5 GWP100[14] factors, summed together, and then divided by the fuel's energy content given in megajoules (MJ).[15] The fuel's energy content is defined in two ways: as the lower-heating-value (LHV) heat of combustion for liquid and gaseous fuel and as the delivered quantity of energy at a given outlet (charging station, home outlet, etc.) for electricity. A fuel's CI is thereby quantified in the composite units of grams CO_2e per megajoule (g CO_2e/MJ).

To calculate WTW fuel-pathway CI scores, the CTFP relies on the **G**reenhouse gases, **R**egulated **E**missions and **E**nergy use in **T**ransportation (GREET) model, published by the Systems Assessment Center of the U.S. Department of Energy's Argonne National Laboratory (ANL).[16] GREET is widely recognized and applied in regulatory settings for its comprehensiveness and flexibility, as well as the continual support and refinement it receives from both ANL and its global user base. At New Mexico's request, ERG developed NM-GREET v1.0 (i.e., the NM-GREET_v1.0.xlsm workbook) from the latest available release of R&D GREET as of fall 2024 when the development cycle began: R&D GREET 2023-rev1.[17] The "R&D" version of GREET is the main development version from which other federal and state regulatory versions, like 45V GREET and the California-modified GREET model (CA-GREET), are typically adapted.

Fuel pathways developed in NM-GREET by ERG and detailed in this report are included in either the rule's Lookup Table or Temporary Pathway Table. A pathway in GREET can be defined as a sequence of material and energy commodities exchanged by unit processes—i.e., extractive operations, processing facilities, transportation modes, storage structures, dispensing stations, highway and nonroad vehicle use—and specific technologies therein, all terminating in the production of one unit of an energy commodity of interest, or in the operation of a vehicle over some distance or trip with defined cargo (either people or goods).

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[14] IPCC AR5 GWP100 factors are global warming potential values for a 100-year time horizon, taken from the Intergovernmental Panel on Climate Change's Fifth Assessment Report.

[15] Gunnar Mhyre et al., "Anthropogenic and Natural Radiative Forcing," in *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. Thomas F. Stocker et al. (Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2013), https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter08_FINAL.pdf.

[16] U.S. Department of Energy, "GREET," accessed May 20, 2025, https://www.energy.gov/eere/greet.

[17] Michael Wang et al., "Development of R&D GREET 2023 Rev1 to Estimate Greenhouse Gas Emissions of Sustainable Aviation Fuels for 40B Provision of the Inflation Reduction Act" (Argonne National Laboratory, April 1, 2024), https://doi.org/10.2172/2348933.

3.2 Modeling Approach

This chapter serves as the technical documentation for the data sources and methods by which NM-GREET v1.0 was adapted from the GREET1 Excel workbook of the 2023-rev1 release of R&D GREET. NM-GREET's development and core components share many similarities with the approaches leveraged by other jurisdictions in their own adaptations of state-specific GREET models, derived from CA-GREET and/or R&D GREET. Because GREET generally reflects U.S. conditions, values for key GREET and external-model parameters were chosen and implemented to best reflect the typical lifecycle CIs and associated upstream supply chain activities of CTFP fuels sold in New Mexico (both produced in-state and imported).

This chapter summarizes both global parameter settings (i.e., those that affect all pathways) and common design patterns used to develop stagewise GHG emissions across pathways. Taken together, these summaries, the external data sources detailed later in Section 3.2.3, and the pathway-specific parameters discussed in their respective sections collectively serve as a recipe for recreating NM-GREET v1.0 from scratch. Wherever possible, ERG prioritized transparency, readability, and reproducibility. Not only do these principles benefit interested stakeholders during the initial cycles of model development and public comment: they also help to minimize technical debt and streamline model updates in the years to come.

From GREET1 2023-rev1's "release-default" state (i.e., a freshly downloaded copy from ANL),[18] the modifications ERG made to construct NM-GREET fall into two categories: adding new tabs and parameterization (i.e., altering the contents of cells on release-default GREET1 tabs). ERG stored the details of each parameter on a new tab named *Parameters_NM*. Two more new tabs are present in NM-GREET—*Results_NM* and *CI_Table*—on which formulas to quantify the stagewise emissions of GHG species by pathway are developed and subsequently aggregated into WTW CI totals. For each of the lookup and temporary fuel pathways detailed here, any external model and/or data source used to parameterize NM-GREET and refine its CI score has been referenced accordingly.

3.2.1 Parameters

GREET is a parametric LCA model, in which the magnitudes of material and energy flows within and between unit processes are defined by formulas and input parameters rather than static scalar estimates. For each parameter, GREET contains a release-default value—typically chosen to best reflect a U.S.-national-average representation of said parameter. In composing statewide-average estimates of the typical CIs and upstream supply chain activities of transportation fuels sold in New Mexico (both produced in state and imported), New Mexico–specific parameters were included when possible; the national-average default selections were used when New Mexico–specific parameters were unavailable.

In NM-GREET, parameter alterations can be broken down into three categories based on which pathways' CI values they affect. A parameter affects either (1) every pathway, (2) a subset of pathways with some shared attribute (e.g., any fuel derived from animal waste [AW] biomethane), or (3) just a single pathway. A parameter is defined here as "significantly affecting" a pathway if changing it from GREET1's release-default value to the NM-GREET value causes the CI of said pathway to change by at least ± 0.1 g CO_2e/MJ. To delineate which NM-GREET parameter alterations

[18] Argonne National Laboratory, "GREET1 2023r1," April 30, 2024, https://greet.anl.gov/files/greet-2023rev1.

affect which pathways and how, the full table of said alterations on the *Parameters_NM* tab is reorganized into many separate tables within this report.

These separated parameters tables are embedded at different hierarchical levels of this chapter's sections to reflect which pathway or group thereof is significantly affected by a given parameter. If a parameter significantly affects only a single pathway, it is described in a parameter table within that pathway's subsection. If a parameter significantly affects multiple pathways, it is described in a table within a parent section containing each of those pathways. If a parameter significantly affects every pathway (i.e., is a "global" parameter), it is listed below in Table 3-1 or detailed in a subsection of Section 3.2.3. Putting these rules together, a single-pathway section without a parameter table is therefore only significantly affected by global parameters and those listed in tables of its parent section(s), if present.

Table 3-1. NM-GREET parameters affecting all pathways

Parameter	Value		GREET Label	Description
	Default	NM		
Year	2022	2022	Target Year for Simulation	Per NMED's Climate Change Bureau
GWP_of_ GHG_Ref	AR6/ GWP	AR5/ GWP	AR Edition/Type	Global warming potential of GHGs (g CO_2e)

All of this report's parameter tables, like the one above, share formatting and field conventions with NM-GREET's *Parameters_NM* table. The "Parameter" column contains the address—and thereby also the identity—of a parameter, given as either a <sheet>!<A1-cell> style reference or a named range identifier (e.g., the "Year" named range sets the GREET model year). The "Default" and "NM" value columns contain the release-default and altered, New Mexico–specific parameter values. The "GREET Label" column provides context for how GREET defines the parameter. Lastly, the "Description" column adds context and/or justification for how the "NM" value was chosen.

Note that in addition to the NM-GREET_v1.0.xlsm workbook, ERG derived a "baseline" version (the NM-GREET_v1.0_baseline.xlsm workbook) with one difference: the "Year" parameter is set to 2018 instead of 2022. This difference affects GREET's collections of time-series parameter estimates (i.e., on tabs named with the _TS suffix), formatted as arrays of both historical and projected values across 1990–2050. Crucially, GREET's "Year" (i.e., "Target Year for Simulation") model-year parameter indexes the selection of each and every one of its time-series parameters, making it by far the most influential parameter choice in the entire model. At the request of NMED's Climate Change Bureau, ERG kept the "Year" parameter of NM-GREET v1.0 set to GREET1 2023-rev1's release-default value of 2022, representing the most current non-projected data in the model. Note that the majority of tables on GREET's **_TS* tabs contain only base-five year indices, such that setting "Year" to 2022 causes GREET to round down to the nearest base-five year—2020—when values are chosen from those tables.

IPCC AR5 100-year global warming potential (GWP) values were chosen via the "GWP_of_GHG_Ref" parameter to convert masses of emitted GHG into CO_2e masses. By default, GREET assumes carbon monoxide (CO) and VOCs will oxidize into CO_2 in the atmosphere, which is why it incorporates the "CO_2 (w/ C in VOC & CO)" indicator rather than solely "CO_2" into its calculation of total GHG emissions. For both CO and VOCs, GREET multiplies the emitted mass of each species by its carbon mass fraction (i.e., g carbon/g species, labeled as "Carbon ratio of [species]"), then divides by the mass of carbon in CO_2 in order to derive said species' CO_2e GWP mass:

$$GWP_{species}\left[\frac{g\ CO_2e}{g\ species}\right] = m_{C,species}\left[\frac{g\ C}{g\ species}\right] / m_{C,CO_2}\left[\frac{g\ C}{g\ CO_2}\right] \qquad \textbf{Equation 3-1}$$

GREET repeatedly performs this same calculation within each "CO_2 (w/ C in VOC & CO)" result cell, but ERG avoids this redundancy on the *Results_NM* tab by pre-calculating the resulting GWP factors for both VOCs—which GREET uniformly approximates as being 85 percent carbon by mass—and CO. The resulting, composite set of IPCC-sourced and GREET-specific GWP factors is presented in Table 3-2.

Table 3-2. NM-GREET GWP factors (from AR5)

GWP100 Factors ($g\ CO_2e/g$ species)	
Species	**Value**
CO_2	1
CH_4	30
N_2O	265
VOCs	3.12
CO	1.57

Finally, while GREET is predominantly an attributional LCA (ALCA) model, it also includes consequential LCA (CLCA) elements, as outlined in the recent National Academies report on LCA and low carbon fuel standard programs.[19] Some CLCA elements can be controlled via GREET's parameters, such as whether co-products are accounted for via system expansion (i.e., exporting a co-product directly to another firm or into a marketplace, leading to an assumed one-to-one reduction in production elsewhere). Other CLCA elements—namely counterfactual scenario emissions credits—are not yet controllable via parameters, instead requiring GREET users to rewrite formulas if they wish to exclude or disaggregate the effect of those elements.

In tailoring R&D GREET into NM-GREET, ERG avoided system expansion wherever possible, since one-to-one substitution (also known as "displacement" in LCA) is not empirically supported by economic modeling or data. Instead, market-based allocation—wherein the burdens of a process are distributed across its co-products according to their relative economic value—is given preference, in part to stay "consistent with the aims of market-based [public programs] to reducing emissions" like the CTFP.[20] Additionally, GREET's instances of mass-based allocation often do not account for significant differences in the composition (e.g., protein content) and utility of co-products, and its energy-based allocation does not consider the energy commodities' entropic

[19] National Academies of Sciences, Engineering, and Medicine, *Current Methods for Life-Cycle Analyses of Low-Carbon Transportation Fuels in the United States* (Washington, DC: The National Academies Press, 2022), https://doi.org/10.17226/26402.

[20] National Academies of Sciences, Engineering, and Medicine, *Current Methods for Life-Cycle Analyses of Low-Carbon Transportation Fuels in the United States* (Washington, DC: The National Academies Press, 2022), https://doi.org/10.17226/26402.

states (i.e., heat is far less useful than electricity) or their logistical constraints (e.g., transporting and storing electricity poses different challenges than a liquid fuel does).

3.2.2 Results

The *Results_NM* tab contains the definitions of NM-GREET pathways and stages of activity therein, including metadata mappings between GREET1 (i.e., tab, section header, and stage header) and the New Mexico pathway (i.e., ID, name, stage, stage category) as well as formulas to estimate the emitted quantities of GHG species within each pathway-stage. In each column of *Results_NM*, the set of "Source," "GREET Tab," "GREET Section," and "GREET Stage" fields together serve as a pointer to the location—within or external to GREET1—on which the subsequent GHG-emissions formulas primarily rely. For example, column D of *Results_NM* estimates the GHG emissions from onroad combustion of clear gasoline. ERG developed these formulas by combining elements from the per-distance and per-energy "Vehicle Operation" formulas of the *Results* tab. However, since both the *Results_NM* column D and *Results* vehicle operation formulas both primarily rely on values from the *Vehicles* tab, the "GREET Tab" field points to *Vehicles* rather than *Results*.

To define the scope of fuel pathways, ERG adhered to GREET's nomenclature and definitions of lifecycle stages: "Feedstock" production, "Fuel" processing, and "On-Road" vehicle emissions. These three core stages are reused across all pathways in NM-GREET and this report, but the specific supply-chain activities within each stage vary by pathway. Furthermore, pathways with agricultural crop feedstocks also include a separate "ILUC" stage for indirect land use change, as detailed below in Section 3.2.3. For all biological-feedstock fuel pathways, ERG disaggregated and lists "Biogenic CO_2 Uptake" as a separate stage in this report, but on the *Results_NM* tab these emissions are incorporated into the On-Road stage. Finally, once the stagewise CIs defined on *Results_NM* are calculated, those results are aggregated on the *CI_Table* tab into well-to-pump and pump-to-wheel subtotals and finally a WTW total CI for each pathway. The well-to-pump subtotal is defined as the sum of stagewise CIs from feedstock, fuel, and ILUC; pump-to-wheel is the sum of on-road and, wherever present, biogenic CO_2 uptake.

Two key patterns are reused across formulas developed on *Results_NM*:

- **Using loss factors to normalize GHG emissions to the energy content of fuel delivered to a vehicle.** As on GREET1's *Results* tab, GHG emissions formulas on *Results_NM* incorporate stagewise loss factors—themselves often calculated as composites of loss factors for specific activities within a stage. Scaling emissions by these factors ensures that results can be added across stages. For example, absent this scaling, emissions from fossil clear gasoline's Feedstock stage would have units of g CO_2e/MJ of crude oil at refinery rather than MJ of gasoline at pump, and thus could not be aggregated into a WTW CI.
- **Accounting for biogenic CO_2 uptake and reemission via the -1/+1 method.** For biogenic CO_2 emissions, ERG followed the GREET convention of applying the -1/+1 method, given that all of NM-GREET's biofuel pathway feedstock crops have short growth cycles (i.e., no woody biomass feedstocks are modeled). This method represents CO_2 sequestration during plant growth as a negative emission, followed by positive emissions wherever the biogenic carbon atoms are re-released to the atmosphere as CO_2—primarily upon fuel combustion. However, the sequestered and re-released CO_2 quantities are not always identical: the -1/+1 method also considers the different impacts of biogenic carbon embedded in non-CO_2 emissions such as CH_4. Emissions of biogenic CH_4 are treated identically to fossil CH_4 in GREET.

Finally, in order to ensure that the CI scores of temporary pathways (Table 5 in the NM CTFP rule) represent conservative estimates, other states' LCFS programs have all adopted a standard routine for calculating said scores. For each unique category of temporary fuel pathways (e.g., compressed biomethane from landfills), find the maximum CI score among submitted Tier 1 and 2 applications for that pathway. With this maximum CI as an input, multiply it by 105% and round up to the nearest base-5 integer in order to yield that pathway category's temporary CI. This routine can be more succinctly represented via the following formula:

$$y = ceiling\left(\frac{x * 1.05}{5}\right) * 5\text{ , } where\ y = CI_{temporary}\ and\ x = CI_{max} \qquad \textbf{Equation 3-2}$$

Since NMED does not yet possess a collection of Tier 1 and 2 pathway applications from which to sample these pathway-maximum CI values, ERG instead used NM-GREET to estimate "Total" pathway CIs as the inputs (x) to this formula. The "Adjusted Total" outputs (y) are then the resulting CIs embedded in Table 5 of the rule.

3.2.3 Key Assumptions

Results from select external models are incorporated into NM-GREET in order to best represent the fuel sold within New Mexico, as well as to mitigate limitations in R&D GREET's model scope and data resolution. These results fall into three categories: ILUC, crude oil supplied to Petroleum Administration for Defense District 3 (PADD3), and national-average manure methane emissions.

3.2.3.1 Indirect Land-Use Change

In order to estimate the GHG emissions resulting from indirect land-use change (ILUC) arising from additional demand for biological-crop-derived fuels in NM-GREET, NMED and ERG adopt and reuse the ILUC factors developed by the California Air Resources Board (CARB) for CA-GREET.[21]

Table 3-3. ILUC CIs

Fuel Pathway	ILUC Value ($g\ CO_2e/MJ$)
Corn ethanol	19.8
Sorghum ethanol	19.4
Sugarcane ethanol	11.8
Soybean biodiesel or renewable diesel	29.1
Canola biodiesel or renewable diesel	14.5
Palm biodiesel or renewable diesel	71.4

Given the complexity of ILUC modeling, the absence of scientific consensus on model structure and parameterization, and the still-sizable uncertainty ranges surrounding ILUC factors calculated by an array of prominent models, NMED and ERG opted to reuse CARB's 2015 ILUC analysis and resulting factors. Performing novel ILUC analysis requires significant time and effort in order to achieve accuracy, and even then, the resulting ILUC factors arrive with substantial quantitative uncertainty. Given the limited time and resources available to NMED and its supporting contractors in preparing the proposed rule, NMED opted to adopt ILUC factors used across multiple existing

[21] California Air Resources Board, "Detailed Analysis for Indirect Land Use Change," 2015, ww2.arb.ca.gov/sites/default/files/classic/fuels/lcfs/iluc_assessment/iluc_analysis.pdf.

LCFS programs rather than compose a new NM-specific ILUC analysis (or meta-analysis, comparing multiple models) and resulting factors. NMED and ERG recognize that CARB's ILUC factors are not the most recently published, but nonetheless chose to use them for the following reasons:

- CARB's ILUC assessment was conducted by a regulatory body with (1) extensive expert review and (2) robust stakeholder input via a transparent, rigorous engagement process.
- The International Council on Clean Transportation (ICCT) recommended reusing CARB's ILUC values in their peer review of the WA CFP program's carbon intensity modeling.[22]
- Whereas GREET's CCLUB-based ILUC factors are lower than those from CARB and thereby suggest that CARB's factors may overestimate the impact of ILUC, a pair of recent ILUC model-review and -validation studies—EPA's 2023 Model Comparison Exercise[23] and Lark et al. (2022)[24]—suggest that CARB's factors may instead be underestimated.

Thus, despite its age, CARB's assessment better aligns model inputs and assumptions with reality as validated by both the scientific data and collective stakeholder experience.

Furthermore, there is no single harmonized ILUC model, and each ensemble of available models and underlying data have their respective strengths and weaknesses. CARB's and other ILUC factors adopted for regulatory application (e.g., those developed for the federal Renewable Fuel Standard) have typically been calculated via a pairing of models: (1) a macroeconomic model which estimates the quantity of land-use change induced by a shift in demand for crop-based biofuels and their feedstocks, and (2) a biophysical land-use-change and land-management-change GHG emissions model, which produces the emissions factors by which the first model's results are multiplied to yield ILUC factors.

To -date, the distinctions and variance among these models has best been summarized by EPA's 2023 Model Comparison Exercise (MCE) Technical Document, a meta-analysis of ILUC models and their results.[25] The MCE highlights that uncertainty in ILUC factors is a result of both structural uncertainty originating in the selection of the aforementioned economic and biophysical models, as well as numeric uncertainty attached to each of said models' parameters. The economic portion of models (i.e., how markets respond to the demand for bio-based fuels) was structured differently between examined models, and this also caused varying sensitivity in the ILUC factors to parameterization, even with the consensus that new demand would result in land use changes. For example, the MCE highlights a key limitation of GTAP (i.e., GTAP-BIO, database v10): it lacks robust modeling of commodity substitutability and competition in the global vegetable oil market. Whenever soybean oil is diverted to produce fuel, other vegetable oils will replace it to varying

[22] International Council on Clean Transportation (ICCT), "Washington Clean Fuels Standard—Carbon Intensity Model Peer Review," April 6, 2022, https://ecology.wa.gov/getattachment/3ff97fb5-9ba4-4507-8741-4be625e4e690/CIModelPeerReview20220406.pdf.

[23] U.S. Environmental Protection Agency, "Model Comparison Exercise Technical Document," 2023, https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P1017P9B.txt.

[24] Tyler J. Lark et al., "Environmental Outcomes of the US Renewable Fuel Standard," *Proceedings of the National Academy of Sciences* 119, no. 9 (March 2022): e2101084119, https://doi.org/10.1073/pnas.2101084119.

[25] U.S. Environmental Protection Agency, "Model Comparison Exercise Technical Document," 2023, https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P1017P9B.txt.

degrees; this substitution is a key driver of ILUC and its resulting GHG emissions. Unlike other models in the MCE—whose results included significant replacement of the soybean oil diverted from the international food market with palm, canola, and other crop oils—GTAP's results project an overall reduction in oil crops consumed as food, with little replacement. This discrepancy suggests that CARB's 2015 ILUC factors, obtained from GTAP (i.e., GTAP-BIO and AEZ-EF), may underestimate the extent of ILUC emissions induced by demand for fuels derived from oil crops.

Similar to the MCE's findings, ILUC factors used in the federal Renewable Fuel Standard (RFS) have also been shown to be underestimates. A recent study by Lark et al. (2022) sought to validate an ILUC factor for corn ethanol from the 2007 RFS program by performing a retrospective analysis of domestic ILUC driven by the additional production of 5.5 billion gallons of corn ethanol.[26] Lark et al. attribute this additional ethanol as demand induced by the 2007 RFS expansion. To this additional fuel volume, the authors attribute and calculate a domestic ILUC factor of 29.7 g CO_2e / MJ—a result which far exceeds EPA's original regulatory impact assessment (RIA) projection of -3.8 g / MJ for domestic ILUC emissions by 2022. Furthermore, the authors use this corrected ILUC factor to calculate a revised CI for corn ethanol of 115.7 g/MJ (as produced in 2022, or higher in preceding years)—24% higher than the program's corresponding baseline gasoline CI of 91.3 g/MJ. This series of mismatches demonstrates both the risk of underestimation and its unintended consequences, as well as the importance of working toward periodic validation routines for ILUC factors with historic data.

On the other hand, R&D GREET's default ILUC factors calculated via its CCLUB module are significantly lower than those from CARB's 2015 analysis across pathways. Just last year, the primary authors of GREET's CCLUB model published their own comparative analysis of ILUC modeling.[27] Unlike EPA's MCE, Taheripour et al. used only one macroeconomic model, GTAP-BIO, and instead focused their comparison on two different land-use-change emissions models, CCLUB and AEZ-EF—the latter of which was used to calculate CARB's 2015 ILUC factors. For an array of crop-based jet fuel production pathways and corresponding additional-demand scenarios, the authors found AEZ-EF's ILUC factors to be more extreme than those from CCLUB. Wherever both models yielded positive ILUC factors, AEZ-EF's exceeded those of CCLUB by 33–62% (using values from Table 2, with CCLUB's factors as the denominator); when both negative, AEZ-EF's were 34–191% lower than CCLUB's. The authors conclude by noting the difficulty in pinpointing root causes of these differences—due to variation in underlying data, model assumptions, and system boundaries—and emphasize the importance of model validation, particularly by way of remote-sensing technologies.

In summary, the aforementioned ILUC meta-analyses and validation study demonstrate how scientists in this field continue to grapple with many of the same open questions, disagreements, and quantitative uncertainty which have persisted since CARB's 2015 analysis. Given the large range of uncertainty surrounding these estimates, NMED and ERG consider CARB's ILUC factors to be a middle-of-the-road estimate and reuse them throughout the NM-GREET CI calculations and CTFP rule.

[26] Tyler J. Lark et al., "Environmental Outcomes of the US Renewable Fuel Standard," *Proceedings of the National Academy of Sciences* 119, no. 9 (March 2022): e2101084119, https://doi.org/10.1073/pnas.2101084119.

[27] Farzad Taheripour et al., "Biofuels Induced Land Use Change Emissions: The Role of Implemented Land Use Emission Factors," *Sustainability* 16, no. 7 (January 2024): 2729, https://doi.org/10.3390/su16072729.

3.2.3.2 OPGEE Well-to-Refinery Crude Oil Modeling

ERG modified NM-GREET to substitute GREET1's default modeling of crude oil's well-to-refinery-gate (WTRG) CI with an estimate derived from the Oil Production Greenhouse gas Emissions Estimator (OPGEE) v2.0c model, U.S. Energy Information Administration (U.S. EIA) data, and the work of Masnadi et al. (2018).[28] Unlike R&D GREET, OPGEE allows users to model GHG emissions from the extraction, processing, and transportation of crude oil by defined-origin mixtures as consumed within a certain Petroleum Administration for Defense Districts (PADD) region.[29] This improved resolution allowed ERG to model the mixture of crude oil produced domestically within and imported internationally into PADD3, the gulf coast region which includes New Mexico, so as to best characterize the supply chains of petroleum-derived fuels consumed in-state. Many other regulatory applications of GREET, such as for clean fuel programs akin to CTFP in other states, also incorporate OPGEE modeling and results into their WTRG crude oil CI calculations.

In 2018 Masnadi et al. published carbon intensity estimates for 98% of global crude production for the 2015 production year, which were modeled with field-specific data.[30] ERG combined data and results from the supplementary material of Masnadi et al.'s work with OPGEE v2.0c and domestic crude oil production and foreign import data from U.S. EIA,[31] as detailed in the Fuel Carbon Intensities appendix. The resulting weighted-average PADD3 CIs are calculated as 11.83 CO_2e/MJ refinery input for 2018 and 11.46 g/MJ for 2022. Integrating these WTRG CIs into NM-GREET's *Petroleum* tab in both the v1.0 and baseline versions of NM-GREET causes a ~4–5 g/MJ increase in the pathway CI scores of crude-oil-derived transport fuels (i.e., gasoline, diesel, and liquefied petroleum gas) and only modest ≤0.2 g/MJ increases in other pathways.[32]

In order to ensure that all fuel pathways incorporate this Feedstock-stage CI into the petroleum-derived fuels they consume as process and/or transportation fuels within their supply chains, ERG increased the Fuel-stage (i.e., WTRG) carbon intensity of unrefined crude oil on the *Petroleum* tab such that it matched the above pair of PADD3-specific 2018 and 2022 estimates. Using the 2022 adjustment to illustrate this change, ERG made up the difference between R&D GREET's release-default WTRG CI of 7,911 g CO_2e per million British thermal units (mmBtu) and our calculated 2022 PADD3 value of 12,096 g CO_2e/mmBtu (i.e., converted from 11.46 g/MJ) by simply increasing the Fuel stage CO_2 emissions (in cell *Petroleum!B279*) by the difference between the CI values. Therefore, ERG added 4,185 g/mmBtu (i.e., 12,096 minus 7,911) of CO_2 emissions to the WTRG CI of unrefined crude oil, which has a release-default value of 5,129 g/mmBtu. Prioritizing the

[28] Hassan M. El-Houjeiri et al., "Oil Production Greenhouse Gas Emissions Estimator OPGEE v2.0 User Guide & Technical Documentation," 2017, https://pangea.stanford.edu/departments/ere/dropbox/EAO/OPGEE/OPGEE_documentation_v2.0.pdf; Mohammad S. Masnadi et al., "Global Carbon Intensity of Crude Oil Production," *Science* 361, no. 6405 (August 31, 2018): 851–53, https://doi.org/10.1126/science.aar6859.

[29] U.S. Energy Information Administration, "Petroleum Administration for Defense Districts," February 7, 2012, https://www.eia.gov/todayinenergy/detail.php?id=4890.

[30] Mohammad S. Masnadi et al., "Global Carbon Intensity of Crude Oil Production," *Science* 361, no. 6405 (August 31, 2018): 851–53, https://doi.org/10.1126/science.aar6859.

[31] U.S. Energy Information Administration, "Crude Oil Production, Annual," 2025, https://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_a.htm; U.S. Energy Information Administration, "PAD District Imports by Country of Origin: Gulf Coast (PADD3), Crude Oil, Annual," 2025, https://www.eia.gov/dnav/pet/pet_move_impcp_a2_r30_epc0_IP0_mbbl_a.htm.

[32] Petroleum fuels are consumed within the supply chains of all liquid fuel pathways, but marginal increases in the CI of petroleum has only a limited impact on the CI scores of these other pathways.

transparency and traceability of these calculations, ERG inserted a condensed version of these calculations as the following formula into the *Petroleum*-tab WTRG CO_2 emissions cell, where "MJ2mmBtu" references GREET's named range for converting MJ to mmBtu:

$$= (11.46/MJ2mmBtu - 7{,}911.2) + 5{,}128.8 \quad \textbf{Equation 3-3}$$

3.2.3.3 45V Manure Biomethane Counterfactual and Fuel Processing

Avoided methane emissions credits are constructed from pairs of counterfactual scenarios: a baseline or "status quo" scenario (which is avoided) and a "counterfactual" alternative (which may be enacted via public policy, private investment, and/or additional decision points). When considering the diversion of animal manure from some traditional manure management practice to an anaerobic digester system that produces biomethane for consumption in NM, our status quo scenario is defined as the national-average array of manure management practices, and our alternative scenario as the array of available anaerobic digester (AD) technologies.

However, the structure of R&D GREET only allows users to access a single AD technology at a time, and working around this limitation would thereby require extensive re-writes of the formulas from the *RNG* and *Waste* tabs. Instead, NM-GREET simply relies on 45V-GREET's generic counterfactual methodology for avoided GHG emissions for manure-derived biomethane, which has already done the work of estimating this national-average counterfactual.[33] This recent analysis used production-weighted-national-average statistics and modeling of both (1) manure generation by all major animal types in U.S. animal agriculture, and (2) emissions from U.S.-average manure management practices as the "status quo" scenario. Then, the total net difference in GHG emissions between that status quo and the alternative—diversion into a mixture of the three most prevalent anaerobic digester technologies (covered lagoon, mixed plug flow, and complete mix)—is calculated. Together, these elements produced a "generic" avoided methane emissions potential per unit energy of biomethane, agnostic of the specific manure source, management practice, or digester system. This agnosticism allows us to apply the resulting avoided emissions CI broadly across all relevant temporary pathways' CI scores.

Reproducing the calculations outlined in the 45V report's "Estimated Emissions Per Unit Biomethane" section yields an avoided emission factor of -90.3 g CO_2e/MJ CH_4 in biomethane, only slightly higher than GREET's default factor of -110.3 g CO_2e/MJ. In the following formulas, "manure" denotes manure mass as excreted including moisture, CO_2e values are calculated via AR5 GWP100 factors, and the LHV of CH_4 is obtained from GREET (i.e., at conditions of 32°F and 1 atmosphere):

$$\frac{81{,}696{,}000\ \frac{MT\ CO_2e}{year}}{1{,}460{,}542{,}191\ \frac{MT\ manure}{year}} * \frac{1\ MT\ manure}{10^3\ kg\ manure} * \frac{10^6 g\ CO_2e}{1\ MT\ CO_2e} = 55.9\ \frac{g\ CO_2e}{kg\ manure} \quad \textbf{Equation 3-4}$$

[33] U.S. Department of Energy, "A Generic Counterfactual Greenhouse Gas Emission Factor for Life-Cycle Assessment of Manure-Derived Biogas and Renewable Natural Gas," January 2025, https://www.energy.gov/sites/default/files/2025-01/generic-counterfactual-greenhouse-gas-emission-factor-for-life-cycle-assessment-of-manure-derived-biogas-and-renewable-natural-gas_010225.pdf.

$$55.9\frac{g\ CO_2e}{kg\ manure}*\frac{1\ kg\ manure}{0.61\ scf\ CH_4 in\ biogas}=91.7\frac{g\ CO_2e}{scf\ CH_4 in\ biogas}$$ **Equation 3-5**

$$\frac{91.7\ g\ CO_2e}{scf\ CH_4 in\ biogas}*\frac{1\ scf\ CH_4 in\ biogas}{962.2\ Btu\ (LHV, CH_4)}*\frac{1000\ Btu}{1.05587\ MJ}=90.3\frac{g\ CO_2e}{MJ\ CH_4 in\ biogas}$$ **Equation 3-6**

Finally, since these emissions are considered avoided, a negative sign is prepended to the emission factor. Note that, while the per-MJ value of -90.3 equals the "-90 g CO_2e/MJ" value after rounding on page 11 of the 45V generic counterfactual report, the -91.7 g CO_2e/standard cubic foot (scf) CH_4 in biogas value differs from the "-90 g CO_2e/scf biomethane in biogas" on page 10. Based on the calculations above and subsequent differences in per-scf and per-MJ emission factors in the report, ERG concluded that the -90.3 per-MJ value is correct, whereas the per-scf value should be -91.7.

ERG also integrated the 45V report's estimates of emissions intensities for both digester (i.e., across a "manure-weighted average of the three primary digester technologies"—covered lagoon, mixed plug flow, and complete mix) and upgrader operations. The former emits 39 g CO_2e/MJ by way of its consumption of grid electricity and natural gas (NG), and the latter emits 19.4 g CO_2e/MJ via fugitive biogas plus upstream emissions of consumed grid electricity. For each pathway that includes AW biomethane as a fuel or feedstock, ERG opted to use the sum of these values, 58.4 g CO_2e/MJ, to represent biogas production activities within the Fuel-processing stage.

3.3 Gasoline Pathways

3.3.1 Fossil Clear Gasoline (E0)

The Fossil Clear Gasoline (E0) pathway approximates a weighted average of crude-oil-derived gasoline supplied to New Mexico, as delivered in "clear" state before any potential blending with other fuels, such as ethanol. As detailed in Section 0 of this report, the Feedstock stage is composed of PADD3-weighted average crude oil extraction activities, followed by transport to a refinery. The Fuel processing stage includes the refining of crude oil into gasoline followed by transportation and distribution to refueling stations. Finally, the On-Road stage models gasoline combustion within a light-duty, passenger internal combustion engine vehicle (ICEV).

The parameter listed in Table 3-4 is altered from GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. ERG decreased the value of "Petro_FRFG_EtOH" from 10 to 0 percent in order to model tailpipe emissions from combusting clear gasoline (E0) on the *Vehicles* tab rather than E10.

Table 3-4. Parameters relevant to the Fossil Clear Gasoline (E0) pathway

Parameter	Value		GREET Label	Description
	Default	NM		
Petro_FRFG_EtOH	10.0%	0.0%	Ethanol blending level (by volume)	Set to 0% so *Results_NM* formulas can reuse calculations from *Vehicles* tab for clear gasoline

Table 3-5 below, summarizes the cumulative CI and the CI values by stage. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Petroleum* sheet Section 5.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-5. Summary of the Fossil Clear Gasoline (E0)'s stagewise CIs

Stage	Total CI* (g CO2e/MJ)
Feedstock	9.9
Fuel	13.7
On-Road	73.1
Total, WTW	**96.7**

** Values may not always sum to equal the total due to rounding.*

3.3.2 Corn Ethanol (E100)

The Corn Ethanol (E100) pathway estimates the typical WTW CI of corn-based ethanol supplied to New Mexico, as delivered before any potential blending with other fuels. The Feedstock lifecycle stage is composed of corn farming and transport to an ethanol production plant. The Fuel processing stage includes an industry-weighted average of ethanol production plant types—using dry and wet milling, with and without the extraction of a corn oil co-product—followed by transportation and distribution to refueling stations. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, the ILUC and Biogenic CO_2 Uptake stages are incorporated to account for the effects of feedstock crop growth.

Certain parameters listed in Table 3-6 are altered from GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. ERG increased the value of "Vehicles_EtOHDediVehi_EtOHShare" from 85 percent to 100 percent in order to model tailpipe emissions from combusting E100 on the *Vehicles* tab rather than E85. Since CARB ILUC factors are applied, GREET's internal estimation of ILUC is disabled via the "EtOH_CornEtOH_LandChange_Option" parameter. Finally, as described in Section 3.2.1, market-based allocation is given preference over other available modes; for this reason, ERG altered the three enumerated allocation-selector parameters from their default values to "3 - Market-Based Allocation."

Table 3-6. Parameters relevant to the Corn Ethanol (E100) pathway

Parameter	Value		GREET Label	Description
	Default	NM		
Vehicles_ EtOHDediVehi_ EtOHShare	85.0%	100.0%	Ethanol in dedicated vehicle fuel	Set to 100% so *Results_NM* formulas can reuse calculations from *Vehicles* tab for fuel ethanol
EtOH_CornEtOH_ LandChange_ Option	2	0	Inclusion of GHG Emissions from Land Use Change; Corn	Remove GREET's ILUC value for corn ethanol; use CARB value instead
Ethanol_Farming_ Corn_Allocation	1	4	Allocation of corn farming energy between corn grain and	Preference market allocation

			stover	
EtOH_CornEtOH_ CoProductMethod	1	3	Allocation of Corn ethanol w/o corn oil extraction	
Inputs!F503	6	3	Allocation of Corn ethanol w/ corn oil extraction	

The pathway's total WTW CI and those of its stages are provided below in Table 3-7.Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *EtOH* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-7. Summary of Corn Ethanol (E100)'s stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-68.9
Feedstock	23.1
Fuel	23.4
On-Road	71.4
ILUC	19.8
Total, WTW	68.9
Total, WTW, adjusted	**75.0**

** Values may not always sum to equal the total due to rounding.*

3.3.3 Sorghum Ethanol (E100)

The Sorghum Ethanol (E100) pathway estimates the typical WTW CI of sorghum-based ethanol supplied to New Mexico, as delivered before any potential blending with other fuels. The Feedstock lifecycle stage is composed of grain sorghum farming and transport to an ethanol production plant. The Fuel processing stage includes an ethanol production followed by transportation and distribution to refueling stations. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, the ILUC and Biogenic CO_2 Uptake stages are incorporated to account for the effects of feedstock crop growth.

The parameter listed in Table 3-8 is altered from GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. ERG increased the value of "Vehicles_EtOHDediVehi_EtOHShare" from 85 to 100 percent in order to model tailpipe emissions from combusting E100 on the *Vehicles* tab rather than E85. Since GREET's internal estimation of ILUC for sorghum is disabled by default, no parameter alteration was necessary in order to avoid double-counting emissions when applying CARB's ILUC factor. Finally, as described in Section 3.2.1, market-based allocation is given preference over other available modes; for this reason, ERG altered the sorghum-ethanol-plant allocation selector from its default value of "1: Displacement method" to "3: Market value-based method."

Table 3-8. Parameters relevant to the Sorghum Ethanol (E100) pathway

Parameter	Value		GREET Label	Description
	Default	NM		
Vehicles_ EtOHDediVehi_ EtOHShare	85.0%	100.0%	Ethanol in dedicated vehicle fuel	Set to 100% so *Results_NM* formulas can reuse calculations from *Vehicles* tab for fuel ethanol
EtOH!C270	1	3	Co-products handling methods of sorghum ethanol plant	Preference market allocation

The pathway's total WTW CI and those of its stages are provided below in Table 3-9. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *EtOH* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-9. Summary of Sorghum Ethanol (E100)'s stagewise CIs

Stage	**Total CI*** (g CO_2e/MJ)
Biogenic CO_2 Uptake	-68.9
Feedstock	23.7
Fuel	19.4
On-Road	71.4
ILUC	14.5
Total, WTW	60.2
Total, WTW, adjusted	**65.0**

** Values may not always sum to equal the total due to rounding.*

3.4 Diesel Pathways

3.4.1 Fossil Clear Diesel (B0)

The Fossil Clear Diesel (B0) pathway approximates a weighted average of crude-oil-derived diesel supplied to New Mexico, as delivered in "clear" state before any potential blending with other non-fossil-diesel fuels. As detailed in Section 0, the Feedstock stage is composed of PADD3-weighted average crude oil extraction activities, followed by transport to a refinery. The Fuel processing stage includes the refining of crude oil into diesel followed by transportation and distribution to refueling stations. Finally, the On-Road stage models diesel combustion within a light-duty passenger vehicle with a compression-ignition direct-injection (CIDI) engine.

The pathway's total WTW CI and those of its stages are provided below in Table 3-10. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Petroleum* sheet Section 5.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-10. Summary of Fossil Clear Diesel (B0)'s stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	11.5
Fuel	7.9
On-Road	75.6
Total, WTW	**95.0**

** Values may not always sum to equal the total due to rounding.*

3.4.2 Biodiesel (B100)

The Biodiesel (B100) pathways approximate categorical averages of crop- and waste-oil-derived biodiesel (BD) fuels supplied to New Mexico, as delivered in their pure state before any potential blending with fossil diesel fuels. For both BD temporary pathways, ERG made the following parameter alterations from GREET's release-default state in order to disaggregate overlapping GREET pathway formulas and ensure that modeled fuels are broadly representative of those sold in New Mexico:

Table 3-11. Parameters relevant to all Biodiesel (B100) pathways

Parameter	Value		GREET Label	Description
	Default	NM		
Vehicles_ BDCIDI_ BDShare	20%	100%	Biodiesel in CIDI fuel	Causes *Vehicles*-tab results to reflect pure BD, on which *Results_NM* formulas depend

3.4.2.1 Virgin Non-Palm Plant Oil

The Virgin Non-Palm Plant Oil pathway estimates the typical WTW CI of soy-derived BD supplied to New Mexico, as delivered before any potential blending with other diesel fuels. The Feedstock lifecycle stage is composed of soy farming and transport to a refinery. The Fuel processing stage includes soy oil extraction, transesterification, and transportation plus distribution to refueling stations. The On-Road stage models BD100 combustion within a light-duty passenger CIDI vehicle. Finally, ILUC and Biogenic CO_2 Uptake stages are incorporated to account for the effects of feedstock crop growth.

Certain parameters listed in Table 3-12 are altered to GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. Since CARB ILUC factors are applied, GREET's internal estimation of ILUC is disabled via the "Soybean_LUC_Selector" parameter. Also, as described in Section 3.2.1, market-based allocation is given preference over other available modes. For this reason, ERG altered the enumerated "BD_SoybeanOilExtraction_Allocation" selector from "4 - Mass-Based Allocation" to "3 - Market-Based Allocation."

Table 3-12. Parameters relevant to the Virgin Non-Palm Plant Oil Biodiesel (B100) pathway

Parameter	Value		GREET Label	Description
	Default	NM		
Soybean_ LUC_ Selector	2	0	Inclusion of GHG Emissions from Induced Land Use Change	Exclude GREET estimate; replace with CARB estimate on *Results_NM*
BD_Soybean OilExtraction_ Allocation	4	3	Process level allocation for all biooil-based fuels: Oil Extraction Process for Soybean	Preference market allocation

The pathway's total WTW CI and those of its stages are provided below in Table 3-13. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *BioOil* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-13. Summary of Virgin Non-Palm Plant Oil Biodiesel (B100)'s stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-71.2
Feedstock	13.2
Fuel	9.7
On-Road	75.9
ILUC	29.1
Total, WTW	56.6
Total, WTW, adjusted	**60.0**

** Values may not always sum to equal the total due to rounding.*

3.4.2.2 Waste Animal Fat or Cooking Oil

The Waste Animal Fat or Cooking Oil pathway estimates the typical WTW CI of tallow-derived BD supplied to New Mexico, as delivered before any potential blending with other diesel fuels. The estimated WTW CI of tallow BD is sufficiently close to that of BD derived from used cooking oil that ERG solely relied on the modeling of tallow BD to represent this composite category of temporary pathways. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats waste animal fat as being obtained burden-free at the point of disposal. The Fuel processing stage includes rendering fat to tallow, tallow transport to a refinery, transesterification of tallow to BD, and transportation plus distribution to refueling stations. The On-Road stage models BD100 combustion within a light-duty passenger CIDI vehicle. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The pathway's total WTW CI and those of its stages are provided below in Table 3-14. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *BioOil* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-14. Summary of Waste Animal Fat or Cooking Oil Biodiesel (B100)'s stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-71.4
Feedstock	0.0
Fuel	15.2
On-Road	76.1
Total, WTW	19.9
Total, WTW, adjusted	**25.0**

** Values may not always sum to equal the total due to rounding.*

3.4.3 Renewable Diesel (R100) and Naphtha

The production of renewable diesel (RD) at biorefineries typically also yields renewable naphtha (RN) and renewable jet fuel as co-products. In allocating the cumulative GHG emissions from feedstock origin to exiting the biorefinery across these co-products, GREET relies on the fuels' LHV energy contents, such that each Joule of each fuel is attributed the same proportion of the total emissions. This energy-based allocation plus the near-total negation of combustion emissions by initial biogenic CO_2 uptake mean that renewable diesel, naphtha, and jet fuel co-products should have roughly equivalent WTW CIs—an assumption ERG uses to extend the following RD temporary pathway CIs as applying to their RN co-product as well.

3.4.3.1 Virgin Non-Palm Plant Oil

The Virgin Non-Palm Plant Oil Renewable Diesel (R100) pathway estimates the typical WTW CI of soy-derived RD supplied to New Mexico, as delivered before any potential blending with other fuels. The Feedstock lifecycle stage is composed of soy farming and transport to a refinery. The Fuel processing stage includes soy oil extraction, RD and naphtha production, and transportation plus distribution to refueling stations. The On-Road stage models RD100 combustion within a light-duty passenger CIDI vehicle. Finally, ILUC and Biogenic CO_2 Uptake stages are incorporated to account for the effects of feedstock crop growth.

Certain parameters listed in Table 3-15 are altered to GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. Since CARB ILUC factors are applied, GREET's internal estimation of ILUC is disabled via the "Soybean_LUC_Selector" parameter. Also, as described in Section 3.2.1, market-based allocation is given preference over other available modes. For this reason, ERG altered the enumerated "BD_SoybeanOilExtraction_Allocation" selector from "4 - Mass-Based Allocation" to "3 - Market-Based Allocation."

Table 3-15. Parameters relevant to the Virgin Non-Palm Plant Oil Renewable Diesel (R100) and Naphtha pathways

Parameter	Value		GREET Label	Description
	Default	NM		
Soybean_ LUC_Selector	2	0	Inclusion of GHG Emissions from Induced Land Use Change	Exclude GREET estimate; replace with CARB estimate on *Results_NM*
BD_Soybean OilExtraction_ Allocation	4	3	Process level allocation for all biooil-based fuels: Oil Extraction Process for Soybean	Preference market allocation

The pathway's total WTW CI and those of its stages are provided below in Table 3-16. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *BioOil* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-16. Summary of Virgin Non-Palm Plant Oil Renewable Diesel (R100) and Naphtha's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-72.6
Feedstock	13.3
Fuel	15.9
On-Road	73.3
ILUC	29.1
Total, WTW	59.0
Total, WTW, adjusted	**65.0**

** Values may not always sum to equal the total due to rounding.*

3.4.3.2 Waste Animal Fat or Cooking Oil

The Waste Animal Fat or Cooking Oil Renewable Diesel (R100) and Naphtha pathway estimates the typical WTW CI of tallow-derived RD supplied to New Mexico, as delivered before any potential blending with other fossil-diesel fuels. The estimated WTW CI of tallow RD is sufficiently close to that of RD derived from used cooking oil that ERG solely relies on the modeling of tallow RD to represent this composite category of temporary pathways. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats waste animal fat as being obtained burden-free at the point of disposal. The Fuel processing stage includes rendering fat to tallow, tallow transport to a refinery, RD and naphtha production, and transportation plus distribution to refueling stations. The On-Road stage models RD100 combustion within a light-duty passenger CIDI vehicle. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The pathway's total WTW CI and those of its stages are provided below in Table 3-17. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *BioOil* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-17. Summary of Waste Animal Fat or Cooking Oil Renewable Diesel (R100) and Naphtha's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-72.6
Feedstock	0.0
Fuel	17.6
On-Road	73.3
Total, WTW	18.3
Total, WTW, adjusted	**20.0**

** Values may not always sum to equal the total due to rounding.*

3.5 Propane Pathways

3.5.1 Fossil Liquefied Petroleum Gas

The Fossil Liquefied Petroleum Gas (LPG) pathway estimates the typical WTW CI of LPG supplied to New Mexico. By default, GREET defines LPG as being produced with national-average production shares of 86.6% from NG and 13.4% from crude oil. For the fraction of LPG derived from NG, the Feedstock stage is composed of NG recovery (i.e., extraction of conventional and shale gas), processing, and pipeline transmission to an LPG plant. The Fuel processing stage includes LPG production, followed by transportation and distribution to refueling stations. For the fraction of LPG derived from crude oil, the Feedstock stage is composed of a PADD3-weighted average of crude oil extraction activities (as detailed in Section 0), followed by transport to a refinery. The Fuel processing stage includes the refining of crude oil into LPG, followed by transportation and distribution to refueling stations. Finally, the On-Road stage models fuel combustion within a light-duty passenger vehicle with a light-duty passenger ICEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-18. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Petroleum* sheet Section 5.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-18. Summary of Fossil LPG's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	7.1
Fuel	-4.2
On-Road	64.8
Total, WTW	**67.7**

** Values may not always sum to equal the total due to rounding.*

3.6 Natural Gas Pathways

3.6.1 Fossil Natural Gas

The Fossil Natural Gas pathways in NM-GREET—including both compressed (CNG) and liquified (LNG) gases—are composed of national-average mixes of shale and conventional NG produced domestically. Leaks of NG to the atmosphere are characterized for each activity within the Fuel and Feedstock stages. Since GREET does not contain parameters to differentiate fugitive emissions during NG recovery by basin, regions therein, or consumption mix in a given state, ERG instead relied on GREET's release-default national-average WTW estimates of 0.94 percent (i.e., Inputs!G136 and Inputs!H136) for both shale and conventional NG. Furthermore, the U.S. NG pipeline network is heavily interconnected, such that in order to compose a New-Mexico-consumption-weighted-average fugitive emissions rate for NG ERG would first need high-resolution data and modeling of NG supply chain activities, fugitive emissions, and inter-state distribution rates.

3.6.1.1 Fossil CNG

The Fossil CNG pathway estimates the typical WTW CI of fossil CNG supplied to New Mexico. The Feedstock lifecycle stage is composed of NG recovery (i.e., extraction of conventional and shale gas), processing, and pipeline transmission to refueling stations. The Fuel processing stage includes NG compression. Finally, the On-Road stage models fuel combustion within a light-duty passenger ICEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-19. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *NG* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-19. Summary of Fossil CNG's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	13.7
Fuel	3.0
On-Road	57.6
Total, WTW	**74.3**

** Values may not always sum to equal the total due to rounding.*

3.6.1.2 Fossil LNG

The Fossil LNG pathway estimates the typical WTW CI of fossil CNG supplied to New Mexico. The Feedstock lifecycle stage is composed of NG recovery (i.e., extraction of conventional and shale gas), processing, and pipeline transmission to a liquefaction plant. The Fuel processing stage includes liquefaction, truck transportation and distribution to refueling stations, and storage. Finally, the On-Road stage models fuel combustion within a light-duty passenger ICEV.

The parameter listed in Table 3-20 is altered to GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. An in-state liquefaction efficiency of 80 percent is chosen to reflect local conditions and align with parameter estimates from similar programs.

Table 3-20. Parameters relevant to the Fossil LNG pathway

Parameter	Value		GREET Label	Description
	Default	NM		
NG_LNG_ Liq_Eff_ NANG_TS	=AL58	80%	NA NG Liquefaction Efficiency	Alignment with similar programs in other jurisdictions

The pathway's total WTW CI and those of its stages are provided below in Table 3-21. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *NG* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-21. Summary of Fossil LNG's stagewise CIs

Stage	Total CI* ($g\ CO_2e/MJ$)
Feedstock	8.6
Fuel	20.9
On-Road	57.6
Total, WTW	**87.1**

** Values may not always sum to equal the total due to rounding.*

3.6.2 Animal Waste Biomethane

The Animal Waste (AW) Biomethane (a.k.a. renewable natural gas) Temporary Pathway Table pathways—including both compressed (AW CNG) and liquified (AW LNG) gases—in NM-GREET are composed of national-average mixes of livestock manure and anaerobic digester technologies used to convert manure into biomethane. Details on how these feedstock and AD national averages are defined can be found in Section 3.2.3.3.

3.6.2.1 AW CNG

The AW CNG pathway estimates the typical WTW CI of AW CNG supplied to New Mexico. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats AW as being obtained burden-free at the point of generation. The Fuel processing stage includes manure hauling via truck to a local AD installation, AD and biogas upgrader operation, pipeline transmission to refueling stations, and compression to CNG. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The pathway's total WTW CI and those of its stages are provided below in Table 3-22. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *RNG* sheet Section 3, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-22. Summary of AW CNG's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	0.0
Fuel	61.4
On-Road	57.6
Total, WTW	62.7
Total, WTW, adjusted	**70.0**
Total, WTW, with credit	-27.4
Total, WTW, with credit, adjusted	**-25.0**

Counterfactual Additionality Credit

As outlined, fuel producers that meet the additionality criteria for AD installations may apply the counterfactual avoided emissions credit of -90.0 g CO_2e/MJ to this Temporary Pathway Table pathway, bringing its total CI down to -27.3 g CO_2e/MJ.

3.6.2.2 AW LNG

The AW LNG pathway estimates the typical WTW CI of AW LNG supplied to New Mexico. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats AW as being obtained burden-free at the point of generation. The Fuel processing stage includes manure hauling via truck to a local AD installation, AD and biogas upgrader operation, pipeline transmission to a liquefaction plant, liquefaction, transportation and distribution to refueling stations, and storage. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The parameter listed in Table 3-23 is altered to GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. An in-state liquefaction efficiency of 80 percent is chosen to reflect local conditions and align with parameter estimates from similar.

Table 3-23. Parameters relevant to the AW LNG pathway

Parameter	Value		GREET Label	Description
	Default	NM		
LFG_LNG_ Liq_Eff	89%	80%	NG Small Scale Liquefaction Efficiency (powered by RNG)	Alignment with similar programs in other jurisdictions

The pathway's total WTW CI and those of its stages are provided below in Table 3-24. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *RNG* sheet Section 3, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-24. Summary of AW LNG's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	0.0
Fuel	70.9
On-Road	57.6
Total, WTW	72.1
Total, WTW, adjusted	**80.0**
Total, WTW, with credit	-18.5
Total, WTW, with credit, adjusted	**-15.0**

** Values may not always sum to equal the total due to rounding.*

Counterfactual Additionality Credit

As outlined, fuel producers that meet the additionality criteria for AD installations may apply the counterfactual avoided emissions credit of -90.0 g CO_2e/MJ to this Temporary Pathway Table pathway—bringing its total CI down to -18.2 g CO_2e/MJ.

3.6.3 Landfill Biomethane

The Landfill (LF) Biomethane Temporary Pathway Table pathways—including both compressed (LF CNG) and liquified (LF LNG) gases—in NM-GREET are composed of biomethane derived from landfill gas (LFG) as is generated by landfills containing a U.S.-average composition of non-recycled municipal solid waste.

3.6.3.1 LF CNG

The LF CNG pathway estimates the typical WTW CI of LF CNG supplied to New Mexico. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats LFG as being obtained burden-free at the point of generation. The Fuel processing stage includes LFG upgrading, pipeline transmission to refueling stations, and compression to CNG. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The pathway's total WTW CI and those of its stages are provided below in Table 3-25. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *RNG* sheet Section 3, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-25. Summary of LF CNG's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	0.0
Fuel	21.1
On-Road	57.6
Total, WTW	21.4
Total, WTW, adjusted	**25.0**

** Values may not always sum to equal the total due to rounding.*

3.6.3.2 LF LNG

The LF LNG pathway estimates the typical WTW CI of LF LNG supplied to New Mexico. The Feedstock lifecycle stage is devoid of activity and emissions, since GREET treats LFG as being obtained burden-free at the point of generation. The Fuel processing stage includes LFG upgrading, pipeline transmission to a liquefaction plant, liquefaction, transportation and distribution to refueling stations, and storage. The On-Road stage models fuel combustion within a light-duty passenger ICEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of carbon embedded in the final fuel product.

The parameter listed in Table 3-26 is altered to GREET's release-default state to ensure that this model pathway is representative of fuel commercially available in New Mexico. An in-state liquefaction efficiency of 80 percent is chosen to reflect local conditions and align with parameter estimates from similar.

Table 3-26. Parameters relevant to the LF LNG pathway

Parameter	Value		GREET Label	Description
	Default	NM		
LFG_LNG_ Liq_Eff	89%	80%	NG Small Scale Liquefaction Efficiency (powered by RNG)	Alignment with similar programs in other jurisdictions

The pathway's total WTW CI and those of its stages are provided below in Table 3-27. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *RNG* sheet Section 3, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-27. Summary of LF LNG's stagewise CIs

Stage	Total CI* ($g\ CO_2e/MJ$)
Biogenic CO_2 Uptake	-56.3
Feedstock	0.0
Fuel	29.8
On-Road	57.6
Total, WTW	31.0
Total, WTW, adjusted	**35.0**

** Values may not always sum to equal the total due to rounding.*

3.7 Hydrogen Pathways

Of the hydrogen (H_2) fuels summarized in this section, six are defined as Lookup Table pathways and four as Temporary Pathway Table pathways. The compressed gaseous hydrogen (C.H_2) and liquid hydrogen (L.H_2) fuels derived from steam methane reforming (SMR) of fossil methane, proton exchange membrane (PEM) electrolysis of water using certified zero-carbon, and PEM electrolysis with North-American-average-grid electricity are all Lookup Table pathways. In turn, G.H_2 and L.H_2 produced via SMR of AW or LF biomethane are defined as four Temporary Pathway Table pathways. Additionally, the AW-biomethane-SMR temporary pathways can also claim a counterfactual avoided emissions credit by meeting the criteria outlined in Section 3.2.3.3.

Certain parameters, listed in Table 3-28, are altered to GREET's release-default state in order to ensure that the modeled fuels are broadly representative of those sold in New Mexico. As described in Section 3.2.1, market-based allocation is given preference over other available modes. For this reason, ERG altered the two enumerated allocation-selector parameters from their default values of "1 -- Displacement method" to "3 -- Market-Based Allocation". Furthermore, ERG updated the price of process-heat steam generated via fossil NG from its default value of $0 per Btu (as embedded in "MeOH_FTD!L59") to $1.02E-05 per Btu, derived from a recent national-average NG price of $10 per thousand scf as reported by the U.S. Energy Information Administration.[34]

Table 3-28. Parameters relevant to all Hydrogen pathways

Parameter	Value		GREET Label	Description
	Default	NM		
Inputs! F267	1	3	Central Plant G.H2; NG/RNG; 6.8) Selection of Method for Estimating Credits of Co-Products for NG Based Fuel Pathways (Co-products are defined in Section 6.7)	Preference market allocation, as detailed in Section 3.2.1
Inputs! F269	1	3	Central Plant L.H2; NG/RNG; 6.8) Selection of Method for Estimating Credits of Co-Products for NG Based Fuel Pathways (Co-products are defined in Section 6.7)	
Hydrogen! K37	=MeOH_FTD!L59	=10/(NG_LHV*10^3)	$/Btu, Steam, Market value-based allocation	Use national-average NG price ($/thousand scf)[35] and NG LHV to update GREET's per-Btu steam price

[34] U.S. Energy Information Administration, "Natural Gas Prices," accessed June 19, 2025, https://www.eia.gov/dnav/ng/NG_PRI_SUM_A_EPG0_PCS_DMCF_M.htm.

[35] U.S. Energy Information Administration, "Natural Gas Prices," accessed June 19, 2025, https://www.eia.gov/dnav/ng/NG_PRI_SUM_A_EPG0_PCS_DMCF_M.htm.

3.7.1 H2 via SMR of Fossil Methane

3.7.1.1 Fossil C.H2

The Fossil C.H_2 pathway estimates the typical WTW CI of fossil C.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.1.1's Feedstock stage, followed by NG pipeline transmission to a central SMR plant. The Fuel processing stage includes H_2 production via SMR, transportation and distribution of gaseous H_2 to refueling stations, compression and precooling, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger fuel cell electric vehicle (FCEV).

The pathway's total WTW CI and those of its stages are provided below in Table 3-29. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-29. Summary of Fossil C.H2's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	10.2
Fuel	84.2
On-Road	0.0
Total, WTW	94.4
Total, WTW, adjusted	**100.0**

** Values may not always sum to equal the total due to rounding.*

3.7.1.2 Fossil L.H2

The Fossil L.H_2 pathway estimates the typical WTW CI of L.H_2 produced by SMR of fossil CNG supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.1.1's Feedstock stage, followed by NG pipeline transmission to a central SMR plant. The Fuel processing stage includes H_2 production via SMR, liquefaction and bulk storage, transportation and distribution to refueling stations, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger FCEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-30. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-30. Summary of Fossil L.H2's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	13.3
Fuel	122.4
On-Road	0.0
Total, WTW	135.7
Total, WTW, adjusted	**145.0**

** Values may not always sum to equal the total due to rounding.*

3.7.2 H_2 via SMR of AW Biomethane

3.7.2.1 AW C.H2

The AW C.H_2 pathway estimates the expected WTW CI of AW C.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.2.1's Feedstock and Fuel stages, except that biomethane is transmitted via pipeline to a central SMR plant rather than a refueling station and is not initially compressed. The fuel processing stage includes H_2 production via SMR with process heat derived from fossil NG (i.e., not biomethane), transportation and distribution of gaseous H_2 to refueling stations, compression and precooling, and storage and dispensing with associated losses. The On-Road stage models fuel combustion within a light-duty passenger FCEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of the carbon emitted during SMR of biomethane.

The pathway's total WTW CI and those of its stages are provided below in Table 3-31. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-31. Summary of AW C.H2's stagewise CIs

Stage	Total CI* ($g\ CO_2e/MJ$)
Biogenic CO_2 Uptake	-56.3
Feedstock	30.7
Fuel	27.9
On-Road	0.0
Total, WTW	88.3
Total, WTW, adjusted	**95.0**
Total, WTW, with credit	-1.8
Total, WTW, with credit, adjusted	**0.0**

** Values may not always sum to equal the total due to rounding.*

Counterfactual Additionality Credit

As outlined in Section 3.2.3.3, biomethane producers that meet the additionality criteria for AD installations may apply a counterfactual avoided emissions credit of -90.0 g CO_2e/MJ to the feedstock AW NG for this AW C.H_2 Temporary Pathway Table pathway. Once applied, this credit brings the pathway's WTW CI down to -1.8 g CO_2e/MJ.

3.7.2.2 AW L.H2

The AW L.H_2 pathway estimates the expected WTW CI of AW L.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.2.1's Feedstock and Fuel stages, except that biomethane is transmitted via pipeline to a central SMR plant rather than a refueling station and is not initially compressed. The Fuel processing stage includes H_2 production via SMR with process heat derived from fossil NG (i.e., not biomethane), liquefaction and bulk storage, transportation and distribution to refueling stations, and storage and dispensing with associated losses. The On-Road stage models fuel combustion within a light-duty passenger FCEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of the carbon emitted during SMR of biomethane.

The pathway's total WTW CI and those of its stages are provided below in Table 3-32. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-32. Summary of AW L.H2's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	60.9
Fuel	122.4
On-Road	0.0
Total, WTW	127.0
Total, WTW, adjusted	**135.0**
Total, WTW, with credit	37.0
Total, WTW, with credit, adjusted	**40.0**

** Values may not always sum to equal the total due to rounding.*

Counterfactual Additionality Credit

As outlined in Section 3.2.3.3, biomethane producers that meet the additionality criteria for AD installations may apply a counterfactual avoided emissions credit of -90.0 g CO_2e/MJ to the feedstock AW NG for this AW L.H_2 Temporary Pathway Table pathway. Once applied, this credit brings the pathway's WTW CI down to 37.0 g CO_2e/MJ.

3.7.3 H2 via SMR of LF Biomethane

3.7.3.1 LF C.H2

The LF C.H_2 pathway estimates the expected WTW CI of LF C.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.3.1's Feedstock and Fuel stages, except that biomethane is transmitted via pipeline to a central SMR plant rather than a refueling station and is not initially compressed. The Fuel processing stage includes H_2 production via SMR with process heat derived from fossil NG (i.e., not biomethane), transportation and distribution of gaseous H_2 to refueling stations, compression and precooling, and storage and dispensing with associated losses. The On-Road stage models fuel combustion within a light-duty passenger FCEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of the carbon emitted during SMR of biomethane.

The pathway's total WTW CI and those of its stages are provided below in Table 3-33. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-33. Summary of LF C.H2's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	18.2
Fuel	84.2
On-Road	0.0

Total, WTW	46.1
Total, WTW, adjusted	**50.0**

** Values may not always sum to equal the total due to rounding.*

3.7.3.2 LF L.H_2

The LF L.H_2 pathway estimates the expected WTW CI of LF L.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of the set of activities defined in Section 3.6.3.1's Feedstock and Fuel stages, except that biomethane is transmitted via pipeline to a central SMR plant rather than a refueling station and is not initially compressed. The Fuel processing stage includes H_2 production via SMR with process heat derived from fossil NG (i.e., not biomethane), liquefaction and bulk storage, transportation and distribution to refueling stations, and storage and dispensing with associated losses. The On-Road stage models fuel combustion within a light-duty passenger FCEV. Finally, a Biogenic CO_2 Uptake stage is incorporated to account for the biosphere origin of the carbon emitted during SMR of biomethane.

The pathway's total WTW CI and those of its stages are provided below in Table 3-34. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-34. Summary of LF L.H2's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Biogenic CO_2 Uptake	-56.3
Feedstock	23.7
Fuel	122.4
On-Road	0.0
Total, WTW	89.8
Total, WTW, adjusted	**95.0**

** Values may not always sum to equal the total due to rounding.*

3.7.4 H2 via PEM Electrolysis

3.7.4.1 C.H2 from North-American-Average Grid Electricity

The C.H_2 from North-American-Average Grid Electricity pathway estimates the expected WTW CI of average-grid C.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of electricity generation across a national-average collection of electricity generating units, followed by transmission to an electrolyzer. The Fuel processing stage includes H_2 production via PEM electrolysis, transportation and distribution of gaseous H_2 to refueling stations, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger FCEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-35. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-35. Summary of C.H2 from North-American-Average Grid Electricity's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	203.5
Fuel	14.3
On-Road	0.0
Total, WTW	217.8
Total, WTW, adjusted	**230.0**

** Values may not always sum to equal the total due to rounding.*

3.7.4.2 L.H2 from North-American-Average Grid Electricity

The L.H_2 from North-American-Average Grid Electricity pathway estimates the expected WTW CI of average-grid L.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of electricity generation across a national-average collection of electricity generating units, followed by transmission to an electrolyzer. The Fuel processing stage includes H_2 production via PEM electrolysis, liquefaction and bulk storage, transportation and distribution to refueling stations, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger FCEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-36. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-36. Summary of L.H2 from North-American-Average Grid Electricity's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	219.8
Fuel	46.9
On-Road	0.0
Total, WTW	266.7
Total, WTW, adjusted	**285.0**

** Values may not always sum to equal the total due to rounding.*

3.7.4.3 C.H2 from Zero-Carbon Electricity

The C.H_2 from Zero-Carbon Electricity pathway estimates the expected WTW CI of zero-feedstock-carbon C.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of zero-carbon electricity generation, as defined in the Zero-Carbon Electricity pathway, followed by transmission to an electrolyzer. The Fuel processing stage includes H_2 production via PEM electrolysis, transportation and distribution of gaseous H_2 to refueling stations, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger FCEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-37. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-37. Summary of C.H2 from Zero-Carbon Electricity's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	0.0
Fuel	14.3
On-Road	0.0
Total, WTW	14.3
Total, WTW, adjusted	**20.0**

** Values may not always sum to equal the total due to rounding.*

3.7.4.4 L.H2 from Zero-Carbon Electricity

The L.H_2 from Zero-Carbon Electricity pathway estimates the expected WTW CI of zero-feedstock-carbon L.H_2 supplied to New Mexico. The Feedstock lifecycle stage is composed of zero-carbon electricity generation, as defined in the Zero-Carbon Electricity pathway, followed by transmission to an electrolyzer. The Fuel processing stage includes H_2 production via PEM electrolysis, liquefaction and bulk storage, transportation and distribution to refueling stations, and storage and dispensing with associated losses. Finally, the On-Road stage models fuel consumption within a light-duty passenger FCEV.

The pathway's total WTW CI and those of its stages are provided below in Table 3-38. Formulas defining this pathway's stagewise emissions on *Results_NM* primarily refer to and derive from GREET1's *Hydrogen* sheet Section 4.1, *Vehicles* sheet Section 3, and *Results* tab Section 2.

Table 3-38. Summary of L.H2 from Zero-Carbon Electricity's stagewise CIs

Stage	Total CI* (g CO_2e/MJ)
Feedstock	0.0
Fuel	46.9
On-Road	0.0
Total, WTW	46.9
Total, WTW, adjusted	**50.0**

** Values may not always sum to equal the total due to rounding.*

3.8 Data Sharing

In the broader CTFP analysis, ERG has supplied iterations of the CI table to NMED for feedback and BRG as inputs for their economic optimization model. These New Mexico–specific CIs go on to inform the rule's credit and deficit generation over time, as well as statewide fuel projections by policy scenario.

4. Projected Emission Reductions

4.1 Background

New Mexico's program is expected to generate emission reductions from changes to the amount of transportation fuels produced, imported, or dispensed for use within the state, particularly switching from fossil diesel to renewable diesel and to a lesser extent biodiesel. To estimate emissions, ERG has calculated state-specific emission factors for both onroad vehicles and nonroad equipment and then coupled the EFs with BRG projections of diesel fuel volume deltas by policy scenario. The product of the EFs and fuel volume deltas yields separate estimates for onroad and nonroad emission reductions for several key criteria air pollutants and precursors, namely nitrogen oxides (NOx), primary particulate exhaust (PM2.5), sulfur dioxide (SO2), and volatile organic compounds (VOC). All EFs have been developed using county-scale runs of EPA's latest Motor Vehicle Emission Simulator release (MOVES5) and then aggregated over the state's 33 counties. The two distinct policy scenarios analyzed are described in detail below.

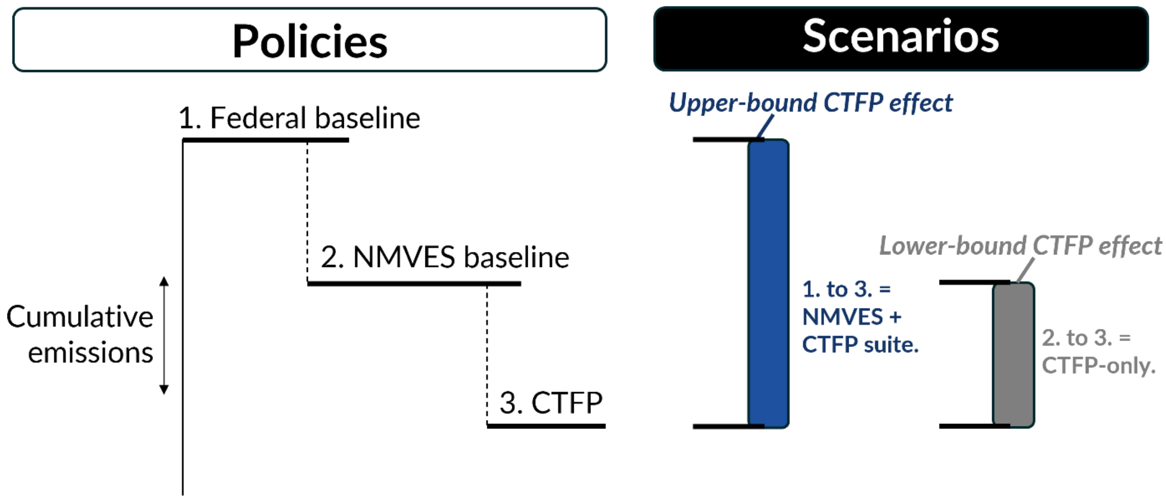
The first scenario considers the CTFP in combination with New Mexico's New Motor Vehicle Emission Standards,[36] labeled as "NMVES + CTFP" suite. Under this scenario, ERG considered the effect of the CTFP both as a standalone policy *and* combined with the NMVES as a supporting policy. This scenario provides an upper-bound estimate of the CTFP's impact on emission reductions. To make this determination, ERG took the difference of New Mexico transportation sector emissions with both the NMVES and CTFP in place (Line 3 in Figure 4-1) from those with neither the NMVES nor the CTFP in place (represented by Line 1 in Figure 4-1). In the latter case, the assumed effective policy is the latest EPA national standard: the 2024 Multi-Pollutant Rule for light-duty vehicles (LDVs) and the 2024 Phase 3 Rule for medium and heavy-duty vehicles (MHDVs).[37] This scenario provides an upper-bound estimate of the CTFP's effect because it attributes the combined emission reductions from the complementary CTFP and NMVES policies under the umbrella of the current program.

The second scenario is "CTFP-only." Instead of looking at the policy's combined effect as a standalone and supporting policy, this scenario only considers the CTFP as a standalone policy. The CTFP-only scenario gauges the policy's impact by subtracting New Mexico transportation sector emissions with both the NMVES and the CTFP in place (Line 3 in Figure 4-1) from a baseline that includes the NMVES (Line 2 in Figure 4-1). This provides a lower-bound estimate of the CTFP's effect because it considers this program as a standalone policy with no emissions reduction attributed to its role in supporting the NMVES.

[36] New Mexico Environment Department, "New Motor Vehicle Emissions Standards (Advanced Clean Cars II/Advanced Clean Trucks)," accessed May 29, 2025, https://www.env.nm.gov/climate-change-bureau/transportation/.

[37] U.S. Environmental Protection Agency, "Final Rule: Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles," accessed May 29, 2025, https://www.epa.gov/regulations-emissions-vehicles-and-engines/final-rule-multi-pollutant-emissions-standards-model.

Figure 4-1. Illustrative diagram of the policies and scenarios analyzed for cumulative emissions over a projection period



1. MOVES5 runs with federal Phase-3 Multi-Pollutant Rule
2. MOVES5 runs with NMVES ZEV requirements
3. Fuel markets model applied to NMVES fleet + VMT

Note: Illustrative depiction, does not represent actual quantities.

The CTFP's actual effect on New Mexico transportation sector emissions is likely somewhere between the upper-bound ("CTFP + NMVES") and lower-bound ("CTFP-only") scenarios. It is clear that the CTFP will play an important role in bolstering NMVES benefits through an initial bank of credits to build out fueling supply equipment (FSE) for zero-emission vehicles (ZEVs) along with a more continuous stream of credits to maintain FSE infrastructure. Therefore, the lower-bound "CTFP-only" estimate thus likely understates the policy's true effect on transportation emissions.

At the same time, the NMVES would certainly generate New Mexico transportation sector emission reductions even without the CTFP, so the upper-bound "CTFP + NMVES" estimate likely overstates the CTFP's true effect on emission reductions. It is difficult to ascertain exactly where the CTFP's effect would lie between these two bookend scenarios, but they both have been analyzed to cover the greatest range of possible outcomes.

4.1.1 Emissions Analysis

For this analysis, ERG received transportation fuel projections from BRG's fuel and credit markets model (FCMM) for both the "CTFP-only" and the "NMVES + CTFP" scenarios described later in Section 4.2.3 and detailed in Appendix B of BRG's BCA Report. In practice, BRG's fuel projections for the CTFP scenario only included volumetric changes to certain diesel blends. This report refers to these as projected fuel volumes, which then serve as inputs to calculate changes to transportation emissions for each scenario. To calculate the expected CTFP emission reductions, ERG coupled New Mexico-specific EFs for both onroad vehicles and nonroad equipment with corresponding fuel volume changes from BRG. The product of the EFs and transportation fuel volumes yields separate estimates for onroad and nonroad reductions in criteria air pollutant (CAP) emissions. Criteria pollutants include ozone (O_3) precursors like NO_x and VOCs, as well as particulate matter 2.5 micrometers or less in diameter ($PM_{2.5}$) and SO_2.

ERG developed all EFs for the "CTFP-only" and "NMVES + CTFP" scenarios using county-scale runs of EPA's latest Motor Vehicle Emission Simulator release (MOVES5) that ERG then aggregated over the entire state.[38] The MOVES5 model incorporates recent emission research and test results, as well as any current federal regulations, including EPA's Multi-Pollutant and Phase 3 Rules mentioned above for LDVs and MHDVs, respectively. Although MOVES includes emissions data for the most prevalent fuels, the model does not have data for all the eligible fuels in New Mexico's program. This fuel data gap pertains particularly to biomass-based diesels (BBDs), including both onroad and nonroad use of RD and nonroad use of BD. For BBDs, ERG applied published RD and BD fuel effects to base MOVES EFs. These fuel effects become important because under the "CTFP-only" scenario; the incremental impact of the CTFP on CAP emissions results entirely from increased blending of BBDs into the pool of diesel fuel produced, imported, or dispensed for use in New Mexico.

For the benchmarking and calibration of transportation fuel volume estimates forecast by BRG, ERG provided state fuel consumption by transportation mode, including for onroad (highway), nonroad, aviation, and rail. Ultimately, BRG only incorporated the onroad and nonroad benchmarks in FCMM transportation fuel projections. The following section details these MOVES-derived benchmarks.

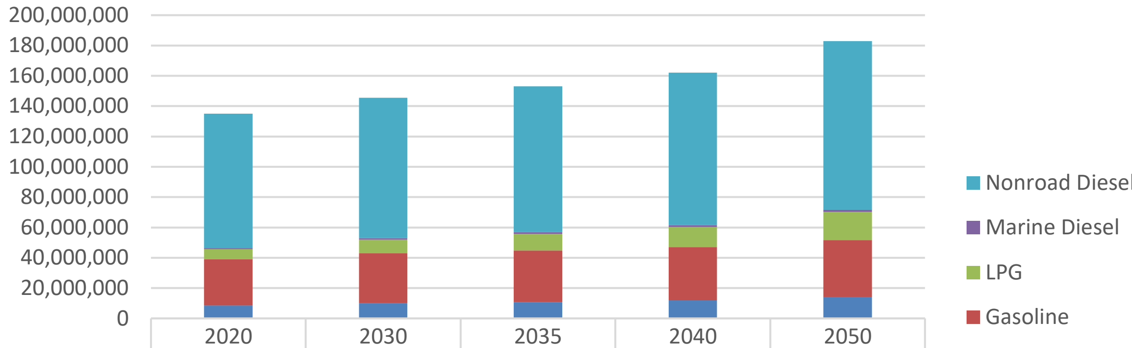
4.1.2 Benchmarking

4.1.2.1 Nonroad Benchmarks

To inform BRG's FCMM fuel projections, ERG provided aggregate MOVES5 nonroad energy consumption by fuel converted into gallons of gasoline equivalent (GGE) for comparability. These nonroad runs yielded intuitive results that BRG incorporated into the FCMM. Figure 4-2 shows MOVES nonroad fuel estimates for the years explicitly modeled (2020, 2030, 2035, 2040, and 2050). BRG directly applied these nonroad fuel estimates to the FCMM.

[38] U.S. Environmental Protection Agency, "MOVES and Mobile Source Emissions Research," accessed May 20, 2025, https://www.epa.gov/moves.

Figure 4-2. Estimated MOVES nonroad fuel use over time for New Mexico (LPG, CNG, and gasoline blends in GGE and diesel blends in DGE)



	2020	2030	2035	2040	2050
Nonroad Diesel	88,415,308	92,489,982	96,017,704	100,419,699	111,365,615
Marine Diesel	943,936	1,116,946	1,195,832	1,278,302	1,448,624
LPG	6,404,259	9,088,741	10,962,638	13,277,562	18,316,894
Gasoline	30,749,751	32,941,115	34,007,886	35,185,709	37,627,040
CNG	8,430,604	9,908,742	10,812,452	11,867,946	14,166,067

4.1.2.2 Onroad Benchmarks

By contrast, BRG did not directly apply MOVES5 projected onroad fuel use to its transportation FCMM. Instead, BRG's FCMM calculated onroad fuel use with MOVES5 annual vehicle populations, VMT, and fuel economy, adjusting their output to more closely align with ZEV adoption with the NMVES policy in place. ERG has documented initial New Mexico vehicle populations and VMT from MOVES prior to any adjustment in Section 4.2.2 of this report. BRG further describes their method for making these adjustments to fleet and VMT estimates in Appendix A of their BCA Report.

4.2 Modeling Approach

4.2.1 Motor Vehicle Emission Simulator (MOVES)

Since its first official public release in 2010, MOVES has served as the regulatory onroad emission inventory model for highway vehicles, including cars, trucks, and buses. Beginning with MOVES2014, EPA also incorporated modeling capabilities for nonroad equipment, such as equipment used in construction and agriculture, based on NONROAD2008, EPA's predecessor model.[39] In November 2024, EPA released MOVES5, which accounted for the federal GHG rules released earlier in the year. All emissions modeling for the CTFP uses MOVES5 with input data specific to New Mexico and other regulatory programs.

ERG pulled New Mexico county inputs (often called MOVES county databases, or CDBs) from the most recent 2020 National Emissions Inventory (NEI), which EPA publishes every three years. These state-specific CDBs were coupled with custom fuel penetrations by vehicle type over time (referred to as the alternative vehicle fuel and technology, or AVFT, table in MOVES).[40] This CTFP

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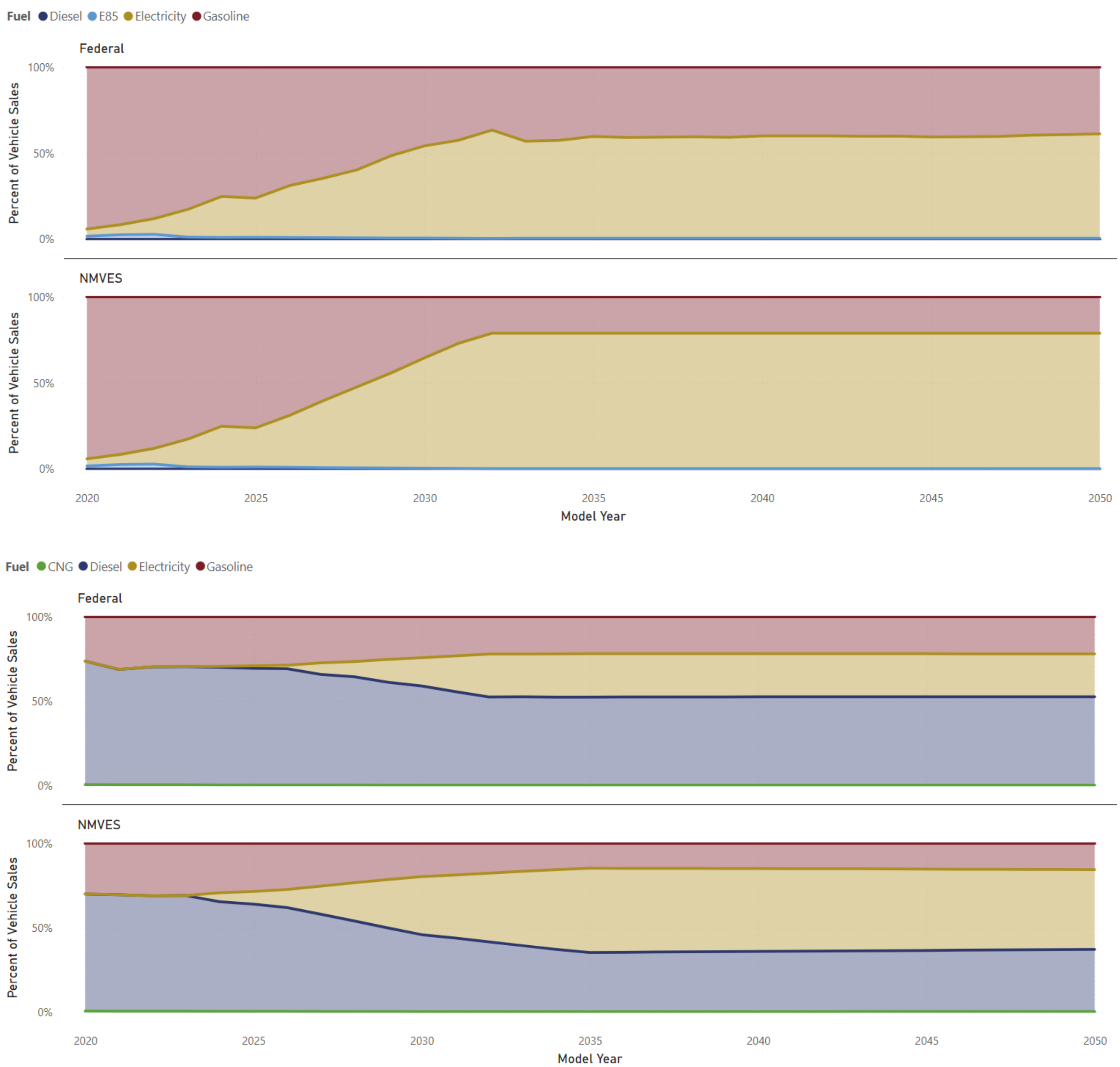
[39] U.S. Environmental Protection Agency, "MOVES2014 Update Log," accessed May 29, 2025, https://www.epa.gov/moves/moves2014-update-log.

[40] U.S. Environmental Protection Agency, "Population and Activity of Onroad Vehicles in MOVES5," November 2024, https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P101CUN7.pdf.

emission analysis required two custom AVFT tables: one to reflect the NMVES (i.e., ACC II and ACT), and another to reflect the latest federal programs (i.e., Multi-Pollutant and Phase 3). Full MOVES run specifications (runspecs) are outlined in Appendix B.

Figure 4-3. Comparison plots of alternative fuel vehicle penetrations under the federal and NMVES programs for passenger cars (top two) and short-haul single unit trucks (bottom two)



Importantly, this approach relates MOVES EFs directly to fuel volumes affected by New Mexico's CTFP. Any changes to baseline fleet and VMT forecasts should have a negligible impact on the projected emission reductions. ERG monetized the health impacts from these emission reductions by pollutant (NO_x, VOCs, $PM_{2.5}$, and SO_2), as described in Chapter 5.

4.2.2 Annual Fleet, Activity, and Fuel Economy Estimates

This analysis compiled VMT and vehicle population estimates from county-level projections from the 2020 NEI, the most recent available at the time of analysis.[41] EPA publishes MOVES CDBs for each U.S. county as part of the NEI process, drawing vehicle population from state registration data and VMT from U.S. Department of Transportation (DOT) Federal Highway Administration (FHWA) data compiled from state transportation departments. ERG converted 2020 NEI CDBs for New Mexico's 33 counties to MOVES5 format with EPA scripts. These CDBs served as the basis for the other CTFP analysis years (2030, 2035, 2040, 2050). This analysis used FHWA VMT growth projections to estimate VMT and population for the analysis years and applied growth rates differently to account for pandemic shutdown effects on 2020 VMT.[42]

Although the 2020 CDBs provide county-specific data on vehicle population and activity, this analysis adjusted 2020 VMT to a pre-pandemic baseline using VMT from the last NEI published prior to the pandemic: 2017. The 2017 NEI provided a consistent basis for adjustment because, like the 2020 NEI, it used data on VMT by MOVES source type and county compiled by FHWA from the New Mexico Department of Transportation (NMDOT).[43] Table 4-1 shows the NEI VMT ratios between 2017 and 2020 VMT as factors to adjust 2020 values back to a pre-pandemic baseline. These adjustments were warranted because 2020 VMT shows marked decreases for passenger vehicles, as well as for some commercial vehicles (light commercial truck, refuse truck, transit bus), but a large increase in short-haul truck activity from higher demand for e-commerce deliveries.

Table 4-1. Pre-pandemic VMT adjustment factors by MOVES vehicle source type

MOVES Source Type	2017 NEI VMT (million miles)	2020 NEI VMT (million miles)	Base Year VMT Adjustment Ratios (2017/2020)
Combination long-haul truck	1,652	1,611	1.03
Combination short-haul truck	846	1,418	0.60
Intercity bus	44	11	4.05
Light commercial truck	1,404	941	1.49
Motor home	21	42	0.49
Motorcycle	394	258	1.52
Passenger car	9,953	6,946	1.43
Passenger truck	13,032	10,969	1.31
Refuse truck	14	9	1.59
School bus	56	114	0.49
Single unit long-haul truck	723	254	2.84

[41] U.S. Environmental Protection Agency, "2020 National Emissions Inventory (NEI) Data," accessed May 29, 2025, https://www.epa.gov/air-emissions-inventories/2020-national-emissions-inventory-nei-data.

[42] Federal Highway Administration, "2024 FHWA Forecasts of Vehicle Miles Traveled (VMT)," June 2024, https://www.fhwa.dot.gov/policyinformation/tables/vmt/vmt_forecast_sum.cfm.

[43] U.S. Environmental Protection Agency, "2017 National Emissions Inventory (NEI) Data," January 2021, https://www.epa.gov/air-emissions-inventories/2017-national-emissions-inventory-nei-data.

MOVES Source Type	2017 NEI VMT (million miles)	2020 NEI VMT (million miles)	Base Year VMT Adjustment Ratios (2017/2020)
Single unit short-haul truck	483	1,429	0.34
Transit bus	39	25	1.53

Table 4-2 shows annual VMT growth projections published by FHWA for a baseline case. FHWA also publishes pessimistic and optimistic growth projections. This analysis chose baseline projections to reflect VMT moderate growth. FHWA developed these projections from a pre-pandemic baseline (2019), with one set of growth rates applied for 2040 (also applied to 2030 and 2035) and a lower set of rates applied for 2050.

Table 4-2. Published FHWA VMT growth projections (baseline scenario)

Vehicle Class	Annual Growth	
	2019–2040	2019–2050
Light-duty vehicles	0.5%	0.4%
Single-unit trucks	2.1%	1.9%
Combination trucks	1.3%	1.1%

Equation 4-1 delineates county-level VMT for a future year y as a projection based on its 2020 CDB activity, a defined pandemic adjustment factor α from Table 4-1, and an FHWA growth rate g from Table 4-3. Equation 4-2 describes statewide VMT as simply the summation of all county-level VMT for each year, such that

$$VMT_{y,s,c} = VMT_{2020,s,c} \cdot \alpha_s \cdot (1 - g_s)^{y-2019} \quad \textbf{Equation 4-1}$$

$$VMT_{y,s} = \sum\nolimits_{c \in C} VMT_{y,s,c} \quad \textbf{Equation 4-2}$$

where $c \in C$ is each county c in the full set of 33 New Mexico counties C for a chosen future analysis year y and MOVES source type s.

This analysis projected county-level vehicle populations in the same manner using the FHWA growth estimates. However, as pandemic effects were attributed only to vehicle activity, this analysis did not apply the base year adjustment to vehicle population, only to VMT. For the 2020s, this analysis applied growth rates to 2020 vehicle population. Table 4-3 shows the aggregate VMT and vehicle population adjustments to 2020 CDBs.

Table 4-3. Computed VMT and vehicle population growth rates by MOVES source type from base year 2020

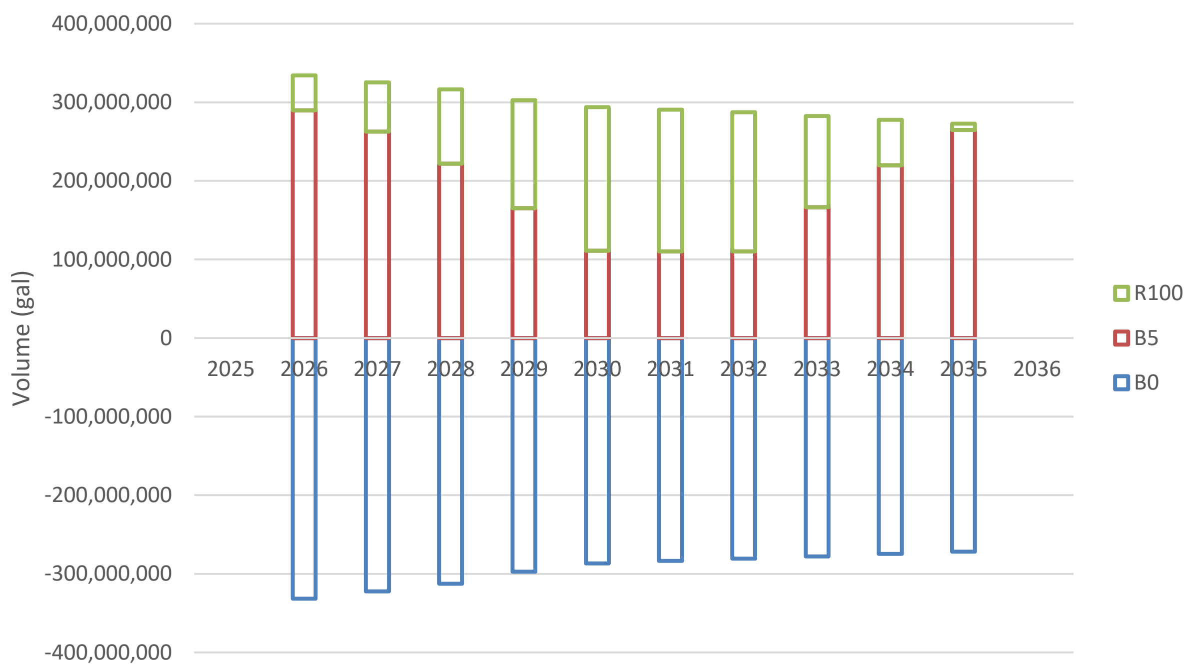
VMT Growth Rates From 2020	2020–2030	2020–2035	2020–2040	2020–2050
Combination long-haul trucks	1.18	1.26	1.35	1.44
Combination short-haul trucks	0.69	0.73	0.78	0.84
Intercity buses	5.08	5.64	6.26	7.25
Light commercial trucks	1.58	1.62	1.66	1.69
Motor homes	0.62	0.69	0.76	0.89
Motorcycles	1.61	1.65	1.69	1.72
Passenger cars	1.51	1.55	1.59	1.62
Passenger trucks	1.39	1.42	1.46	1.48
Refuse trucks	2.00	2.22	2.46	2.85
School buses	0.61	0.68	0.76	0.88
Single unit long-haul trucks	3.57	3.96	4.40	5.09
Single unit short-haul trucks	0.43	0.47	0.52	0.61
Transit buses	1.93	2.14	2.37	2.75
Vehicle Population Growth Factors From 2020	**2020–2030**	**2020–2035**	**2020–2040**	**2020–2050**
Combination long-haul trucks	1.14	1.21	1.29	1.39
Combination short-haul trucks	1.14	1.21	1.29	1.39
Intercity buses	1.23	1.37	1.52	1.76
Light commercial trucks	1.05	1.08	1.10	1.13
Motor homes	1.23	1.37	1.52	1.76
Motorcycles	1.05	1.08	1.10	1.13
Passenger cars	1.05	1.08	1.10	1.13
Refuse trucks	1.23	1.37	1.52	1.76
School buses	1.23	1.37	1.52	1.76
Single-unit long-haul trucks	1.23	1.37	1.52	1.76
Single unit short-haul trucks	1.23	1.37	1.52	1.76
Transit buses	1.23	1.37	1.52	1.76

The resulting MOVES vehicle populations and VMT, particularly for light-duty ZEVs, only offered a starting point for additional adjustment that would match New Mexico's current NMVES policy. BRG documents adjustments to the MOVES fleet and activity in Appendix A of their BCA Report.

4.2.3 Use of BRG-Derived Transportation Fuel Volumes in Emission Calculations

BRG used statewide MOVES estimates for vehicle populations and VMT to project annual onroad and nonroad transportation fuel use, including electricity. BRG forecasts that most fuel volumes will not change between New Mexico's NMVES and CTFP policies—such that differences only arise in volumes of R100 and a modest biodiesel blend (B5) displacing finished fossil diesel (B0).[44] Volumetric changes to these finished diesel blends under the "CTFP-only" scenario produce all emission reductions from that scenario, as shown for onroad volumes in Figure 4-4 and Table 4-4 and for nonroad volumes in Figure 4-5 and Table 4-5.

Figure 4-4. Annual onroad transportation fuel volume forecast of B0, B5, and R100 under New Mexico's CTFP (in gallons of fuel), from BRG



[44] These changes in fuel volumes (via BRG's FCMM analysis) and any subsequent impacts on emissions, health, and I-O results have not been adjusted to reflect CI corrections made since the September 2nd NOI.

Table 4-4. Table of forecast CTFP onroad transportation fuel volumes by fuel type and year (in gallons of fuel), provided by BRG

Year	B0	B5	R100
2026	-331,680,946	289,929,989	44,239,988
2027	-322,283,905	262,573,835	62,780,060
2028	-312,498,308	221,839,750	94,750,335
2029	-297,105,218	165,292,344	137,255,726
2030	-286,712,776	111,227,907	182,380,585
2031	-283,725,661	110,069,080	180,480,454
2032	-280,736,989	110,078,586	177,370,611
2033	-277,746,866	166,289,072	116,145,544
2034	-274,754,618	219,626,165	57,889,459
2035	-271,758,873	264,574,361	8,304,150
Cumulative Total	**-2,939,004,159**	**1,921,501,089**	**1,061,596,912**

Figure 4-5. Annual nonroad transportation fuel volume forecast of B0, B5, and R100 under New Mexico's CTFP (in gallons of fuel), from BRG

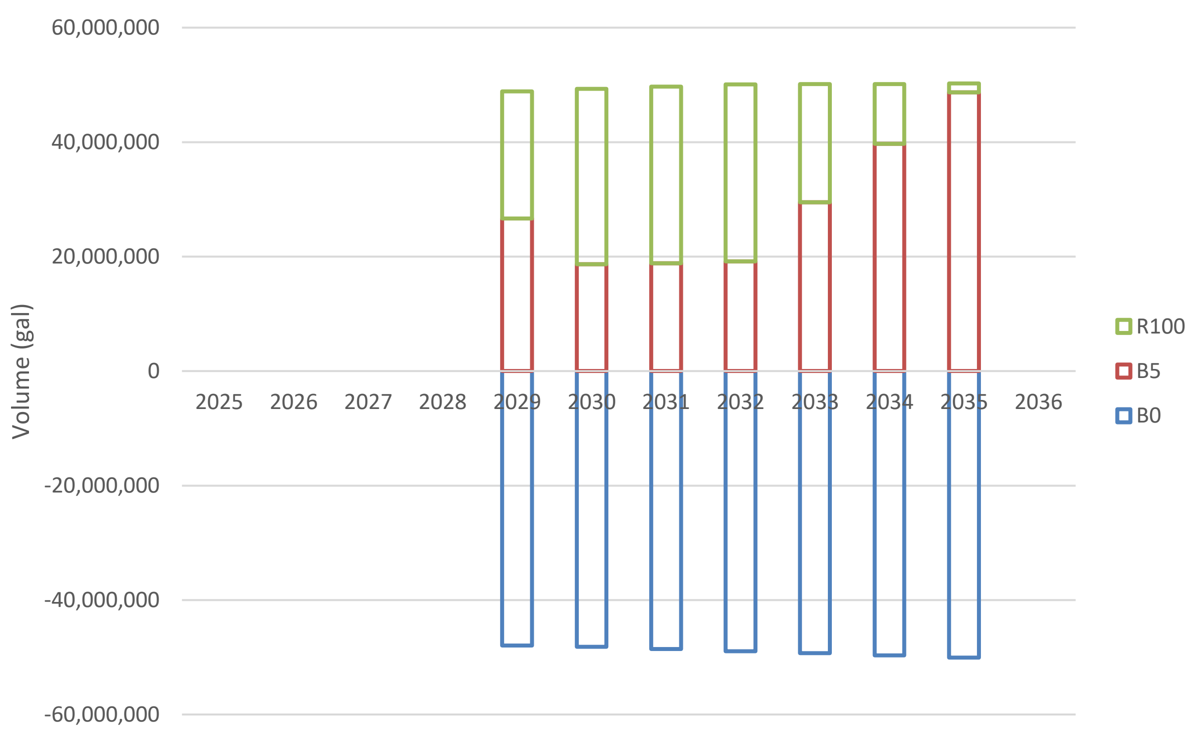


Table 4-5. Table of forecast CTFP nonroad transportation fuel volumes by fuel type and year (in gallons of fuel), provided by BRG

Year	B0	B5	R100
2026	0	0	0
2027	0	0	0
2028	0	0	0
2029	0	0	0
2030	-47,960,303	26,682,369	22,156,549
2031	-48,178,929	18,690,627	30,647,052
2032	-48,550,189	18,834,654	30,883,213
2033	-48,921,449	19,182,381	30,908,742
2034	-49,292,709	29,511,904	20,612,756
2035	-49,663,969	39,699,085	10,463,956
Cumulative Total	**-50,035,229**	**48,712,443**	**1,528,929**

For completeness, ERG calculated EFs for all onroad and nonroad fuels produced, imported, or dispensed for use in New Mexico. However, only changes to finished diesel blends affected criteria pollutant emission differences under the "CTFP-only" scenario. The following sections discuss how ERG modeled diesel fuel effects, including blends not available in the default MOVES5 database.

4.2.4 Development of New Mexico-Specific Emission Factors

There are 33 counties in New Mexico, and each county has unique MOVES inputs for onroad vehicle populations and miles traveled from the state's 2020 NEI submission. This analysis used the state's 2020 NEI submission to create CDBs for four future evaluation years (2030, 2035, 2040, and 2050) according to the growth rates described above in Section 4.2.2. This analysis did not explicitly model the uptake of alternative fuels, which came from BRG's transportation fuel markets model as detailed in Section 4.2.3. However, this analysis applies policy-specific alternative fuel vehicle adoption using the MOVES AVFT table for the NMVES (consistent with California's clean car and truck programs) and federal baseline policies, described above in Section 4.2.1.

Other MOVES county-scale inputs from the 2020 NEI, such as vehicle age distributions and fuel properties, were used but not changed over time or by policy. These inputs equated to 165 annual MOVES county-scale runs (33 counties over five years) for the NMVES baseline policy and another 165 runs for the federal baseline policy. These 330 total MOVES runs form the basis of the NMVES EFs developed to estimate statewide CTFP benefits.

ERG developed statewide onroad emission factors EF dependent on MOVES fuel type f, pollutant p, and year y by aggregating county emission inventories EI per energy consumption estimates ε for each calendar year, as laid out in Equation 4-3 below, such that:

$$EF_{f,p,y} = \sum_{c \in C} EI_{f,p,y,c} / \varepsilon_{f,p,y,c}. \qquad \textbf{Equation 4-3}$$

where $c \in C$ is each county c across the set of all 33 New Mexico counties C. This analysis then pairs these statewide EFs per energy unit with CTFP fuel volume projections and energy density conversions by fuel, as shown below in Table 4-6. Here, ERG calculated volume-weighted averages of energy density values from the proposed Table 7 in the draft discussion rule.[45]

Table 4-6. Summary of energy densities by fuel blend (based on published CTFP values)

Fuel	Energy Density (MJ/gallon)
B0	134.48
B5	134.06
R100	129.95

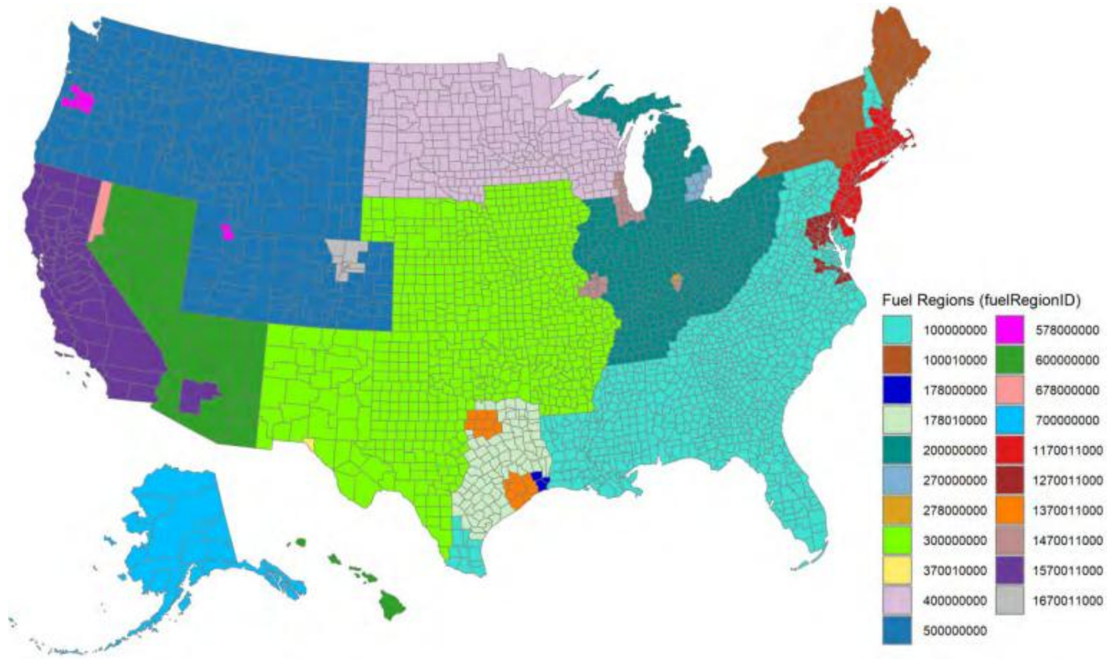
For ease of implementation, ERG did not differentiate EFs by MOVES vehicle (regulatory) class. Rather, ERG summed emission inventories and energy over all classes. This leads to a set of onroad transportation fuel volumes and EFs to calculate onroad emission reductions and another set of nonroad transportation fuel volumes and EFs to calculate nonroad reductions.

Although most criteria pollutants can be modeled on a yearly basis to expedite runtime, certain pollutants must be run on an hourly basis to account for diurnal and seasonal effects. This applies to VOC evaporative emissions from fuel tank permeation, leaks, and vapor venting as the vehicle soaks (with its engine off). Evaporative emissions depend more on ambient temperature than on start or running tailpipe exhaust, so MOVES requires users to specify a month and hour of the day for modeling evaporative VOC. ERG chose to run representative 24-hour days in January and July to derive average VOC evaporative EFs by county and then added these to the tailpipe VOC EFs ERG had formulated from MOVES annual county runs.

In addition to the default exhaust and VOC evaporative runs, ERG performed some other targeted MOVES runs to derive EFs for non-default blends of gasoline and diesel; namely, E15, B0, and B5. MOVES contains different fuel regions, and New Mexico's fuel region (which also covers parts of Texas, Oklahoma, and some other states in the Central Plains) assumes that the default gasoline blend contains roughly 10 percent ethanol and the default diesel blend contains 3.75 percent biofuel, as shown in Figure 4-6 below.

[45] See Table 7 of Subsection (G) of Title 20, Chapter 2, Part 92, Section 701 of the New Mexico Administrative Code (20.2.92.701 NMAC).

Figure 4-6. MOVES fuel region map for 2024 (screenshot from EPA's MOVES5 Regional Fuels Report)



To model E15, B0, and B5 in New Mexico, ERG modified the default blends using the MOVES Fuel Wizard and ran them in Bernalillo County (Albuquerque and its suburbs, which is the state's largest metropolitan area) as a representative county. As with the statewide EFs, ERG computed E15, B0, and B5 exhaust and evaporative EFs using emission inventories and energy consumption by fuel and pollutant. In total, ERG performed 330 statewide exhaust runs, along with 330 statewide evaporative runs and another 30 representative special blend runs for developing New Mexico-specific onroad EFs.

ERG developed New Mexico nonroad EFs in much the same fashion, running nonroad emission inventories according to a 24-hour day for both weekdays and weekends. ERG then found a daily average for each month and multiplied that by the number of days per month to calculate annual nonroad emissions. As with onroad EFs, ERG formulated nonroad EFs using county emission inventories by fuel and pollutant, along with brake-specific fuel consumption (BSFC, in grams) and MOVES default fuel densities (in grams per gallon of fuel) instead of energy consumption.[46]

As discussed, MOVES does not explicitly model all years. This analysis also needed to provide New Mexico EFs for interim years between every five-year increment from 2020 to 2050. ERG accomplished this through linear piecewise interpolations by fuel and pollutant. Since ERG generated transportation fuel volumes for each year in this period, having explicit annual EFs by fuel facilitated the calculation of CTFP emission reductions.

[46] U.S. Environmental Protection Agency, "Exhaust and Crankcase Emission Factors for Nonroad Compression-Ignition Engines in MOVES3.0.2," September 2021, https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P1013KWQ.pdf.

Despite a robust database, MOVES does not model certain diesel blends, such as B5 for nonroad applications and R100 for both onroad and nonroad applications. ERG applied B5 and R100 fuel effects from external sources, as detailed in Section 4.3.

4.3 Fuel Effects

Fossil diesel (B0, or "clear diesel") is well studied and available for modeling in MOVES for onroad and nonroad applications. As discussed in Section 4.2.4, ERG has developed B0 EFs for the previously noted criteria pollutants (NO_x, VOCs, $PM_{2.5}$, and SO_2) using the MOVES Fuel Wizard for Bernalillo County. ERG performed a similar onroad analysis of B5, which is one of the most common BD blends available commercially in the United States today. However, MOVES does not have any information on nonroad fuel effects for B5, so ERG had to rely on external data sources for developing nonroad B5 EFs. Likewise, MOVES does not have default data on RD (R100) for onroad or nonroad applications, so ERG also developed R100 EFs from external sources. This section describes how ERG derived CAP emissions from onroad and nonroad R100 use, in addition to nonroad B5 use.

This analysis projects BD and RD volumes for onroad and nonroad applications under the CTFP. However, because directly applicable MOVES data were not available, this analysis developed emission adjustments to reflect two recent studies of BD and RD fuel effects on diesel engine emissions: a meta-analysis of BD effects on modern diesel engines published by the International Council on Clean Transportation (ICCT),[47] and a study of RD emissions research and testing published by the University of California Riverside College of Engineering-Center for Environmental Research and Technology (UCR CE-CERT).[48]

4.3.1 Source of Biodiesel Effects

BD effects for onroad vehicles operating on a B20 blend from MOVES5 were the basis for adjustments used in the CTFP analysis, as shown in Table 4-7 below. These effects were aggregated from a meta-analysis of several published studies conducted on legacy onroad engines without exhaust aftertreatment (pre-2007 model year). In MOVES, modern (2007 or later) engines are assumed to have equivalent emissions whether they run on B0 or B20. A similar meta-analysis published in 2021 by the ICCT found comparable results.[49]

[47] Jane O'Malley and Stephanie Searle, "Air Quality Impacts of Biodiesel in the United States" (International Council on Clean Transportation, March 2021), https://theicct.org/wp-content/uploads/2021/06/US-biodiesel-impacts-mar2021.pdf.

[48] Thomas Durbin et al., "Low Emission Diesel (LED) Study: Biodiesel and Renewable Diesel Emissions in Legacy and New Technology Diesel Engines," November 2021, https://ww2.arb.ca.gov/resources/documents/low-emission-diesel-led-study-biodiesel-and-renewable-diesel-emissions-legacy.

[49] Jane O'Malley and Stephanie Searle, "Air Quality Impacts of Biodiesel in the United States" (International Council on Clean Transportation, March 2021), https://theicct.org/wp-content/uploads/2021/06/US-biodiesel-impacts-mar2021.pdf.

Table 4-7. B20 emission effects from MOVES and ICCT meta-analyses relative to B0 (summary table replicated from ERG's 2022 white paper for the City of Portland)[50]

<table>
<tr><th rowspan="2"></th><th colspan="3">ICCT 2021</th><th colspan="2">MOVES5</th></tr>
<tr><th>Pre-2004</th><th>2004 EGR/CR</th><th>2007+ DPF/SCR</th><th>Pre-2007</th><th>2007+ DPF/SCR</th></tr>
<tr><td>NO_x</td><td>↑2%</td><td>↑4%</td><td rowspan="4">Not reported</td><td>↑2%</td><td rowspan="4">No effect applied</td></tr>
<tr><td>PM</td><td>↓6%</td><td>—</td><td>↓16%</td></tr>
<tr><td>HC</td><td>↓4%</td><td>↑7%</td><td>↓14%</td></tr>
<tr><td>CO</td><td>—</td><td>↑10%</td><td>↓13%</td></tr>
</table>

Although ERG generated specific B5 onroad emissions using the MOVES built-in Fuel Wizard, ERG could not make those same fuel adjustments for nonroad modeling. Lacking specific B20 fuel effects for nonroad use in ERG's CTFP MOVES runs, ERG scaled the MOVES onroad effects from Table 4-7 for B5 nonroad emissions in the CTFP. Note the slight NO_x disbenefit for legacy BD engines. The same effects, however, do not carry over to modern BD engines with the latest aftertreatment—namely, selective catalytic reduction (SCR) and diesel particulate filter (DPF).

4.3.2 Source of Renewable Diesel Effects

This analysis synthesized RD effects from the 2021 UCR study, which tested three engines of different vintages and use cases. The study includes one legacy (EPA Tier 3) nonroad engine, one modern (EPA Tier 4) nonroad engine, and one recent (model year 2007+) onroad engine for varying RD and BD blends, as shown in Table 4-8 below. The CTFP analysis focused on R100 fuel effects.

Table 4-8. Renewable diesel emission effects from UCR study relative to B0 (table also replicated from ERG's 2022 Portland white paper)

<table>
<tr><th rowspan="2"></th><th>Onroad</th><th colspan="2">Nonroad</th></tr>
<tr><th>Modern (model year 2007+)</th><th>Legacy (Tier 3)</th><th>Modern (Tier 4)</th></tr>
<tr><th colspan="4">R100</th></tr>
<tr><td>NO_x</td><td>—</td><td>↓ 5%</td><td>—</td></tr>
<tr><td>PM</td><td>—</td><td>↓ 27%–38%</td><td>—</td></tr>
<tr><td>HC</td><td>—</td><td>↓ 35%–45%</td><td>—</td></tr>
<tr><td>CO</td><td>↓ 5%</td><td>↓ 14%–22%</td><td>↓ 44%</td></tr>
</table>

Without UCR test data for legacy onroad engines, ERG decided to apply legacy R100 effects from nonroad testing for onroad applications as well. Considering that most legacy effects were presented as ranges, ERG selected and applied the midpoint effect for each pollutant to the base MOVES fossil diesel (B0) EFs.

[50] American Lung Association, "Who Is Most Affected by Outdoor Air Pollution?," accessed June 3, 2025, https://www.lung.org/clean-air/outdoors/who-is-at-risk.

4.3.3 Simulate B5 Emissions (Nonroad Only)

As noted above, ERG was able to model onroad B5 emissions using built-in MOVES5 fuel functionality. For nonroad B5 emissions, ERG needed to apply fuel effects by vehicle vintage externally. To determine vintage depending on evaluation year (2020, 2030, 2035, 2040, and 2050), ERG calculated the legacy-modern splits (pre-2007 or 2007+) for Bernalillo County. In practice, this means that B5 effects will be greater in earlier years. Besides NO_x (which modestly increases legacy engine CAP emissions), all other CAPs have dampening reductions from 2020 to 2050 compared to B0 as affected legacy engines leave the fleet, as shown in Table 4-9 below.

Table 4-9. Vintage-weighted CTFP B5 fuel effects from 2020 to 2050

Fuel	Pollutant	Year	Adjustment Factor
B5	THC	2020	0.974
B5	THC	2030	0.985
B5	THC	2035	0.0991
B5	THC	2040	0.995
B5	THC	2050	0.999
B5	CO	2020	0.974
B5	CO	2030	0.981
B5	CO	2035	0.87
B5	CO	2040	0.992
B5	CO	2050	0.998
B5	NO_x	2020	1.003
B5	NO_x	2030	1.001
B5	NO_x	2035	1.000
B5	NO_x	2035	1.000
B5	NO_x	2040	1.000
B5	NO_x	2050	1.000
B5	$PM_{2.5}$	2020	0.968
B5	$PM_{2.5}$	2030	0.976
B5	$PM_{2.5}$	2035	0.983
B5	$PM_{2.5}$	2040	0.989
B5	$PM_{2.5}$	2050	0.998
B5	VOC	2020	0.974
B5	VOC	2030	0.985
B5	VOC	2030	0.985
B5	VOC	2035	0.991
B5	VOC	2040	0.995
B5	VOC	2050	0.999

4.3.4 Simulate R100 Emissions (Onroad and Nonroad)

Given that it is not possible to model renewable diesel effects in MOVES currently, ERG needed to apply R100 effects externally for both onroad and nonroad use by vehicle vintage. To apply the following R100 fuel effects appropriately, ERG used the same Bernalillo legacy-modern splits, as described in the previous subsection on B5 emissions. Likewise, ERG also saw a similar trend of R100 effects converging towards fossil diesel (R0) emissions over time for all pollutants except CO, which has significantly lower emissions than R0 for modern nonroad engines, as shown in Table 4-10. As a result, RD loses benefits over time due fleet turnover and fossil diesel emission improvements rather than lost efficacy.

Table 4-10. Vintage-weighted onroad and nonroad CTFP R100 fuel effects from 2020 to 2050

Fuel	Pollutant	Year	Nonroad Adjustment Factor	Onroad Adjustment Factor
R100	THC	2020	0.701	0.777
R100	THC	2030	0.826	0.925
R100	THC	2035	0.898	0.967
R100	THC	2040	0.948	0.980
R100	THC	2050	0.993	1.000
R100	CO	2020	0.764	0.904
R100	CO	2030	0.710	0.941
R100	CO	2035	0.666	0.947
R100	CO	2040	0.625	0.948
R100	CO	2050	0.572	0.950
R100	NO_x	2020	0.972	0.979
R100	NO_x	2030	0.990	0.994
R100	NO_x	2035	0.995	0.997
R100	NO_x	2040	0.998	0.998
R100	NO_x	2050	1.000	1.000
R100	$PM_{2.5}$	2020	0.741	0.725
R100	$PM_{2.5}$	2030	0.809	0.799
R100	$PM_{2.5}$	2035	0.861	0.849
R100	$PM_{2.5}$	2040	0.913	0.885
R100	$PM_{2.5}$	2050	0.982	1.000
R100	VOC	2020	0.701	0.777
R100	VOC	2030	0.826	0.925
R100	VOC	2035	0.898	0.967
R100	VOC	2040	0.948	0.980
R100	VOC	2050	0.993	1.000

4.4 Baseline Emission Adjustments

In contrast to the CTFP scenario, the NMVES and federal baseline are not directly tied to changes in fuel volumes and instead rely on ERG's initial MOVES modeling. However, BRG has continued to modify MOVES fleet and activity estimates, as well as fuel projections—particularly for the NMVES and federal baseline scenarios—over this rulemaking to ensure that New Mexico's current electrification and other fuel switching targets can reasonably be achieved. While the CTFP emission benefits could quickly be recalculated with the latest volumes and corresponding EFs, this was not the case for two static baseline scenarios.

To account for changes to the NMVES and federal baseline fuel projections and their effects on emissions, ERG derived separate annual emission adjustments by scenario using the initial (unmodified) MOVES-based volumes and the BRG-modified volumes for the final rule. In Equation 4-4, ERG summarized an adjusted baseline emission inventory E' between the NMVES and the federal baseline as the initial (MOVES) emission inventory E multiplied by the ratio of the final volume over the initial volume for each fuel f, scenario s, and year y, such that

$$E_{f,s,y}{}' = E_{f,s,y} \cdot \left(V_{f,s,y,final}/V_{f,s,y,initial}\right). \qquad \textbf{Equation 4-4}$$

Lacking differential impacts by criteria pollutant, ERG decided to apply the same adjustment ratios to each pollutant, which still yields to some differences over time. Table 4-11 and Table 4-12 supply specific emission adjustment ratios for the NMVES and federal baseline scenario, respectively. Emission results for the final rule include adjustments to both baseline scenarios. As noted before, emission adjustments to the CTFP scenario were simply recalculated using updated fuel volumes.

Table 4-11. Adjustment ratios for NMVES scenario for BRG-supplied fuel projections, based on differences between MOVES raw fuel projections and after BRG modification

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	1.167	1.167	1.041	1.041	1.000	0.082	0.000	1.125	1.000	1.000
2026	1.172	1.172	1.041	1.041	1.000	0.094	0.000	1.137	1.000	1.000
2027	1.162	1.162	1.037	1.037	1.000	0.195	0.000	1.148	1.000	1.000
2028	1.143	1.143	1.031	1.031	1.000	0.321	0.000	1.158	1.000	1.000
2029	1.121	1.121	1.024	1.024	1.000	0.445	0.000	1.168	1.000	1.000
2030	1.097	1.097	1.015	1.015	1.000	0.554	0.000	1.176	1.000	1.000
2031	1.115	1.115	1.026	1.026	1.000	0.595	0.282	1.184	1.000	1.000
2032	1.131	1.131	1.039	1.039	1.000	0.634	0.314	1.191	1.000	1.000
2033	1.144	1.144	1.051	1.051	1.000	0.669	0.328	1.199	1.000	1.000
2034	1.160	1.160	1.063	1.063	1.000	0.691	0.336	1.206	1.000	1.000
2035	1.191	1.191	1.076	1.076	1.000	0.693	0.342	1.212	1.000	1.000
2036	1.199	1.199	1.082	1.082	1.000	0.718	0.363	1.205	1.000	1.000
2037	1.207	1.207	1.088	1.088	1.000	0.740	0.381	1.198	1.000	1.000
2038	1.218	1.218	1.094	1.094	1.000	0.756	0.397	1.191	1.000	1.000
2039	1.235	1.235	1.100	1.100	1.000	0.766	0.411	1.185	1.000	1.000
2040	1.271	1.271	1.105	1.105	1.000	0.761	0.423	1.178	1.000	1.000
2041	1.293	1.293	1.099	1.099	1.000	0.766	0.449	1.170	1.000	1.000
2042	1.307	1.307	1.093	1.093	1.000	0.775	0.473	1.163	1.000	1.000

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2043	1.313	1.312	1.087	1.087	1.000	0.790	0.496	1.155	1.000	1.000
2044	1.309	1.309	1.081	1.081	1.000	0.810	0.518	1.148	1.000	1.000
2045	1.298	1.298	1.074	1.074	1.000	0.832	0.539	1.141	1.000	1.000
2046	1.280	1.280	1.068	1.068	1.000	0.856	0.559	1.135	1.000	1.000
2047	1.260	1.260	1.061	1.061	1.000	0.878	0.578	1.128	1.000	1.000
2048	1.242	1.242	1.055	1.055	1.000	0.897	0.596	1.122	1.000	1.000
2049	1.242	1.242	1.048	1.048	1.000	0.907	0.614	1.116	1.000	1.000
2050	1.251	1.251	1.041	1.041	1.000	0.913	0.631	1.111	1.000	1.000

Table 4-12. Adjustment ratios for federal baseline scenario for BRG-supplied fuel projections, based on differences between MOVES raw fuel projections and after BRG modification

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	1.012	1.012	1.005	0.987	1.000	5.663	1.000	1.001	1.000	1.000
2026	1.027	1.027	1.006	0.987	1.000	1.508	1.000	1.001	1.000	1.000
2027	1.038	1.038	1.007	0.989	1.000	1.263	1.000	1.001	1.000	1.000
2028	1.054	1.054	1.009	0.991	1.000	1.045	1.000	1.000	1.000	1.000
2029	1.076	1.076	0.997	0.979	1.000	0.889	1.000	1.000	1.000	1.000
2030	1.024	1.024	1.000	0.982	1.000	0.743	1.000	1.000	1.000	1.000
2031	1.010	1.010	1.000	0.982	1.000	0.856	1.000	1.000	1.000	1.000
2032	0.993	0.993	1.000	0.982	1.000	0.955	1.000	1.000	1.000	1.000
2033	0.994	0.994	1.000	0.982	1.000	0.948	1.000	1.000	1.000	1.000
2034	1.009	1.009	1.000	0.982	1.000	0.901	1.000	1.000	1.000	1.000
2035	1.012	1.012	1.000	0.982	1.000	0.900	1.000	1.000	1.000	1.000
2036	1.009	1.009	1.000	0.982	1.000	0.916	1.000	1.000	1.000	1.000
2037	1.008	1.007	1.000	0.982	1.000	0.925	1.000	1.000	1.000	1.000
2038	1.005	1.005	1.000	0.982	1.000	0.933	1.000	1.000	1.000	1.000
2039	1.004	1.004	1.000	0.982	1.000	0.935	1.000	1.000	1.000	1.000
2040	1.010	1.010	1.000	0.982	1.000	0.924	1.000	1.000	1.000	1.000
2041	1.013	1.013	1.000	0.982	1.000	0.921	1.000	1.000	1.000	1.000
2042	1.012	1.012	1.000	0.982	1.000	0.923	1.000	1.000	1.000	1.000
2043	1.013	1.013	1.000	0.982	1.000	0.922	1.000	1.000	1.000	1.000
2044	1.014	1.014	1.000	0.982	1.000	0.923	1.000	1.000	1.000	1.000
2045	1.012	1.012	1.000	0.982	1.000	0.926	1.000	1.000	1.000	1.000
2046	1.008	1.008	1.000	0.982	1.000	0.931	1.000	1.000	1.000	1.000
2047	1.003	1.003	1.000	0.982	1.000	0.937	1.000	1.000	1.000	1.000
2048	0.996	0.996	1.000	0.982	1.000	0.943	1.000	1.000	1.000	1.000
2049	0.989	0.989	1.000	0.982	1.000	0.949	1.000	1.000	1.000	1.000
2050	0.989	0.989	1.000	0.982	1.000	0.948	1.000	1.000	1.000	1.000

Generally, ERG found that these adjustments dampen NMVES emission reductions through less aggressive electrification curves, while still achieving the state's GHG targets, which allows for more reductions to be met via CTFP and other fuels (see Appendix B for more adjustment details). The next section presents emission results through 2050 for all monetized pollutants considered.

4.5 Results

4.5.1 Annual Emission Reductions by Pollutant

Annual emission reductions by criteria pollutant and analysis year have been calculated as the summation of three elements: (1) MOVES-generated emission factor EF by fuel f, pollutant p, and year y, (2) fuel volume delta V between the CTFP and NMVES policies by fuel and year, and (3) energy density ρ of the given fuel, as shown in Equation 4-5, such that

$$e_{p,y} = \sum_{f \in F} EF_{f,p,y} \cdot V_{f,y} \cdot \rho_f, \qquad \textbf{Equation 4-5}$$

where $f \in F$ is the given fuel f within the full set of possible fuels F (namely B0, B5, and R100) for the specified pollutant p and chosen year y. ERG used specific energy densities by blend, provided earlier in Table 4-6. Cumulative reductions CR are simply the annual emissions summed over the span of active CTFP years Y (that is, $y \in Y$ will be 2026 through 2035) as shown in Equation 4-6, such that

$$CR_p = \sum_{y \in Y} e_{p,y}. \qquad \textbf{Equation 4-6}$$

For the final CTFP rule, ERG has prepared annual emission reductions expected for the combined suite of CTFP and NMVES policies over their entire time horizon (2026 to 2050). Given that BRG has provided onroad and nonroad CTFP fuel forecasts separately, ERG also presents individual onroad and nonroad emission results. For more complete context, all CTFP reductions are referenced against the NMVES policy and all NMVES benefits are referenced against the federal baseline. Figure 4-7 through Figure 4-10 summarize emission reductions by policy scenario for NO_x, VOC, PM, and SO_2, respectively.

Figure 4-7. Annual NO_x reductions for NMVES and CTFP scenarios by mode (in tons)

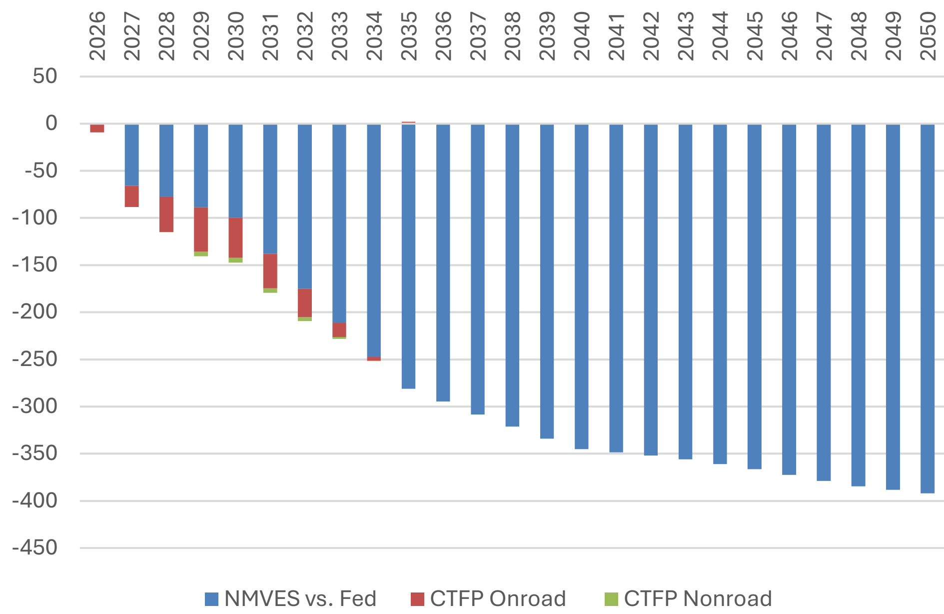


Figure 4-8. Annual VOC reductions for NMVES and CTFP scenarios by mode (in tons)

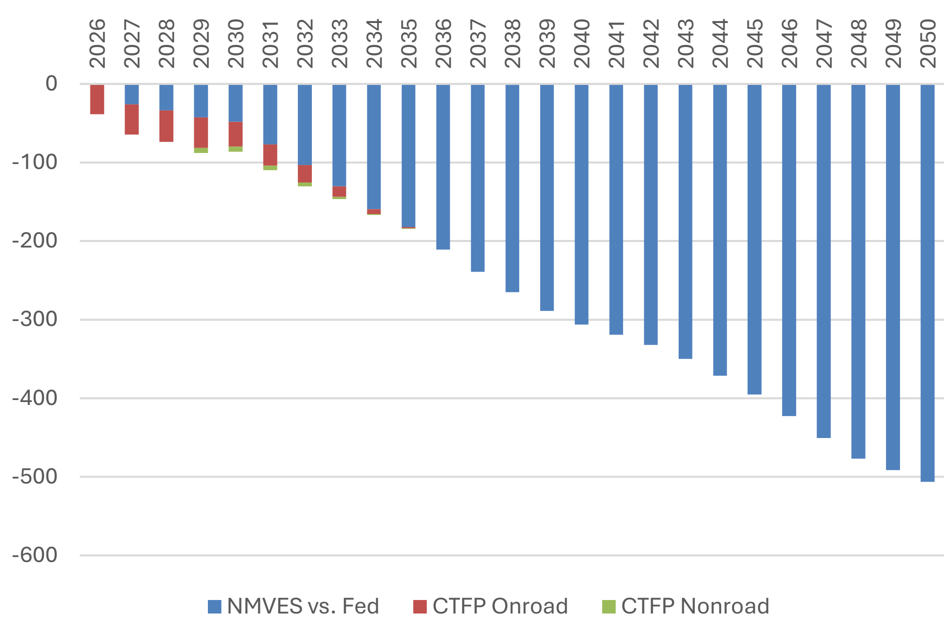


Figure 4-9. Annual $PM_{2.5}$ reductions for NMVES and CTFP scenarios by mode (in tons)

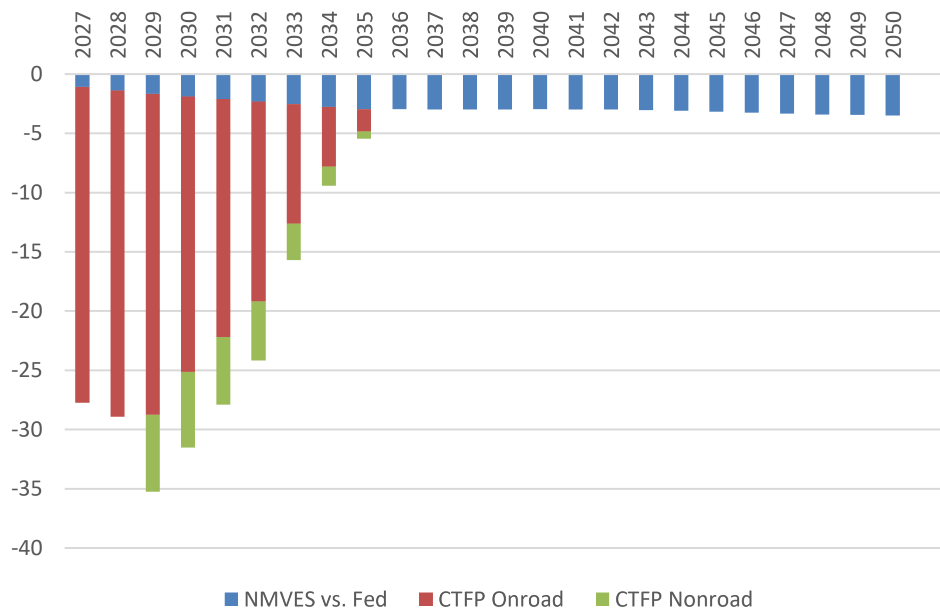
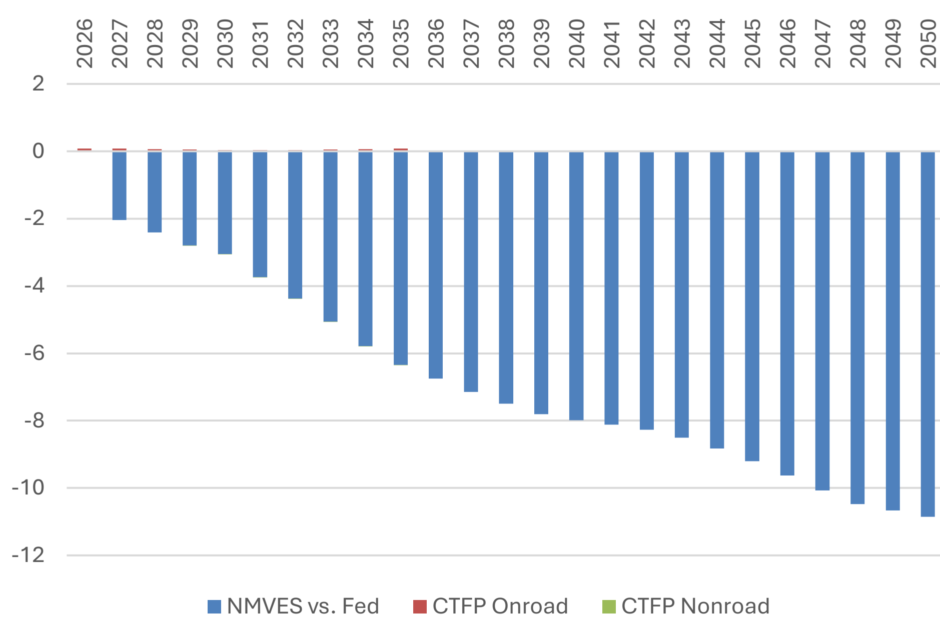


Figure 4-10. Annual SO_2 reductions for NMVES and CTFP scenarios by mode (in tons)



In general, ERG found that emission reductions for most pollutants are driven by the NMVES, although the CTFP is dominant as a driver of reductions in $PM_{2.5}$, at least for the early years. There are modest initial CTFP emission increases for SO_2 (probably from the prevalence of low-sulfur fuel use in New Mexico); otherwise, emissions appear to decrease monotonically over time.

4.5.2 Emissions Reduced for Combined Program and CTFP-Only Policy

It is often helpful to consider the combined impacts of both the CTFP and the NMVES to understand the magnitude of benefits from the individual policies. On the following pages, ERG provides emission results for the suite of policies in two different formats. Table 4-13 is an aggregation of Table 4-14, which shows annual emission reductions independently for the three policy scenarios ERG explicitly modeled: (1) NMVES (as compared to the federal baseline), (2) CTFP onroad, and (3) CTFP nonroad. Table 4-13 presents annual results for the CTFP-only policy (which adds the CTFP onroad and nonroad results from Table 4-14 for each year together by pollutant), along with the combined NMVES and CTFP policy suite (which adds all three columns from Table 4-14 together by pollutant) for the best comparability between these two policy scenarios.

4.6 Data Sharing

These summaries of emission reductions have been shared with ERG's Economics team for use in COBRA (health effects) and IMPLAN (macroeconomic) modeling that is documented carefully in subsequent sections of this report. Emission results have also been thoroughly reviewed and validated by NMED and BRG prior to inclusion in the CTFP final rule.

Table 4-13. Annual emission reductions through 2050 by pollutant for the combined NMVES and CTFP policy suite, as well as the CTFP alone (negative values equate to reductions in tons)

	NO_x		VOC		$PM_{2.5}$		SO_2	
Year	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**	**Combined**	**CTFP-Only**
2026	-9.12	-9.12	-38.39	-38.39	-26.76	-26.76	0.09	0.09
2027	-88.30	-22.54	-64.53	-38.56	-27.73	-26.65	-1.97	0.08
2028	-115.16	-37.73	-73.92	-40.01	-28.93	-27.56	-2.34	0.06
2029	-140.75	-52.08	-88.02	-45.30	-35.26	-33.59	-2.75	0.05
2030	-147.49	-47.73	-86.10	-37.70	-31.52	-29.64	-3.02	0.03
2031	-179.24	-41.20	-109.55	-32.55	-27.89	-25.79	-3.71	0.03
2032	-209.47	-34.48	-130.46	-27.32	-24.17	-21.87	-4.34	0.03
2033	-228.22	-16.78	-146.48	-15.95	-15.70	-13.17	-5.01	0.05
2034	-251.79	-4.43	-166.81	-7.54	-9.43	-6.66	-5.72	0.06
2035	-278.77	2.26	-184.36	-2.29	-5.46	-2.51	-6.26	0.08
2036	-294.77	0.00	-211.00	0.00	-2.96	0.00	-6.75	0.00
2037	-308.30	0.00	-239.11	0.00	-2.98	0.00	-7.14	0.00
2038	-321.36	0.00	-265.15	0.00	-2.99	0.00	-7.50	0.00
2039	-333.89	0.00	-288.71	0.00	-2.99	0.00	-7.80	0.00
2040	-345.19	0.00	-306.37	0.00	-2.96	0.00	-7.99	0.00
2041	-348.39	0.00	-319.06	0.00	-2.97	0.00	-8.12	0.00
2042	-351.75	0.00	-332.32	0.00	-3.00	0.00	-8.27	0.00
2043	-355.95	0.00	-349.74	0.00	-3.04	0.00	-8.51	0.00
2044	-360.97	0.00	-371.28	0.00	-3.10	0.00	-8.83	0.00
2045	-366.45	0.00	-395.23	0.00	-3.17	0.00	-9.20	0.00
2046	-372.57	0.00	-422.62	0.00	-3.26	0.00	-9.63	0.00
2047	-378.82	0.00	-450.82	0.00	-3.34	0.00	-10.08	0.00
2048	-384.62	0.00	-476.72	0.00	-3.42	0.00	-10.47	0.00
2049	-388.34	0.00	-491.54	0.00	-3.45	0.00	-10.66	0.00
2050	-392.09	0.00	-506.55	0.00	-3.49	0.00	-10.86	0.00
2026-2030	**-500.81**	**-169.21**	**-350.96**	**-199.96**	**-150.2**	**-144.21**	**-9.99**	**0.31**
2031-2040	**-2751.02**	**-94.63**	**-2048.00**	**-85.65**	**-97.51**	**-69.99**	**-62.22**	**0.25**
2041-2050	**-3699.95**	**0.00**	**-4115.87**	**0.00**	**-32.23**	**0.00**	**-94.63**	**0.00**

Table 4-14. Annual emission reductions for (1) NMVES compared to federal baseline, (2) CTFP onroad, and (3) CTFP nonroad through 2050

	NO_x			VOC			$PM_{2.5}$			SO_2		
Year	***NMVES***	***CTFP Onroad***	***CTFP Nonroad***	***NMVES vs. Fed***	***CTFP Onroad***	***CTFP Nonroad***	***NMVES vs. Fed***	***CTFP Onroad***	***CTFP Nonroad***	***NMVES vs. Fed***	***CTFP Onroad***	***CTFP Nonroad***
2026		-9.120			-38.390			-26.763			0.085	
2027	-65.762	-22.537		-25.970	-38.564		-1.079	-26.650		-2.043	0.077	
2028	-77.422	-37.734		-33.910	-40.007		-1.366	-27.565		-2.407	0.065	
2029	-88.664	-47.054	-5.029	-42.717	-38.726	-6.576	-1.663	-27.102	-6.490	-2.798	0.048	0.000
2030	-99.758	-42.517	-5.217	-48.403	-31.403	-6.294	-1.885	-23.263	-6.372	-3.050	0.032	0.000
2031	-138.046	-36.555	-4.641	-77.000	-26.943	-5.604	-2.102	-20.087	-5.700	-3.742	0.032	0.000
2032	-174.991	-30.460	-4.023	-103.147	-22.442	-4.875	-2.302	-16.879	-4.989	-4.373	0.032	0.000
2033	-211.446	-14.727	-2.051	-130.532	-13.008	-2.937	-2.527	-10.075	-3.094	-5.058	0.049	0.000
2034	-247.362	-3.843	-0.587	-159.271	-6.101	-1.442	-2.766	-5.051	-1.610	-5.784	0.064	0.000
2035	-281.033	1.968	0.291	-182.067	-1.835	-0.460	-2.949	-1.899	-0.608	-6.341	0.077	0.000
2036	-294.771			-210.997			-2.964			-6.748		
2037	-308.303			-239.111			-2.979			-7.143		
2038	-321.364			-265.149			-2.986			-7.496		
2039	-333.887			-288.710			-2.985			-7.803		
2040	-345.190			-306.366			-2.959			-7.991		
2041	-348.389			-319.056			-2.974			-8.120		
2042	-351.748			-332.323			-2.995			-8.268		
2043	-355.955			-349.745			-3.038			-8.507		
2044	-360.971			-371.278			-3.100			-8.830		
2045	-366.448			-395.232			-3.172			-9.199		
2046	-372.568			-422.617			-3.256			-9.632		
2047	-378.821			-450.818			-3.342			-10.076		
2048	-384.620			-476.718			-3.417			-10.473		
2049	-388.337			-491.539			-3.452			-10.662		
2050	-392.094			-506.546			-3.488			-10.858		
Total	**-6687.950**	**-242.580**	**-21.258**	**-6229.226**	**-257.421**	**-28.188**	**-65.747**	**-185.333**	**-28.864**	**-167.402**	**-6687.950**	**-242.580**

5. Avoided Health Damages

5.1 Background

5.1.1 Adverse Health Effects on Vehicle Emissions

New Mexico's CTFP, if enacted, will help reduce statewide transportation emissions by lowering the overall CI of the transportation fuel supply through a clean fuel credit market. The reduction of vehicle tailpipe emissions will mitigate CAPs and precursors that exacerbate respiratory symptoms, thereby improving health outcomes. These improvements include mitigating asthma onset and aggravation, cardiovascular disease, reduced lung function, and premature death. Adverse health impacts are especially harmful to vulnerable populations, including older adults, children, and pregnant individuals.[51]

Asthma is one of the most common chronic diseases in New Mexico, with an estimated 9.7 percent of adults afflicted by the disease.[52] Asthma can require hospitalization, routine checkups, medications, and missed work days, which can be costly to the individual and New Mexico's economy.[53] Criteria and precursor pollutant reductions can yield health benefits that are economically quantifiable in monetary (dollar) units. For example, a study in California between 1993 and 2014 found that fine PM and NO_x reductions could reduce the risk of incident asthma in children by up to 20 percent.[54]

5.1.2 Monetization of Health Benefits and/or Damages

ERG input emissions changes, as shown in Table 4-13 from Chapter 4, into EPA's COBRA Health Impacts Screening and Mapping Tool to assess the CTFP's statewide health impacts.[55] Once a COBRA user inputs potential emission increases or decreases, COBRA conducts multiple modeling steps to monetize health benefits and/or damages. COBRA uses the Source Receptor (S-R) Matrix, an air quality model, to estimate changes in total ambient concentrations of air pollutants that are known to be harmful to human health.[56] COBRA uses peer-reviewed epidemiological literature to estimate how changes in outdoor air quality affect the incidence of various health outcomes.[57] COBRA then multiplies the change in incidence by a monetary value associated with the health outcome, such as the average cost of an emergency room visit related

[51] New Mexico Environmental Public Health Tracking, "Asthma," accessed June 3, 2025, https://nmtracking.doh.nm.gov/health/breathing/Asthma.html.

[52] New Mexico Environmental Public Health Tracking, "Asthma," accessed June 3, 2025, https://nmtracking.doh.nm.gov/health/breathing/Asthma.html.

[53] Health Equity Epidemiology Program, Center for Health Protection, New Mexico Department of Health, "NM-IBIS Summary Health Indicator Report: Asthma Prevalence Among Adults," accessed May 23, 2025, https://ibis.doh.nm.gov/indicator/summary/AsthmaPrevAdult.html.

[54] Erika Garcia et al., "Association of Changes in Air Quality With Incident Asthma in Children in California, 1993–2014," *JAMA* 321, no. 19 (May 21, 2019): 1906–15, https://doi.org/10.1001/jama.2019.5357.

[55] U.S. Environmental Protection Agency, "CO-Benefits Risk Assessment Health Impacts Screening and Mapping Tool (COBRA)," accessed May 21, 2025, https://www.epa.gov/cobra.

[56] U.S. Environmental Protection Agency, "COBRA Questions and Answers," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-questions-and-answers.

[57] U.S. Environmental Protection Agency, "User's Manual for the CO-Benefits Risk Assessment (COBRA) Screening Model," accessed May 23, 2025, https://www.epa.gov/cobra/users-manual-co-benefits-risk-assessment-cobra-screening-model.

to exacerbated asthma symptoms. Detailed descriptions of these monetization processes can be found in COBRA's User Manual.[58]

5.2 Modeling Approach

5.2.1 COBRA Description

COBRA allows users to better understand how changes in air pollution from clean energy and fuel programs can impact human health.[59] ERG analyzed the potential health impacts of the CTFP on New Mexico residents under the "CTFP-only" and "NMVES + CTFP" scenarios described in Section 4.1. Under the CTFP-only scenario, health impacts occurred from calendar year 2026 to 2035, the final year that the CTFP projected to be "binding" on New Mexico transportation fuel markets.[60] The second scenario includes combined health impacts under NMVES + CTFP, which accounts for the CTFP's impacts as a standalone policy as well as a supporting policy for the NMVES. This analysis modeled NMVES + CTFP scenario effects from calendar year 2026 to 2040 under the assumption that CTFP-supported infrastructure and other measures continue to support NMVES fleet and VMT impacts even after the CTFP ceases to bind on regulated parties after 2035.

ERG ran COBRA for each calendar year with tailored human population projections, as detailed in Section 5.2.3, and analyzed the following four criteria air pollutants across New Mexico: (1) $PM_{2.5}$, (2) SO_2, (3) NO_x, and (4) VOCs. All results are presented in 2024 U.S. dollars using a discount rate of 2 percent.

ERG input the changes in pollutants and exported COBRA results for the following health outcome categories:

- Mortality [low and high estimates]

- Asthma
  - Symptoms
  - Asthma onset

- Emergency room visits
  - Respiratory
  - All cardiac outcomes
  - Asthma

- Hospital admittance
  - Respiratory
  - Cardio cerebral and peripheral vascular disease
  - Alzheimer's Disease
  - Parkinson's Disease
  - Stroke incidence

[58] U.S. Environmental Protection Agency, "User's Manual for the CO-Benefits Risk Assessment (COBRA) Screening Model," accessed May 23, 2025, https://www.epa.gov/cobra/users-manual-co-benefits-risk-assessment-cobra-screening-model.

[59] U.S. Environmental Protection Agency, "What Is COBRA?," accessed May 20, 2025, https://www.epa.gov/cobra/what-cobra.

[60] For more information on when and why the CTFP "binds," see Subsection 5.1.3 and Appendix B.7 of the benefits-cost analysis in BRG's BCA Report.

    - Out-of-hospital cardiac arrest incidence

- Onset
    - Hay fever/rhinitis incidence
    - Nonfatal heart attacks
    - Lung cancer incidence

- Other impacts
    - Minor restricted activity days
    - Work loss days
    - School loss days

5.2.2 Model Updates and Enhancements

ERG used COBRA Desktop Edition version 5.1.[61] This version includes an updated source-receptor (SR) matrix and health impacts associated with ozone formation. These improvements allowed for additional health outcome categories such as school loss days, asthma symptoms, and hospital admittance for illnesses such as Alzheimer's Disease and Parkinson's Disease. These categories are in addition to those that ERG modeled in its NMVES analysis.[62]

5.2.3 Custom Population Data for New Mexico

ERG imported custom population projections into COBRA for each year from 2026 to 2040 to estimate the health benefits from future emission changes. EPA provides Environmental Benefits Mapping and Analysis Program (BenMAP) population datasets that ERG formatted for COBRA.[63] The BenMAP data are provided in five-year increments from 2030 to 2050. ERG used the BenMAP data because COBRA requires granular population data with projections for each age and county. However, the BenMAP data is national and the estimates for New Mexico were higher than projections from state-level sources.

ERG tailored the BenMAP data to align with the University of New Mexico's (UNM) population projections, which include projections for each county in New Mexico from 2010 to 2050 in five-year increments.[64] UNM's projections from 2025 to 2040 are displayed in Table 5-1. To estimate New Mexico's projected county-level population in years outside of those five-year increments,

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[61] U.S. Environmental Protection Agency, "COBRA Revision History," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-revision-history.

[62] Eastern Research Group, Inc., "New Mexico Advanced Clean Cars II, Advanced Clean Trucks and Heavy-Duty Omnibus Rules: Assessment of Economic, Health and Environmental Impacts" (New Mexico Environment Department & City of Albuquerque Environmental Health Department, 2023), https://www.env.nm.gov/opf/wp-content/uploads/sites/13/2023/10/EIB-23-56-NMED-Exhibits-45-pg-14-48.pdf.

[63] U.S. Environmental Protection Agency, "COBRA Future Input Files," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-future-input-files.

[64] University of New Mexico, "Population Projections," Geospatial and Population Studies, accessed May 23, 2025, https://gps.unm.edu/pop/population-projections.html. University of New Mexico, "Population Projections," Geospatial and Population Studies, accessed May 23, 2025, https://gps.unm.edu/pop/population-projections.html. University of New Mexico, "Population Projections," Geospatial and Population Studies, accessed May 23, 2025, https://gps.unm.edu/pop/population-projections.html.

ERG calculated the population each year between 2025 and 2040 using a series of linear regressions for each five-year increment. ERG adjusted BenMAP's age-specific population projections to be proportional to the UNM county-level population estimates for New Mexico. Although national health benefits were not evaluated, ERG ran COBRA with national estimates for other states to allow for flexibility if other state impacts were to be assessed.

Table 5-1. UNM population projections for New Mexico for 2025, 2030, 2035, and 2040

County	Projected 2025	Projected 2030	Projected 2035	Projected 2040
Bernalillo	680,584	683,372	684,673	684,461
Catron	3,539	3,454	3,340	3,193
Chaves	64,822	64,303	63,626	62,740
Cibola	27,045	26,917	26,751	26,536
Colfax	11,859	11,156	10,275	9,170
Curry	48,474	48,504	48,524	48,532
De Baca	1,568	1,417	1,233	1,006
Dona Ana	224,218	228,058	230,554	231,449
Eddy	65,964	69,139	70,992	71,376
Grant	27,482	26,599	25,491	24,077
Guadalupe	4,326	4,179	3,996	3,762
Harding	646	624	596	560
Hidalgo	3,826	3,466	3,030	2,497
Lea	78,781	82,337	84,395	84,796
Lincoln	20,255	20,123	19,945	19,716
Los Alamos	19,857	20,439	20,791	20,883
Luna	25,500	25,593	25,658	25,687
McKinley	72,972	72,761	72,486	72,203
Mora	3,933	3,599	3,190	2,684
Otero	68,287	68,736	68,780	68,821
Quay	8,536	8,356	8,128	7,835
Rio Arriba	40,266	40,247	40,217	40,185
Roosevelt	19,095	18,986	18,712	18,421
Sandoval	157,468	164,648	169,117	170,460
San Juan	119,657	117,590	113,548	109,362
San Miguel	26,064	24,902	23,435	21,577
Santa Fe	160,347	164,745	167,424	168,148
Sierra	11,323	11,064	10,735	10,313
Socorro	16,008	15,408	14,713	13,992
Taos	35,367	35,949	36,300	36,391
Torrance	14,575	13,947	13,145	12,126
Union	3,895	3,709	3,444	3,178
Valencia	77,118	77,320	77,536	77,825
State Total	**2,143,658**	**2,161,645**	**2,164,780**	**2,153,964**

Table 5-2 presents two examples of New Mexico population data that ERG inputted into COBRA, after adjusting BenMAP's data to be proportional to UNM's total population estimates per county. While the tailored population data has estimates for each individual age, Table 5-2 provides a more condensed overview of age distributions. According to UNM, New Mexico's current population is aging, and the overall population is expected to start declining by 2035.[65] From 2026 to 2040, the largest increases in percentage terms are expected for the 85 and over age group. This is particularly relevant to health benefits because older adults are more susceptible to respiratory illness caused by criteria and precursor pollutants.[66]

Table 5-2. Customized New Mexico population for 2026 and 2040 for COBRA

Age Group	2026	2040	Percent Change
0	29,419	27,141	-8%
1 to 4	119,367	109,378	-8%
5 to 9	148,969	138,328	-7%
10 to 14	147,204	140,769	-4%
15 to 19	118,111	142,373	21%
20 to 24	132,390	137,139	4%
25 to 29	123,627	120,020	-3%
30 to 34	125,769	124,558	-1%
35 to 39	156,191	124,643	-20%
40 to 44	138,569	123,842	-11%
45 to 49	129,708	138,605	7%
50 to 54	107,758	132,058	23%
55 to 59	104,494	122,996	18%
60 to 64	111,706	107,482	-4%
65 to 69	135,993	98,038	-28%
70 to 74	122,938	94,089	-23%
75 to 79	95,055	96,255	1%
80 to 84	67,342	82,585	23%
85 and over	44,530	93,663	110%

5.2.4 Onroad and Nonroad Assumptions

For the CTFP scenario, ERG ran COBRA separately for the onroad and nonroad changes in emissions to appropriately assign emission categories. ERG used the "Highway Vehicles" category for the onroad CTFP emissions and for all NMVES emissions. For the nonroad component of the CTFP emissions, ERG used the "Off-Highway" category. ERG used the highest emission categories as opposed to more granular categories by fuel type because this program is designed to be fuel agnostic. Running COBRA separately for onroad and nonroad also allowed ERG to analyze the onroad and nonroad results independently.

[65] University of New Mexico, "Population Projections," Geospatial and Population Studies, accessed May 23, 2025, https://gps.unm.edu/pop/population-projections.html.

[66] American Lung Association, "Who Is Most Affected by Outdoor Air Pollution?," accessed June 3, 2025, https://www.lung.org/clean-air/outdoors/who-is-at-risk.

5.3 Results

5.3.1 Quantified Health Outcomes

Emission reductions under the CTFP-only and NMVES + CTFP scenarios reduce the incidence of respiratory and other conditions compared to the baseline. The cumulative avoided incidence values from 2026 to 2035 for the CTFP-only scenario and the cumulative avoided incidence values from 2026 to 2040 for the NMVES + CTFP scenario are shown in Table 5-3 for each health outcome. These avoided incidences translate to monetary values, as detailed below.

Table 5-3. Avoided incidence for CTFP-only and NMVES + CTFP scenarios (cumulative)

Health Outcome Category	Cumulative Avoided Incidence for CTFP-Only Scenario	Cumulative Avoided Incidence for NMVES + CTFP Scenario
Total mortality (low estimate)	0.6	2.0
Total mortality (high estimate)	1.2	2.8
Total asthma symptoms	336.7	1,462.8
Total asthma onset	1.9	8.9
Total emergency room visits	0.7	3.0
Total hospital admittance	0.4	0.6
Total onset*	12.6	59.4
Minor restricted activity days	353.0	466.4
Work loss days	59.9	79.0
School loss days	58.6	712.9

** Includes onset of hay fever/rhinitis, nonfatal heart attacks, and lung cancer.*

The total monetized health benefits are presented as a lower- and upper-bound estimates because COBRA has low and high incidence estimates for mortality. The low estimate is based on an evaluation of $PM_{2.5}$ impacts on mortality by the Harvard T.H. Chan School of Public Health.[67] The high estimate represents $PM_{2.5}$ results based on a study from the journal *Environmental Health Perspectives*.[68] Presenting a low-to-high monetary benefits range is EPA's standard practice.[69] All health outcomes other than those for mortality are calculated as point estimates, but the total is a range because it includes the range of mortality incidence values.

The total cumulative monetized health benefits in New Mexico from reduced criteria and precursor pollutants are displayed in Table 5-4. For the CTFP-only scenario (2026 to 2035), cumulative benefits range from an estimated $11.0 million to $20.8 million, whereas cumulative benefits of the combined NMVES + CTFP scenario (2026 to 2040) range from $38.2 million to $51.5 million.

[67] Xiao Wu et al., "Evaluating the Impact of Long-Term Exposure to Fine Particulate Matter on Mortality Among the Elderly," *Science Advances* 6, no. 29 (July 2020): eaba5692, https://doi.org/10.1126/sciadv.aba5692.

[68] C. Arden Pope III et al., "Mortality Risk and Fine Particulate Air Pollution in a Large, Representative Cohort of U.S. Adults," *Environmental Health Perspectives* 127, no. 7 (July 24, 2019): 77007, https://doi.org/10.1289/EHP4438.

[69] U.S. Environmental Protection Agency, "COBRA Questions and Answers," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-questions-and-answers.

Table 5-4. Cumulative statewide health benefits from reduced pollutants by scenario (in million USD, 2024)

Scenario	Timeframe	Cumulative Net Benefits (lower-upper bound)
CTFP-only	2026–2030	$7.0–$13.4
	2026-2035	$11.0–$20.8
NMVES + CTFP	2026–2030	$9.7–$16.5
	2026-2040	$38.2–$51.5

Includes health benefits from both onroad and nonroad fuel use beginning in 2029.

ERG ran COBRA separately for the onroad and nonroad CTFP cases to identify health benefits separately. As displayed in Table 5-5, the onroad cumulative health benefits range from $9.3 million to $17.5 million. The nonroad health benefits begin in 2029 due to the inclusion of dyed fuels under the CTFP pursuant to the proposed rule.[70] Cumulative nonroad health benefits range from $1.7 million to $3.3 million. Onroad contributions account for nearly 85 percent of the total CTFP benefits, and the remaining 15 percent of total benefits are attributed to nonroad.

Table 5-5. Annual statewide health benefits for the CTFP-only onroad and nonroad scenarios (in million USD, 2024)

Calendar Year	$ Onroad Total Health Benefits (lower-upper bound)	$ Nonroad Total Health Benefits (lower-upper bound)	$ Total Health Benefits (lower-upper bound)
2026	$1.1-$2.1		$1.1-$2.1
2027	$1.2-$2.3		$1.2-$2.3
2028	$1.4-$2.5		$1.4-$2.5
2029	$1.4-$2.6	$0.4-$0.7	$1.8-$3.3
2030	$1.3-$2.3	$0.4-$0.7	$1.6-$3.1
2031	$1.1-$2.1	$0.3-$0.7	$1.5-$2.7
2032	$1-$1.8	$0.3-$0.6	$1.3-$2.4
2033	$0.6-$1	$0.2-$0.4	$0.8-$1.4
2034	$0.3-$0.5	$0.1-$0.2	$0.4-$0.7
2035	$0.1-$0.2	$0-$0.1	$0.1-$0.2
Cumulative	$9.3-$17.5	$1.7-$3.3	$11.0-$20.8

Values in the table may not add to cumulative values due to rounding.

The cumulative total health benefits for the NMVES + CTFP scenario range from an estimated $38.2 million to $51.5 million, as shown in Table 5-6. Within an individual year, the annual total health benefits are highest in 2040 and range from $3.5 million to $3.9 million.

[70] See Paragraph 2 of Subsection A of Title 20, Chapter 2, Part 92, Section 102 of the New Mexico Administrative Code (20.2.92.102 NMAC).

Table 5-6. Annual statewide health benefits for the NMVES + CTFP scenario (in million USD, 2024)

Calendar Year	$ Total Health Benefits (lower-upper bound)
2026	$1.1-$2.1
2027	$1.7-$2.9
2028	$2.0-$3.3
2029	$2.5-$4.2
2030	$2.5-$4.0
2031	$2.6-$4.0
2032	$2.8-$4.0
2033	$2.6-$3.5
2034	$2.5-$3.1
2035	$2.7-$3.1
2036	$2.7-$3.1
2037	$2.9-$3.2
2038	$3.1-$3.4
2039	$3.2-$3.6
2040	$3.5-$3.9
Cumulative	**$38.2–$51.5**

5.3.2 Direct Health Damage Benefits and Costs

In addition to benefits, Table 5-7 shows marginal costs in 2035 due to increased NO_x emissions. While the CTFP onroad scenario has modest SO_2 increases for each year (2026 to 2035), these did not result in costs.

Table 5-7. Annual statewide health benefits and costs for the CTFP-only scenario (in million USD, 2024)

Calendar Year	$ Benefits (lower-upper bound)	$ Costs	$ Net Benefits (lower-upper bound)
2026	$1.057-$2.149	$0	$1.057-$2.149
2027	$1.176-$2.293	$0	$1.176-$2.293
2028	$1.351-$2.538	$0	$1.351-$2.538
2029	$1.800-$3.350	$0	$1.800-$3.350
2030	$1.648-$3.050	$0	$1.648-$3.050
2031	$1.469-$2.714	$0	$1.469-$2.714
2032	$1.274-$2.351	$0	$1.274-$2.351
2033	$0.755-$1.414	$0	$0.755-$1.414
2034	$0.358-$0.696	$0	$0.358-$0.696
2035	$0.109-$0.237	-$0.001	$0.108-$0.236
Cumulative	**$10.997-$20.794**	**-$0.001**	**$10.996-$20.793**

As described above, mortality is the only health impact category with lower and upper bounds.

There were no health damages associated with the mortality category; therefore, the costs are reported as a point estimate. For the combined NMVES and CTFP scenario, shown in Table 5-8, there are no costs.

Table 5-8. Annual statewide health benefits and costs for the combined NMVES and CTFP scenario (in million USD, 2024)

Calendar Year	$ Benefits (lower-upper bound)	$ Costs	$ Net Benefits (lower-upper bound)
2026	$1.1-$2.1	$0	$1.1-$2.1
2027	$1.7-$2.9	$0	$1.7-$2.9
2028	$2.0-$3.3	$0	$2.0-$3.3
2029	$2.5-$4.2	$0	$2.5-$4.2
2030	$2.5-$4.0	$0	$2.5-$4.0
2031	$2.6-$4.0	$0	$2.6-$4.0
2032	$2.8-$4.0	$0	$2.8-$4.0
2033	$2.6-$3.5	$0	$2.6-$3.5
2034	$2.5-$3.1	$0	$2.5-$3.1
2035	$2.7-$3.1	$0	$2.7-$3.1
2036	$2.7-$3.1	$0	$2.7-$3.1
2037	$2.9-$3.2	$0	$2.9-$3.2
2038	$3.1-$3.4	$0	$3.1-$3.4
2039	$3.2-$3.6	$0	$3.2-$3.6
2040	$3.5-$3.9	$0	$3.5-$3.9
Cumulative	**$38.2-$51.5**	**$0**	**$38.2-$51.5**

6. Macroeconomic Impacts

6.1 Background

The CTFP is a collaborative, market-based program designed to reduce transportation sector GHG emissions by establishing decreasing statewide annual CI targets for transportation fuels produced, imported, or dispensed for use in New Mexico. Each year, regulated parties producing, importing, or dispensing fuels that have a CI above the annual target will generate deficits that they must offset by purchasing credits from regulated parties producing, importing, or dispensing fuels with a CI below the annual target. This requirement ensures attainment of statewide annual CI targets. This chapter focuses on the following aspects of the CTFP:

1. Impacts of credit revenue and deficit expenditures under the CTFP on New Mexico transportation fuel users and regulated parties.
2. Employment effects of infrastructure built with revenue supported by FSE credits equaling up to 10 percent of previous-quarter deficits.[71]
3. Health benefits from reduced CAP emissions in response to the CTFP.[72] This analysis finds that reducing CAP emissions would improve air quality and reduce the adverse effects of tailpipe exhaust on public health in New Mexico, leading to reduced hospitalizations and fewer lost workdays.

6.1.1 Discussion of Industry Impacted

This analysis finds that the CTFP affects a wide range of industries. Regulated parties generate either credits or deficits from producing, importing, or dispensing transportation fuel for use in New Mexico, depending upon each transportation fuel pathway's CI compared to annual CI targets. Under this rule, consumers include all entities that purchase transportation fuel (e.g., governments, businesses, and households).

The CTFP allows regulated parties to receive a total amount of credits equal to 10 percent of previous-quarter deficits for installing new FSE capacity.[73] Revenue from FSE credits will drive job growth in areas that support FSE, including the installation, operation, and maintenance of fuel stations for ZEVs such as hydrogen fuel cell vehicles (HFCVs), battery electric vehicles (BEVs), and vehicles using CNG.

In addition, hospitals in New Mexico would see decreases in use because of improved health outcomes as CAP emissions decrease due to the CTFP. The improved health outcomes associated with air quality improvements under the CTFP will likely result in reduced hospital revenues and emergency room visits.

[71] Because this analysis uses an annual timestep, it assumes that credits equal 10 percent of previous-year deficits rather than the 10 percent of previous-quarter deficits specified in the CTFP.

[72] CAP emissions include O_3 precursor pollutants like NO_x and VOCs, as well as other harmful pollutants like $PM_{2.5}$ and SO_2. This analysis quantifies the health benefits from reducing these CAP emissions.

[73] Because this analysis uses an annual timestep, it assumes that credits equal 10 percent of previous-year deficits rather than the 10 percent of previous-quarter deficits specified in the CTFP.

6.1.2 Consumer Passthrough Assumptions and Sensitivity Testing

A regulated party may gain credits from selling clean transportation fuel with a CI below the CTFP's annual standard, or it may accrue deficits from selling transportation fuel with a CI above the CTFP's annual standard (e.g., fossil gasoline and diesel). Regulated parties that incur deficits must purchase and retire credits to offset their deficits and remain in compliance with the CTFP. NMED testimony for the CTFP includes a passthrough rates (PTR) analysis that considers the degree to which such program revenues and costs affect regulated party profits, and the degree to which regulated parties pass on program revenues and costs in retail fuel prices for consumers in New Mexico. This analysis considers the widest likely array of potential PTR assumptions by modeling outcomes under two scenarios:

1. A 100 percent PTR scenario, in which all revenue changes from credits and deficits are reflected in retail fuel prices.

2. A 0 percent PTR scenario, in which the industries absorb all revenue changes as a change in operating costs that, in turn, affects profit margins.

6.2 Modeling Approach

To estimate the macroeconomic impacts of New Mexico's CTFP, ERG conducted a series of EIAs using IMPLAN, an I-O model.[74] Typically, EIAs measure the economic effect of a market shock in a specified geographic area, such as a new fuel policy in New Mexico. EIAs model three core components of economic activity, shown in Figure 6-1:

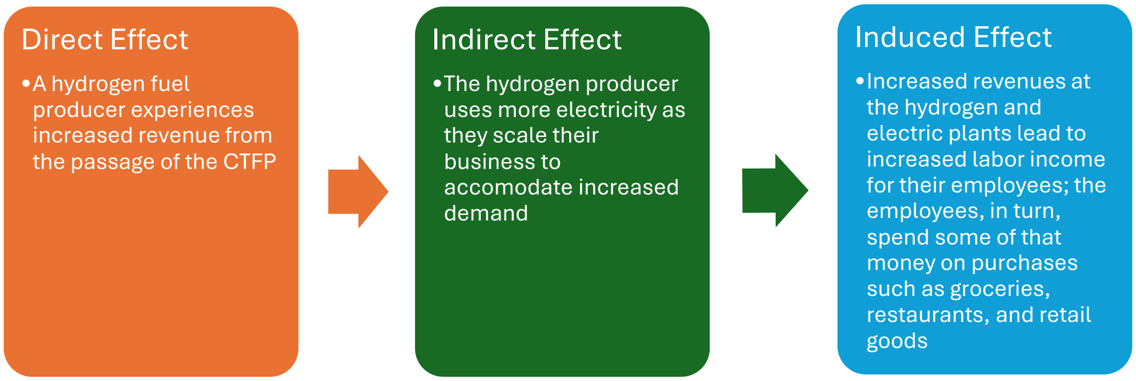
- **Direct effects** are the change's immediate impacts on its own sector.

- **Indirect effects** are the change's impacts on the economic sectors that support the directly affected sector (for example, if a hydrogen FSE is built, the maintenance sector that supports hydrogen FSE will see increased revenue).

- **Induced effects** are the additional economic impacts from changes in labor income due to direct and indirect effects (for example, the staff who work at a facility that generates hydrogen and get paid then spend that money within the local economy, which boosts any industry from which they make purchases, such as grocery, restaurants, and retail).

[74] IMPLAN, "IMPLAN," accessed May 20, 2025, https://implan.com/.

Figure 6-1. Example components of an EIA for hydrogen production



IMPLAN estimates direct, indirect, and induced effects of market shocks on four key macroeconomic metrics:

- **Employment** refers to the number of individuals hired for a salary or for compensation to work within a sector. IMPLAN follows job definitions from the Bureau of Economic Analysis (BEA), which include full-time, part-time, and seasonal positions. Note that IMPLAN jobs are not full-time equivalent (FTE) positions.
- **Labor income** represents the total value of income from employment.
- **Value added, or gross domestic product,** is the increase in a product or service's market value at each stage of production.
- **Economic output, or revenue,** is the total value of all goods and services produced in an economy.

6.2.1 IMPLAN Assumptions

ERG modeled the macroeconomic impacts of New Mexico's CTFP through the IMPLAN platform. To complete this I-O modeling, ERG conducted a series of EIAs accounting for projected CTFP economic costs and benefits each year between 2026 and 2040. ERG bound the geographic scope of this analysis to the state of New Mexico. ERG selected 2023 as the reported dollar and analysis year; this year is also when the latest state data was published in IMPLAN. Assumptions about specific industries are documented in the sections below.

6.2.2 Direct Effects of Credit Market Establishments

6.2.2.1 Direct Effects of Credit Market Establishments

As discussed in the BCA and FCMM documentation, BRG makes annual fuel projections that meet the CTFP annual credit and deficit requirements. These projections serve as inputs to this I-O model's calculation of the effects from CTFP credit markets. Table 6-1 shows projected credits generated across major fuel types under the CTFP. Table 6-2 shows projected deficits across major fuel types. Credits and deficits are shown through 2035 since the fuel credit price drops to $0 in 2036.

Table 6-1. CTFP credits generated annually by fuel type

Year	Ethanol	Biodiesel	Renewable Biodiesel	Electricity	Hydrogen	RNG
2026	208,386	218,695	288,703	168,897	0	58,896
2027	194,483	200,496	398,166	403,175	0	59,195
2028	169,524	174,513	569,612	732,845	0	58,375
2029	130,147	159,395	860,755	1,085,450	0	128,616
2030	54,498	113,414	915,545	1,116,806	0	113,085
2031	44,005	109,889	882,513	1,602,871	10,523	111,777
2032	34,262	106,737	844,133	2,126,648	21,301	110,449
2033	25,360	119,232	537,521	2,610,150	32,331	109,099
2034	17,403	130,269	260,290	3,051,528	43,611	107,729
2035	10,385	138,435	36,240	3,441,143	55,136	106,337

Table 6-2. CTFP deficits generated annually by fuel type

Year	Gasoline Blendstock	Fossil-Derived Diesel	Propane
2026	-435,519	-198,586	0
2027	-600,715	-289,323	0
2028	-890,422	-432,350	0
2029	-1,460,609	-745,814	-3,131
2030	-2,420,342	-1,127,625	-12,468
2031	-2,401,698	-1,172,289	-14,051
2032	-2,366,714	-1,219,901	-15,719
2033	-2,318,423	-1,458,032	-17,472
2034	-2,268,366	-1,702,547	-19,309
2035	-2,233,595	-1,931,872	-21,231

6.2.2.2 Fueling Supply Equipment (FSE)

FSE credits are separate from fuel-based credits under the CTFP. FSE in New Mexico receive credits based on the CI of the fuel that they provide and their new or expanded capacity to dispense this fuel. This analysis directly attributes FSE credits to jobs in the study region, as shown in Table 6-3, and only modeled jobs that would be filled by someone in New Mexico. FSE credits are further explained in the BCA. This analysis calculated direct jobs from FSE credits on a net basis.

Table 6-3. Direct job categories created from FSE credits

Job	IMPLAN Industry
Fuel station installation	323 - All other miscellaneous electrical equipment and component manufacturing
Fuel station maintenance and repair	55 - Maintenance and repair construction of nonresidential structures
General construction labor	47 - Construction of new power and communication structures

Job	IMPLAN Industry
Planning and design	439 - Architectural, engineering, and related services
Administration and legal	437 - Legal services
Fuel station installation	323 - All other miscellaneous electrical equipment and component manufacturing
Fuel station maintenance and repair	55 - Maintenance and repair construction of nonresidential structures
General construction labor	47 - Construction of new power and communication structures

This analysis also modeled FSE credits for facilities serving BEVs, HFCVs, and CNG vehicles. Table 6-4 shows the number of jobs created within each industry.

Table 6-4. Direct jobs created annually from FSE credits

Year	Fuel Station Installation	Fuel Station Maintenance and Repair	General Construction Labor	Planning and Design	Administration and Legal
2026	0.0	0.0	0.0	0.0	0.0
2027	26.8	1.7	8.0	10.7	4.1
2028	37.5	4.2	11.2	14.9	5.8
2029	44.2	7.1	13.2	17.6	6.8
2030	14.3	8.0	4.2	5.7	2.2
2031	22.8	9.5	6.8	9.1	3.5
2032	22.7	10.9	6.8	9.0	3.5
2033	22.6	12.4	6.7	9.0	3.5
2034	22.5	13.9	6.7	9.0	3.5
2035	15.6	14.9	4.7	6.2	2.4
2036–2050	0	14.9	0	0	0

6.2.2.3 Incremental Renewable Energy Credit (REC) Requirement

In addition to fuel-based and FSE credits, the BCA forecasted credits that regulated parties could earn from incremental REC retirement. Retiring incremental RECs allows for electric distribution utilities and other entities to receive more credits per unit of electricity supplied to BEVs and plug-in hybrid electric vehicles (PHEVs) by lowering the CI score of the electricity dispensed to these vehicles. IMPLAN accounts for the cost of these REC retirements as decreased revenue for electric generators, for which these utilities and other entities receive compensation from CTFP credit revenue either directly or from another party purchasing the REC. The value of REC retirement is shown in Table 6-5.

Table 6-5. REC retirement impacts over time

Year	**Incremental REC Retirement** (MWh)	**REC Cost** (2023 USD)
2026	136,479	-$2,447,551
2027	329,318	-$5,905,818
2028	616,407	-$11,054,335
2029	963,735	-$17,283,145
2030–2040	0	$0

6.2.2.4 Banking Impacts on Fossil Fuel Industries

The BCA's FCMM additionally accounts for credits that regulated parties bank for either future sale or retirement.[75] The result is that regulated parties generate surplus credits in the early years of the CTFP that exceed total CTFP deficits. When regulated parties bank CTFP credits, their value diminishes over time. There is a non-financial "opportunity cost" to regulated parties either not selling these credits (if banked by a credit-generator) or spending money to purchase but not retire them (if banked by a deficit-generator). This analysis models this cost as an "impairment cost" that a regulated party bears from unrealized gains, as they are not using the cash on an interest-earning activity. Table 6-6 shows the value of these impairment costs by year. ERG's model considered these costs and allocated them to regulated parties producing gasoline and diesel fuels.

Table 6-6. Banking costs incurred by the fossil fuel industries (in 2023 USD)

Year	Prior Year Inventory Holding Cost	Prior Year Inventory Impairment	Total
2027	-$1,519,724	-$4,645,183	-$6,164,907
2028	-$3,139,603	-$2,373,327	-$5,512,930
2029	-$4,972,226	-$13,582,252	-$18,554,477
2030	-$5,415,110	-$15,690,267	-$21,105,377
2031	-$1,485,767	-$5,218,081	-$6,703,848

6.2.2.5 Biodiesel and Renewable Diesel Supply Costs

Under the CTFP, incremental volumes of BBDs like BD and RD help satisfy CTFP annual targets by generating credits. This is especially the case in earlier program years, when overall CI targets are

[75] Regulated parties that generate CTFP credits may bank them for sale in later years. In addition, regulated parties that generate CTFP deficits may purchase and bank CTFP credits for retirement in a later year.

relatively less strict and these fuels are needed to serve as a "drop-in" substitute in combustion engine vehicles. The portion of New Mexico's statewide vehicle fleet made up by combustion vehicles begins its accelerated decline in later years. CTFP credit revenue helps increase the BBD volumes produced, imported, or dispensed for use in New Mexico by providing regulated parties with a greater incentive to substitute BBDs for fossil diesel in New Mexico compared to other states.[76] As detailed in the BCA's FCMM, CTFP credit prices must incentivize this substitution by covering the incremental cost of bringing BBDs into New Mexico to cover the fossil diesel that they replace. This incremental cost, detailed in Table 6-7, represents a net program cost that compensates for the cost of fuel substitution rather than providing an additional revenue source to regulated parties or New Mexico fuel consumers. This conservatively assumes that no additional biodiesel or renewable diesel refineries open in New Mexico as a result of the CTFP.

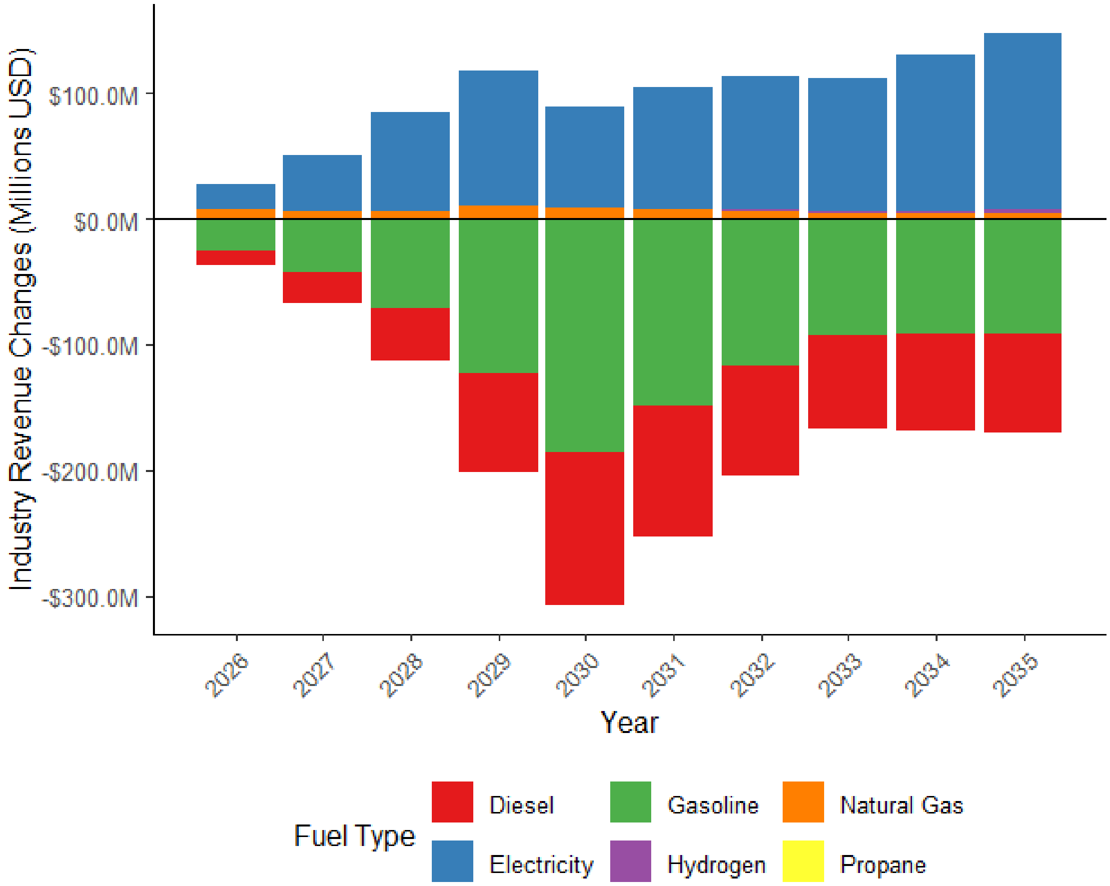
Table 6-7. Biodiesel and renewable diesel import costs (in 2023 USD**)**

Year	Incremental Biodiesel Supply Costs	Incremental Renewable Diesel Supply Costs
2026	-$12,283,574	-$33,966,678
2027	-$9,632,695	-$41,737,322
2028	-$7,868,423	-$60,902,558
2029	-$5,993,079	-$90,184,984
2030	-$3,540,209	-$105,196,240
2031	-$2,971,312	-$88,291,642
2032	-$2,450,123	-$71,543,981
2033	-$3,000,934	-$37,984,092
2034	-$3,982,648	-$19,023,646
2035	-$4,838,232	-$2,751,950

Fuel industries will see various costs and savings from credits, deficits, REC retirement, banking costs, and supply costs. All impacts for the 0 percent PTR scenario are shown in Figure 6-2.

[76] This premium accounts for federal and state revenue sources, fuel sales, and environmental attributes like the fuel pathway's CI considered in the CTFP, as well as the cost of producing and transporting BBDs.

Figure 6-2. Fuel industry revenue changes by year (in 2023 USD)



6.2.2.6 Economic Impacts of Health and Productivity Effects

ERG modeled health impacts with EPA's COBRA, as detailed in the previous chapter. For all health impacts requiring emergency room visits, ERG modeled the cost of a visit as a change in demand for hospital services in IMPLAN. Because reduced tailpipe emissions equate to better air quality, improved health outcomes, and fewer hospital visits, the CTFP is expected to reduce hospital revenue. This analysis did not include mortality impacts.

ERG also simulated changes in productivity as fewer workdays lost to poor health (specifically, respiratory distress and disease). COBRA estimates the value of productivity gained from fewer lost workdays, so ERG modeled this improved productivity in IMPLAN as increased labor income across the entire state of New Mexico, as shown in Table 6-8.

Table 6-8. Annual health and labor impacts over time (in 2023 USD)

Year	Hospital Cost Changes	Labor Income
2026	-$23,836	$2,759
2027	-$29,457	$2,819
2028	-$36,778	$2,990
2029	-$49,652	$3,916
2030	-$45,540	$3,544
2031	-$40,309	$3,148
2032	-$34,707	$2,726
2033	-$19,604	$1,671
2034	-$8,327	$857
2035	-$1,554	$349

6.2.3 Consumer Impacts

As discussed in Section 6.2.2, regulated parties will generate revenue from the sale of credits under the CTFP and incur expenditures from purchasing these credits. This analysis accounts for uncertainty in the degree to which transportation fuel retail prices will incorporate credit revenue or deficit expenditures under the CTFP by modeling EIAs under two PTR scenarios:

1. A 100 percent PTR scenario, in which all revenue changes from credits and deficits are reflected in retail fuel prices.

2. A 0 percent PTR scenario, in which the industries absorb all revenue changes as a change in operating costs that, in turn, affects profit margins. The following section outlines how these assumptions influenced the modeling approach.

In the 100 percent PTR scenario, fuel dispensers in New Mexico incorporate the full amount of credit revenue or deficit expenditures per unit of fuel that they dispense to New Mexico consumers. In such cases, regulated parties would fully account for the revenue and expenditures resulting from CTFP compliance across all stages of the supply chain, up to and including when retailers dispense fuel to consumers. Regulated parties would see no change in profit margins, and fuel consumers would internalize all CTFP fuel market impacts from retail price changes.

By contrast, under the 0 percent PTR scenario, retail transportation fuel prices do not fall in response to CTFP credit market revenue or rise in response to CTFP credit market expenditures. Regulated parties do not pass through any CTFP revenue or expenditures to the point of retail. The analysis assumes that, as a result, regulated parties would fully internalize the CTFP's fuel market effects in the form of commensurate changes to profit margins across the transportation fuel value chain, due to the incremental cost of BBDs as well as incremental REC retirement costs and impairment costs. In this scenario, New Mexico fuel consumers are unaffected by the CTFP.

Direct impacts from both PTR scenarios can be calculated as the number of credits and deficits generated, multiplied by the credit unit price by year (deficit prices are equal to negative credit prices), as shown in Table 6-9.

Table 6-9. Fuel credit price by year

Year	Credit Price (2023 USD/MT)
2026	$111.93
2027	$96.92
2028	$93.70
2029	$82.47
2030	$71.99
2031	$60.90
2032	$50.08
2033	$40.49
2034	$40.57
2035	$40.80

As mentioned, consumers will see changes in retail fuel prices in the 100 percent PTR scenario. New Mexico fuel consumers include households, commercial businesses, and government entities. ERG used data from the CARB Standard Regulatory Impact Assessment (SRIA)[77] to assume the proportion of each fuel that each consumer type purchased, shown in Table 6-10.

Table 6-10. CARB SRIA consumer type spending proportion by fuel type

Consumer	Gasoline, Electricity, Hydrogen	Diesel, Natural Gas, Propane
Household	92.0%	2.0%
Government	1.0%	1.0%
Business	7.0%	97.0%

Changes on the consumer side (100 percent PTR scenario) are modeled in IMPLAN as follows:

- **Household spending** is modeled through IMPLAN's institutional spending patterns, where ERG split costs based on proportions of homes within each income bracket.
- **Government spending** is also modeled through IMPLAN's institutional spending patterns, as a change in state and local government investment.
- **Business spending** is modeled as changes in revenue to specific industries, based on how reliant each industry is on gasoline and diesel.

The 0 percent PTR scenario was modeled with the assumption that credits and deficits result in revenue impacts for fuel industry sectors. These impacts were modeled as changes in the fuel commodity of each specific industry. Since BBD markets in New Mexico are nascent, ERG chose to use the refined petroleum product commodity to model these industries, as the supply chains are

[77] California Air Resources Board, "Low Carbon Fuel Standard 2023 Amendments: Standardized Regulatory Impact Assessment (SRIA)," September 8, 2023, https://ww2.arb.ca.gov/sites/default/files/2023-09/lcfs_sria_2023_0.pdf.

similar. Table 6-11 shows the IMPLAN industry associated with each credit- and deficit-generating industry.

Table 6-11. Fuel mapping to IMPLAN commodities

Consumer	Gasoline, Electricity, Hydrogen
Electricity	3034 - Electricity generation
Hydrogen	3154 - Other basic inorganic chemicals
CNG, RNG	3043 - Natural gas distribution
Gasoline, diesel, renewable diesel, biodiesel, ethanol	3146 - Refined petroleum products

6.2.3.1 Households

Households are a major consumer of fuel, purchasing 92 percent of gasoline, electricity, and hydrogen (Table 6-10). Table 6-12 shows the fuel cost changes over time for households. Households are the largest consumer of both gasoline fuel and low-carbon alternatives, primarily electricity and hydrogen.

Table 6-12. Annual household consumer cost changes (in 2023 USD)

Year	Gasoline	Diesel	Electricity	Hydrogen	Natural Gas	Propane	Total
2026	-$23,388,409	-$233,720	$15,140,016	$0	$131,840	$0	-$8,350,273
2027	-$40,048,960	-$467,881	$30,514,962	$0	$114,739	$0	-$9,887,141
2028	-$65,559,837	-$827,178	$53,005,652	$0	$109,398	$0	-$13,271,965
2029	-$112,248,020	-$1,596,496	$66,457,347	$0	$212,145	-$5,164	-$47,180,188
2030	-$169,932,756	-$2,450,939	$73,964,717	$0	$162,814	-$17,950	-$98,274,114
2031	-$136,231,225	-$2,088,322	$89,798,767	$589,528	$136,134	-$17,113	-$47,812,231
2032	-$107,453,845	-$1,749,317	$97,972,682	$981,314	$110,615	-$15,743	-$10,154,294
2033	-$85,417,444	-$1,468,569	$97,229,058	$1,204,350	$88,348	-$14,148	$11,621,595
2034	-$84,020,324	-$1,524,730	$113,902,538	$1,627,832	$87,416	-$15,668	$30,057,063
2035	-$83,447,636	-$1,585,629	$129,162,444	$2,069,533	$86,768	-$17,324	$46,268,156

6.2.3.2 Businesses

Businesses are the largest consumers of many transportation fuels, particularly diesel and its alternatives, including natural gas and propane (Table 6-10). Table 6-13 shows the fuel cost changes over time for business consumers. The fuel impacts of diesel include deficits generated from fossil diesel and credits generated from biodiesel and renewable diesel.

Table 6-13. Annual business consumer cost changes (in 2023 USD)

Year	Gasoline	Diesel	Electricity	Hydrogen	Natural Gas	Propane	Total
2026	-$1,779,553	-$11,335,414	$1,151,958	$0	$6,394,244	$0	-$5,568,765
2027	-$3,047,204	-$22,692,227	$2,321,791	$0	$5,564,843	$0	-$17,852,797
2028	-$4,988,248	-$40,118,131	$4,033,039	$0	$5,305,786	$0	-$35,767,555
2029	-$8,540,610	-$77,430,047	$5,056,537	$0	$10,289,029	-$250,443	-$70,875,533
2030	-$12,929,666	-$118,870,552	$5,627,750	$0	$7,896,485	-$870,595	-$119,146,578
2031	-$10,365,419	-$101,283,626	$6,832,515	$44,855	$6,602,515	-$829,971	-$98,999,132
2032	-$8,175,836	-$84,841,893	$7,454,443	$74,665	$5,364,819	-$763,516	-$80,887,319
2033	-$6,499,153	-$71,225,606	$7,397,863	$91,635	$4,284,866	-$686,198	-$66,636,593
2034	-$6,392,851	-$73,949,412	$8,666,497	$123,857	$4,239,667	-$759,909	-$68,072,150
2035	-$6,349,277	-$76,903,003	$9,827,577	$157,464	$4,208,245	-$840,216	-$69,899,209

6.2.3.3 Government

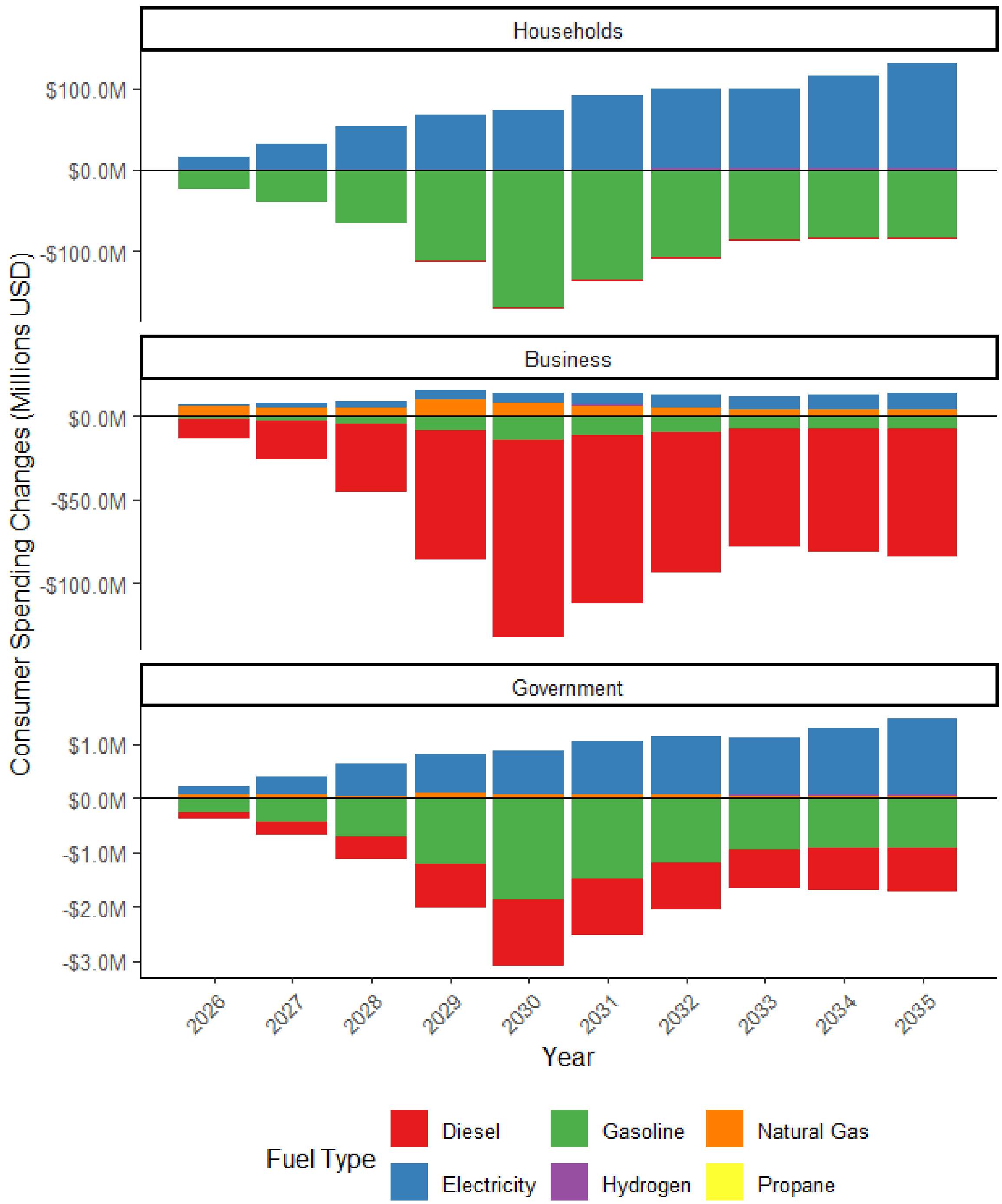
Government impacts are the results of governments spending and saving money to fuel their fleets. Government accounts for about 1 percent of total consumer spending across all fuel types (Table 6-10). Table 6-14 shows government impacts by fuel type over time.

Table 6-14. Annual government consumer cost changes (in 2023 USD)

Year	Gasoline	Diesel	Electricity	Hydrogen	Natural Gas	Propane	Total
2026	-$254,222	-$116,860	$164,565	$0	$65,920	$0	-$140,596
2027	-$435,315	-$233,940	$331,684	$0	$57,370	$0	-$280,201
2028	-$712,607	-$413,589	$576,148	$0	$54,699	$0	-$495,349
2029	-$1,220,087	-$798,248	$722,362	$0	$106,072	-$2,582	-$1,192,482
2030	-$1,847,095	-$1,225,470	$803,964	$0	$81,407	-$8,975	-$2,196,169
2031	-$1,480,774	-$1,044,161	$976,074	$6,408	$68,067	-$8,556	-$1,482,943
2032	-$1,167,977	-$874,659	$1,064,920	$10,666	$55,307	-$7,871	-$919,612
2033	-$928,450	-$734,285	$1,056,838	$13,091	$44,174	-$7,074	-$555,707
2034	-$913,264	-$762,365	$1,238,071	$17,694	$43,708	-$7,834	-$383,991
2035	-$907,040	-$792,814	$1,403,940	$22,495	$43,384	-$8,662	-$238,697

Households begin to save significant amounts towards 2035 as they spend more on electricity and less on gasoline, as shown in Figure 6-3.

Figure 6-3. Consumer spending by consumer type, fuel type, and year (in 2023 USD)



6.3 Results

This section documents the results of the macroeconomic analysis (in 2024 U.S. dollars). ERG shows total impacts on the fuel market (which includes credits and deficits, REC retirements, biodiesel and renewable diesel supply costs, and banking costs), FSE credits, and hospitalization and productivity. The fuel market is the common component between scenarios, since FSE credits and health impacts are not reliant on consumers.

6.3.1 Economic Impact Analysis Results

In this section, ERG documents the full EIA results, including impacts related to the fuel market, FSE credits, and hospitalization and productivity. Here, ERG shows the results for both the 0 percent and 100 percent PTR scenarios. The credit and deficit costs are the only components of this analysis that are subject to the passthrough; therefore, FSE credits and health impacts are equal in both scenarios. Table 6-15 presents the complete results of the 0 percent PTR scenario. These results present all impacts, including impacts related to the fuel market (credits and deficits, REC retirements, biodiesel and renewable diesel supply costs, and bank holding costs), FSE credits, and health and productivity changes. As stated above, IMPLAN results provide estimates across key economic indicators. Employment represents the number of full-time and part-time jobs supported. Labor income includes all wages, salaries, and benefits earned by workers. Value-added reflects the contribution to gross domestic product (GDP). Economic output represents the total value of all goods and services produced.

Table 6-15. Annual results for the 0 percent PTR scenario (in 2024 USD)

Year	Employment	Labor Income	Value Added	Output
2026	5.6	$260,575	-$2,276,120	-$14,377,391
2027	77.9	$4,547,444	$2,418,911	-$9,580,665
2028	103.6	$5,811,311	$1,296,657	-$21,918,723
2029	81.3	$2,424,817	-$17,421,742	-$82,789,262
2030	-148.1	-$17,315,596	-$77,659,252	-$236,820,261
2031	-49.6	-$8,389,496	-$48,207,118	-$160,882,936
2032	8.6	-$2,594,332	-$26,777,980	-$104,029,960
2033	45.6	$1,088,090	-$12,895,910	-$65,596,984
2034	67.0	$3,130,080	-$6,268,878	-$51,874,927
2035	65.5	$3,640,781	-$2,584,385	-$45,078,981

Table 6-16 shows the results of the 100 percent PTR scenario.

Table 6-16. Annual results for the 100 percent PTR scenario (in 2024 USD)

Year	Employment	Labor Income	Value Added	Output
2026	-105.3	-$5,952,495	-$10,629,993	-$18,842,097
2027	-156.3	-$8,934,857	-$15,772,592	-$25,010,784
2028	-318.3	-$18,680,200	-$31,793,308	-$53,515,054
2029	-844.2	-$48,896,607	-$84,601,898	-$147,452,979
2030	-1710.1	-$99,043,848	-$171,230,034	-$307,413,387
2031	-1180.4	-$69,631,487	-$117,451,371	-$212,308,525
2032	-772.7	-$46,931,942	-$76,077,050	-$139,770,919
2033	-499.1	-$31,471,463	-$48,441,880	-$90,779,270
2034	-451.9	-$29,257,279	-$43,341,746	-$82,764,504
2035	-336.8	-$23,723,138	-$31,182,804	-$64,364,888

6.3.1.1 Credit and Deficit Impacts

This section documents ERG's results explicitly for the fuel market. This includes credits, deficits, REC retirements, bank holding costs, and BD and RD supply costs. While more deficits are generated than credits (since some credits were apportioned to FSE credits), the results are negative, largely due to REC retirements, banking costs, and BD and RD supply costs. Table 6-17 shows the breakdown of results for the 0 percent PTR scenario, and Table 6-18 shows results of the 100 percent PTR scenario.

Table 6-17. Direct, indirect, and induced effects annually for the 0 percent PTR scenario (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$8,993,861	-$5,485,195	$124,823
2027	-$17,326,704	-$9,790,960	-$214,940
2028	-$30,092,303	-$16,500,201	-$682,904
2029	-$71,471,707	-$38,608,656	-$3,274,056
2030	-$155,628,931	-$81,800,091	-$10,969,552
2031	-$112,096,241	-$59,197,574	-$7,112,908
2032	-$76,949,450	-$40,904,457	-$4,104,839
2033	-$53,221,357	-$28,498,766	-$2,215,072
2034	-$45,057,933	-$24,351,255	-$1,206,016
2035	-$38,389,883	-$20,974,485	-$348,094

Table 6-18. Direct, indirect, and induced effects annually for the 100 percent PTR scenario (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$11,585,837	-$4,090,019	-$3,143,083
2027	-$25,335,412	-$10,107,821	-$7,319,490
2028	-$46,187,213	-$19,087,533	-$13,596,993
2029	-$106,126,311	-$41,538,844	-$30,352,982
2030	-$191,666,349	-$73,203,716	-$54,121,634
2031	-$135,586,427	-$54,802,606	-$39,443,278
2032	-$90,561,617	-$39,631,864	-$27,506,225
2033	-$60,628,172	-$29,092,864	-$19,396,445
2034	-$55,156,721	-$28,054,230	-$18,293,829
2035	-$39,763,688	-$24,453,206	-$14,781,475

6.3.1.2 FSE Credit Impacts

FSE credits create direct jobs in New Mexico. These jobs have direct, indirect, and induced output impacts, shown in Table 6-19. Direct impacts ranged between $8 million and $22 million until 2035. Starting in 2036, the only remaining jobs supported by the FSE credits are fuel station maintenance jobs, which are assumed to be constant until at least 2040.

Table 6-19. Annual output results from job creation through FSE credits (in 2024 USD)

Year	Direct	Indirect	Induced
2027	$12,436,042	$2,757,102	$2,587,195
2028	$17,729,622	$3,959,808	$3,702,316
2029	$21,338,555	$4,800,605	$4,472,471
2030	$8,005,849	$1,892,714	$1,721,567
2031	$12,144,437	$2,825,715	$2,589,915
2032	$12,398,228	$2,906,704	$2,654,473
2033	$12,649,566	$2,987,056	$2,718,477
2034	$12,898,514	$3,066,782	$2,781,938
2035	$9,996,850	$2,447,912	$2,189,898
2036–2040	$2,949,311	$902,421	$731,797

6.3.1.3 Economic Results of Health Impacts

Health impacts from the CTFP include hospitalization and productivity cost changes, shown in Table 6-20. Negative hospitalization values are a result of improved health outcomes and reduced hospital use in New Mexico. While these are negative impacts within the economy, they provide a benefit in the form of improved health that cannot be accurately captured in this analysis but are discussed in Chapter 5. Productivity cost changes only result in induced impacts from fewer workdays lost and are not assumed to impact business revenue. Improved productivity only increases induced impacts, slightly offsetting the negative induced impacts of hospitalization costs.

Table 6-20. Direct, indirect, and induced health impact annually (in 2024 USD)

Year	Direct	Indirect	Induced
2026	-$16,070	-$4,940	-$4,057
2027	-$19,859	-$6,105	-$5,391
2028	-$24,795	-$7,622	-$7,069
2029	-$33,474	-$10,290	-$9,621
2030	-$30,702	-$9,438	-$8,854
2031	-$27,176	-$8,354	-$7,830
2032	-$23,399	-$7,193	-$6,732
2033	-$13,216	-$4,063	-$3,719
2034	-$5,614	-$1,726	-$1,485
2035	-$1,048	-$322	-$157

6.4 Data Sharing

The macroeconomic analysis contributed to the BCA results, which are shown through 2030 in Table 6-21and through 2040 in Table 6-22 (in 2024 U.S. dollars). ERG averaged the 0 percent PTR scenario and the 100 percent PTR scenario to create a 50 percent PTR scenario, where industries are expected to pass half of the revenue changes onto consumers with fuel price changes. ERG used this 50 percent PTR scenario to estimate the macroeconomic impacts and used these averaged results in the BCA.

It is worth noting that GHG reductions and monetized benefits through the social cost of carbon were supplied by BRG using a combination of the published NM-GREET CI values and their fuel projections, except for hydrogen, electricity, and renewable diesel and biodiesel blends. For hydrogen, BRG has baked in the assumption of a long-term processing shift from steam methane reforming of landfill gas to electrolysis after 2030 rather than one of these pathways defined in NM-GREET. For electricity, BRG applied decreasing CI values over time to account for the expected switch to cleaner and renewable sources of electricity generation, which are not specified annually in NM-GREET. For RD and BD blends, BRG utilized realized feedstock ratios from historical producer data, so again this did not tie back to a particular feedstock-specific NM-GREET pathway.

The BCA also used the health impacts from Chapter 5. As stated above, this health analysis in the EIA only considered costs from changes in hospitalization and productivity (since mortality data is not an appropriate impact in an EIA). In the BCA, ERG used the total avoided costs from the COBRA analysis, including mortality, as well as the indirect and induced impacts from the IMPLAN EIAs. Direct health benefits and costs were updated with the three percent discount rate and included indirect and induced health impacts from the EIA.

ERG also included the FSE credits as direct jobs created within the state. When translating for the BCA, ERG included direct, indirect, and induced output values from the EIA rather than an explicit number of jobs. Finally, ERG included NMVES updates to the BCA. Updates to the NMVES analysis are outlined in Appendix D.2.

Table 6-21. Summary of total CTFP and NMVES benefits and costs through 2030 (in 2024 USD)

NMVES Total*		-$397,615,611	-$397,615,611
CTFP	**Benefits (average)**	**Costs**	**Net**
Fuel Markets**		-$481,018,805	-$481,018,805
Direct fuel markets		*-$293,686,741*	
Indirect and induced		*-$187,332,064*	
Health effects***	$10,240,199		$10,240,199
GHG emissions	$1,227,826,621		$1,227,826,621
Direct Jobs from FSE	$77,218,383		$77,218,383
CTFP TOTAL	$1,315,285,202	-$481,018,805	$834,266,397
NMVES + CTFP suite	$1,315,285,202	-$878,634,417	$436,650,786

**Accounts for indirect and induced consumer effects and baseline of EPA Multi-Pollutant and Phase 3 Heavy-Duty Rules; health benefits averaged.*
***The fuel market impacts are the 50 percent pass-through scenario that averages the results from the 0 percent and 100 percent passthrough scenarios.*
****Represents an average between a lower- and upper-bound estimate of health benefits from criteria pollutant and ozone precursor reductions.*

Table 6-22. Summary of total CTFP and NMVES benefits and costs through 2040 (in 2024 USD**)**

NMVES Total*	$188,043,999		$188,043,999
CTFP	**Benefits (average)**	**Costs**	**Net**
Fuel Markets**		-$959,423,181	-$959,423,181
Direct fuel markets		*-$577,919,646*	
Indirect and induced	*figur*	*-$381,503,535*	
Health effects***	$15,712,160		$15,712,160
GHG emissions	$2,435,963,386		$2,435,963,386
Direct Jobs from FSE	$161,894,181		$161,894,181
CTFP TOTAL	$2,613,569,726	-$959,423,181	$1,654,146,545
NMVES + CTFP suite	$2,801,613,725	-$959,423,181	$1,842,190,544

**Accounts for indirect and induced consumer effects and baseline of EPA Multi-Pollutant and Phase 3 Heavy-Duty Rules; health benefits averaged.*
***The fuel market impacts are the 50 percent pass-through scenario that averages the results from the 0 percent and 100 percent passthrough scenarios.*

****Represents an average between a lower- and upper-bound estimate of health benefits from criteria pollutant and ozone precursor reductions.*

Appendix

Appendices

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A. Fuel Carbon Intensities

A.1 Summary

Crude oil CI was calculated with a well-to-refinery scope using OPGEE v2.0c, [CITE] the work of Masnadi et al. (2018),[CITE] and crude oil production and foreign import data from the U.S. Energy Information Administration. [CITE] Table A-1 details the weighted CIs for PADD3 for 2018 and 2022, which are 11.83 and 11.46 g CO_2e/MJ refinery inputs, respectively. These CIs are for a well-to-refinery gate boundary and are used in place of GREET's default crude-oil-extraction Feedstock stage value across the baseline (2018) and v1.0 default/temporary (2022) versions of NM-GREET.

Table A-1. CI of PADD3 crude oil for 2018 and 2022

Summary Result	2018 Value	2022 Value	Units
Total foreign imports	7.31E+12	4.26E+12	MJ
Total PADD3 production	1.46E+13	1.78E+13	MJ
Import CI (weighted)	12.88	12.15	g CO_2e/MJ refinery input
PADD3 CI (U.S. average)	11.30	11.30	g CO_2e/MJ refinery input
Weighted CI	11.83	11.46	g CO_2e/MJ refinery input

A.2 Methods

Country-specific crude oil CI and crude oil properties (API gravity, energy density) were sourced from Masnadi et al. (2018); they represent ~98% of crude oil production for the study's 2015 scope.[78] These values are detailed in Table A-2. Crude oil production and foreign import data for PADD3 were sourced from the U.S. EIA for 2018 and 2022; please note that only crude oil imports were considered for CI weighting (i.e. oil products such as gasoline blending components were not included).[79] Imports to PADD3 from other PADDs were not included in the calculation. In 2018, total PADD3 crude imports were 1,017,321 thousand bbls and crude production was 2,582,134 thousand bbls. For 2022, PADD3's total imports dropped significantly to just 597,650 thousand bbls and production rose to 3,145,563 thousand barrels.

Import volumes (in bbl) were converted to MJ of lower heating value (LHV) by way of their average API gravity. Carbon intensities (in g CO_2e / MJ refinery input) were then weighted based on the import amount, in MJ, from each country. Across PADD3 crude production, it was assumed that both carbon intensity and crude properties were the same as the U.S. average in Masnadi et al. (2018). Where needed, crude oil API gravity was converted to specific gravity with the following formula:

$$Specific\ Gravity = \frac{131.5 + API\ Gravity}{141.5}$$

LHV energy density, in MJ/kg crude oil, was calculated using OPGEE's "Crude Oil Chemical Composition" table, which is copied in Table A-3. Energy densities for non-integer API gravities

[78] Mohammad S. Masnadi et al., "Global Carbon Intensity of Crude Oil Production," *Science* 361, no. 6405 (August 31, 2018): 851–53, https://doi.org/10.1126/science.aar6859.

[79] U.S. Energy Information Administration, "Crude Oil Production, Annual," 2025, https://www.eia.gov/dnav/pet/pet_crd_crpdn_adc_mbbl_a.htm.

were linearly interpolated from the nearest values available. For all calculations, the volumetric conversion factor of 1 m^3 = 6.28981 bbl was used.

Table A-2. Crude oil CI, 2018 and 2022 import volumes and API gravity by country

Country	CI ($g\ CO_2e/MJ$) (Masnadi, 2018)	2018 Imports (thousand bbl) (U.S. EIA, 2025)	2022 Imports (thousand bbls) (U.S. EIA, 2025)	Average Crude API Gravity (Masnadi, 2018)
Angola	7.8	6,967	949	30.33
Argentina	9.4	2,867	-	27.00
Australia	9.4	529	-	47.25
Azerbaijan	6.8	3,833	-	35.00
Barbados	9.5	50	-	33.00
Belize	9.0	198	-	33.00
Bolivia	9.2	318	-	33.00
Brazil	10.5	19,887	3,982	22.94
Canada	17.7	180,246	214,870	19.65
Chad	10.2	3,554	-	33.00
Colombia	8.8	53,880	58,435	26.58
Ecuador	9.5	12,015	-	41.56
Egypt	10.6	2,761	-	33.00
Equatorial Guinea	6.8	1,943	-	33.00
Gabon	13.1	398	-	33.00
Ghana	6.0	3	-	33.00
Guatemala	9.8	2,501	868	33.00
Iran	17.4	-	507	30.70
Iraq	14.0	144,524	19,994	29.90
Italy	6.7	438	-	33.00
Kuwait	7.1	13,377	6,716	24.20
Libya	11.2	598	-	35.05
Mexico	9.9	216,855	194,883	19.69
Niger	11.5	10,465	-	33.00
Nigeria	12.4	10,465	-	34.74
Peru	11.1	-	259	33.00
Russian Federation	9.7	718	-	33.51
Saudi Arabia	5.1	141,071	75,451	31.97
Trinidad and Tobago	14.4	2,155	9,076	33.00
United Kingdom	8.3	12,508	8,623	34.00
Venezuela	19.9	181,614	-	13.92

Table A-3. Crude Oil API gravity and energy density values from OPGEE v2.0c[80]

API Gravity	Specific Gravity	Lower Heating Value (MJ/kg)	API Gravity	Specific Gravity	Lower Heating Value (MJ/kg)
4	1.04	39.33	25	0.90	41.47
5	1.04	39.52	26	0.90	41.54
6	1.03	39.66	27	0.89	41.61
7	1.02	39.80	28	0.89	41.68
8	1.01	39.94	29	0.88	41.75
9	1.01	40.08	30	0.88	41.82
10	1.00	40.17	31	0.87	41.87
11	0.99	40.26	32	0.87	41.94
12	0.99	40.35	33	0.86	41.98
13	0.98	40.47	34	0.85	42.05
14	0.97	40.56	35	0.85	42.12
15	0.97	40.66	36	0.84	42.17
16	0.96	40.75	37	0.84	42.21
17	0.95	40.82	38	0.83	42.28
18	0.95	40.91	39	0.83	42.33
19	0.94	41.01	40	0.83	42.40
20	0.93	41.08	41	0.82	42.45
21	0.93	41.14	42	0.82	42.52
22	0.92	41.24	43	0.81	42.56
23	0.92	41.31	44	0.81	42.61
24	0.91	41.40	45	0.80	42.66

Values from OPGEE v2.0c 'Fuel Spec' table

A.3 OPGEE v2.0c Copyright Statement

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[80] Hassan M. El-Houjeiri et al., "Oil Production Greenhouse Gas Emissions Estimator OPGEE v2.0 User Guide & Technical Documentation," 2017, https://pangea.stanford.edu/departments/ere/dropbox/EAO/OPGEE/OPGEE_documentation_v2.0.pdf.

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B. Projected Emission Reductions

Fuel penetrations over time by vehicle (source use) type are key inputs for modeling the NMVES and federal baseline scenarios in MOVES. As discussed in Projected Emission Reductions (Chapter 4), these fuel penetrations are summarized through the MOVES AVFT table. ERG used different AVFT tables for each policy scenario.

Light-duty fuel penetrations (for passenger cars, passenger trucks, and light commercial trucks) in the NMVES scenario were adopted from New Mexico's prior rule and should be consistent with California's ACC II Program.[81] Heavy-duty fuel penetrations (for all other MOVES source types) in the NMVES scenario were pulled from EPA's docketed Phase 3 rulemaking files.[82] Luckily, EPA had already developed a side case with a custom AVFT table for California's ACT Program when analyzing the federal GHG Phase 3 Rule for heavy-duty vehicles, so ERG could simply use the ACT AVFT in any MOVES runs. ERG then incorporated the NMVES LD penetrations into the existing ACT AVFT to represent the full NMVES scenario for LDVs and HDVs. The MOVES5 release includes the latest federal regulations, particularly Phase 3 and the LD Multi-Pollutant Rule, so ERG could run default MOVES5 fuel penetrations without any further modification for the federal baseline scenario in New Mexico's clean fuels program. Figures B-1 through B-12 compare fuel penetrations for the NMVES and federal baseline scenarios by MOVES source type.

The other key MOVES inputs for the CTFP emissions analysis were New Mexico county databases from the 2020 NEI, which EPA has conveniently made available through an NEI file transfer protocol (FTP) site.[83] These CDBs contain New Mexico-specific information on VMT, vehicle populations, age distributions, average speeds, fuels, and meteorology. For the NMVES scenario, ERG inserted the custom NMVES AVFT into every CDB. For the federal baseline scenario, the AVFT was left unchanged. ERG also grew 2020 VMT and populations for future evaluation years using growth rates discussed in Section 4.2.2 and created a distinct set of CDBs for each evaluation year and each of New Mexico's 31 counties.

In the interest of model runtime, ERG set up two types of MOVES run specifications (often referred to as runspecs): (1) annual runspecs for all pollutants and processes except evaporative emissions (see Table B-1 below), and (2) hourly runspecs in January and July for VOC evaporative effects in particular (see Table B-2). ERG then developed New Mexico-specific emission factors per unit energy for all pollutants and non-evaporative processes, as well as monthly average VOC evaporative EFs. To determine full VOC emission factors, ERG simply added the VOC non-evaporative and evaporative EFs together. The same VOC evaporative effects were used for both NMVES and federal baseline scenarios. Lastly, ERG did some Bernalillo County runs to model nondefault fuel blends (namely, B0, B5, and E15) with the MOVES Fuel Wizard by policy scenario to expedite processing of fuel effects. Using the Fuel Wizard interface is time consuming, so instead

81 New Mexico Environment Department, "New Motor Vehicle Emissions Standards (Advanced Clean Cars II/Advanced Clean Trucks)," accessed May 29, 2025, https://www.env.nm.gov/climate-change-bureau/transportation/.

82 U.S. Environmental Protection Agency, "Greenhouse Gas Emissions Standards for Heavy-Duty Engines and Vehicles-Phase 3," Docket, accessed June 26, 2025, https://www.regulations.gov/docket/EPA-HQ-OAR-2022-0985.

83 U.S. Environmental Protection Agency, "2020 National Emissions Inventory Data," accessed June 26, 2025, https://gaftp.epa.gov/Air/emismod/2020/2020emissions/.

of creating custom fuels with the Fuel Wizard for each county, ERG selected Bernalillo as a representative county for evaluating these fuel effects.

Table B-3 through B-6 show the fuel volumes forecasts for the NMVES and federal baseline scenarios before and after BRG modifications to New Mexico's statewide fleet and activity. The before case estimates volumes from ERG's initial county-level MOVES runs for each policy scenario, respectively, prior to BRG's ZEV fleet and activity adjustments. The after case computes volumes for the final NMVES and federal rules after BRG's adjustments. These baseline fuel volumes were used to calculate the necessary adjustments to the baseline emission inventories and subsequent benefits, as discussed in Section 0. In either case, baseline volumes assume no CTFP implementation.

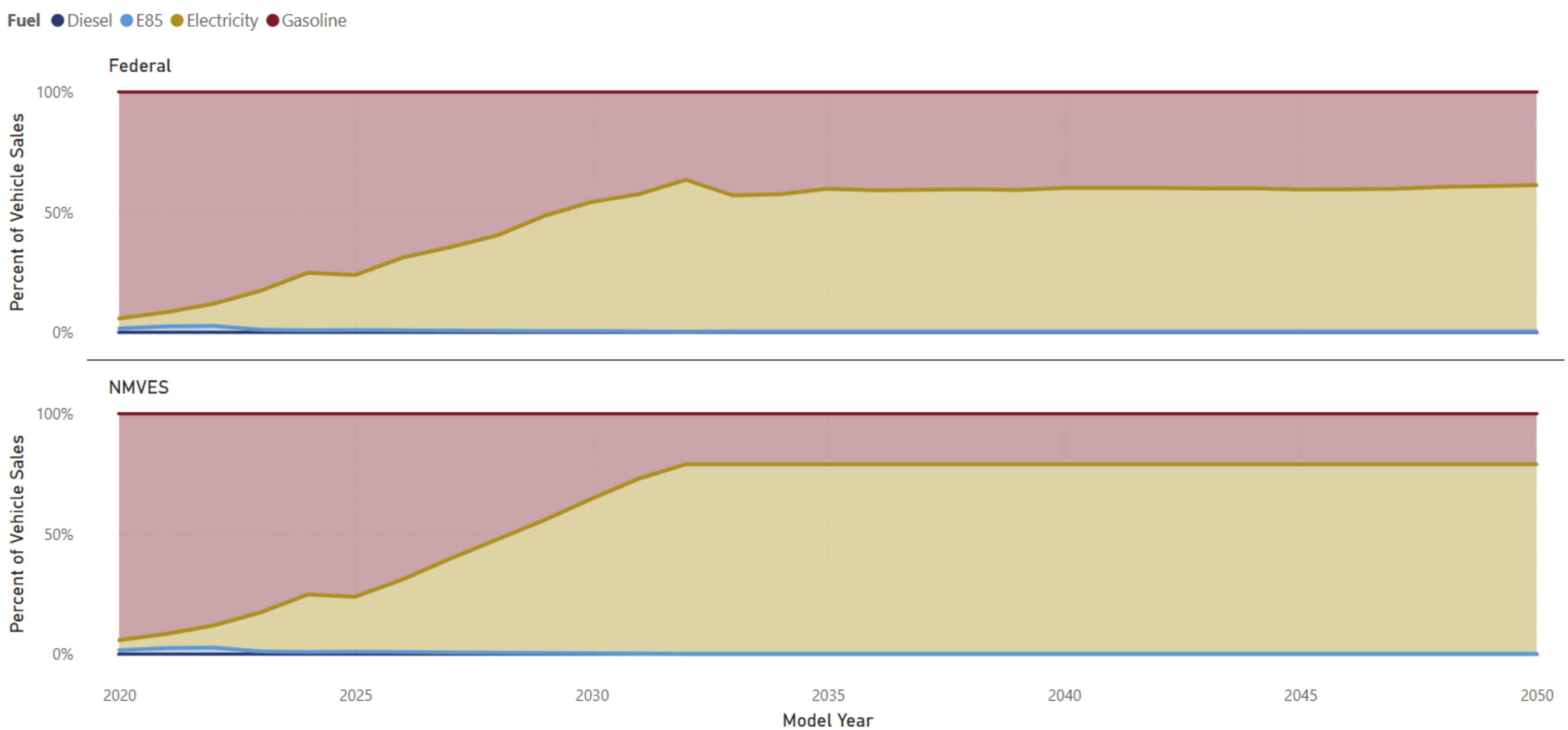

Figure B-1. Passenger car (MOVES sourceTypeID 21) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

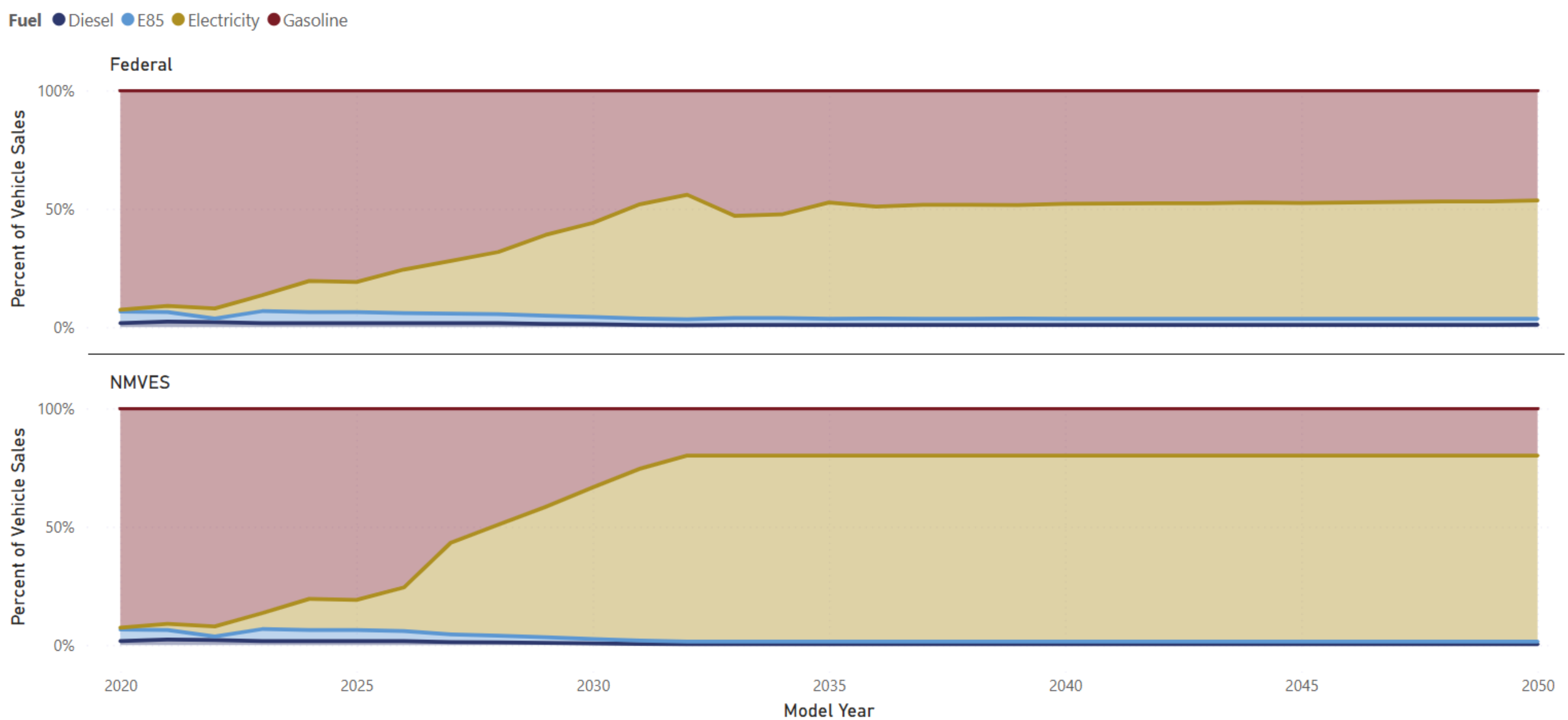

Figure B-2. Passenger truck (MOVES sourceTypeID 31) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

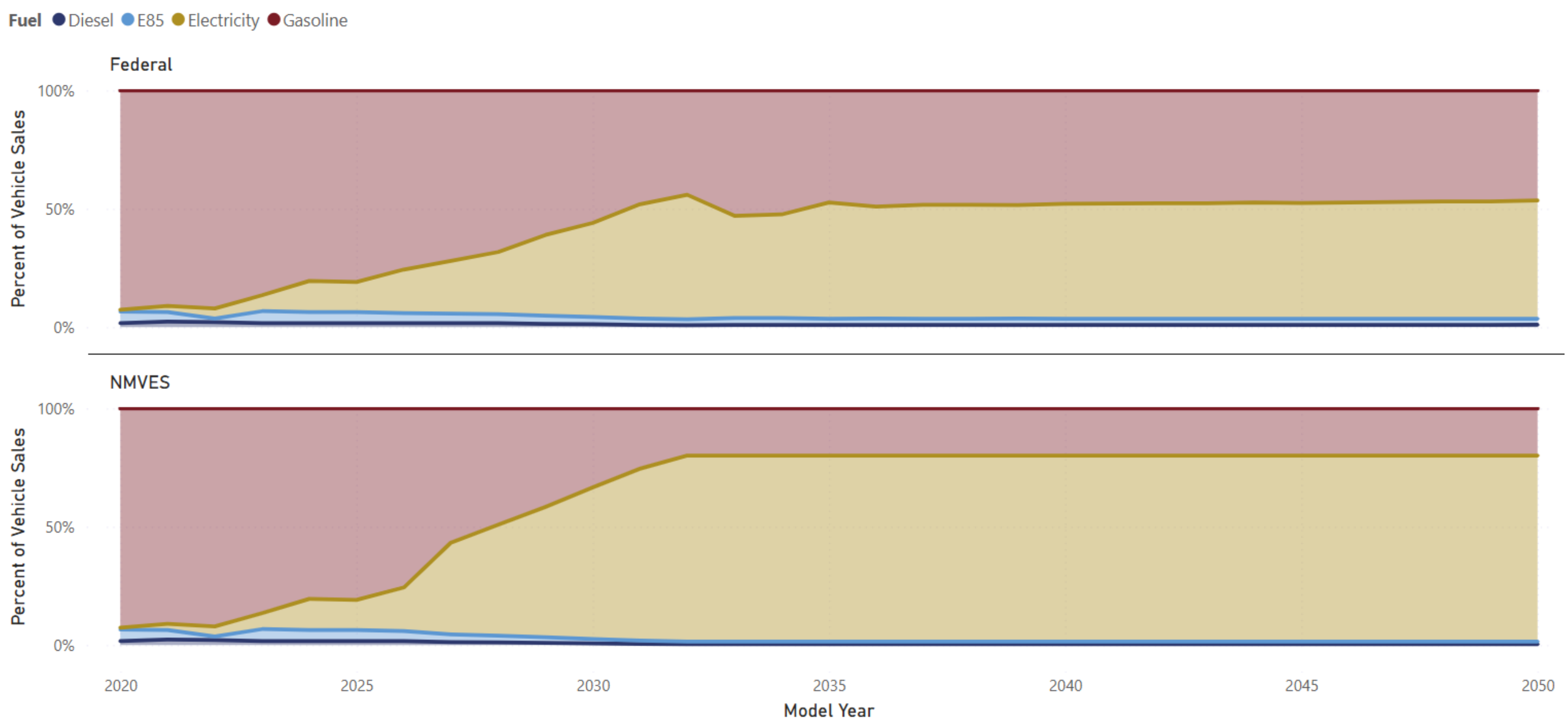

Figure B-3. Light commercial truck (MOVES sourceTypeID 32) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

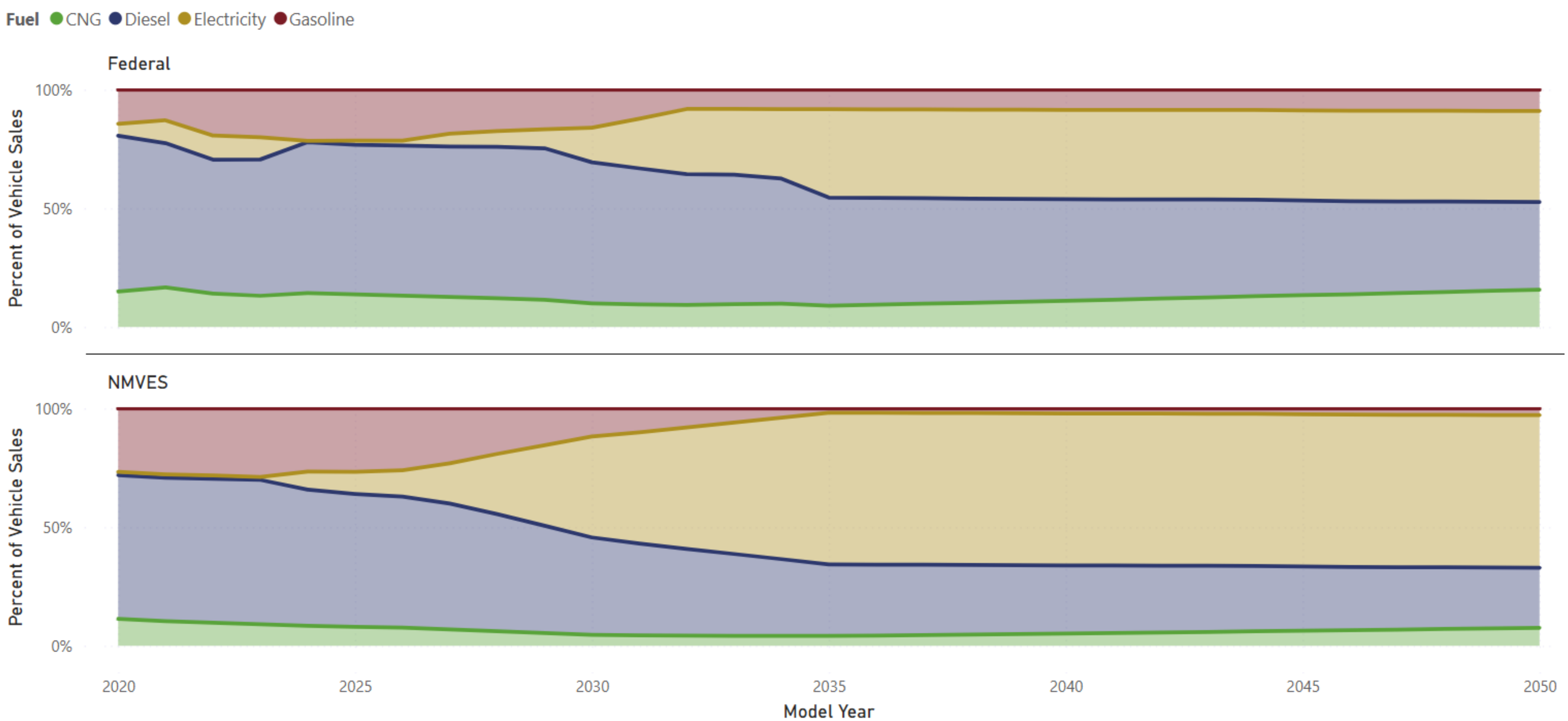

Figure B-4. Other bus (MOVES sourceTypeID 41, not for transit or school applications) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

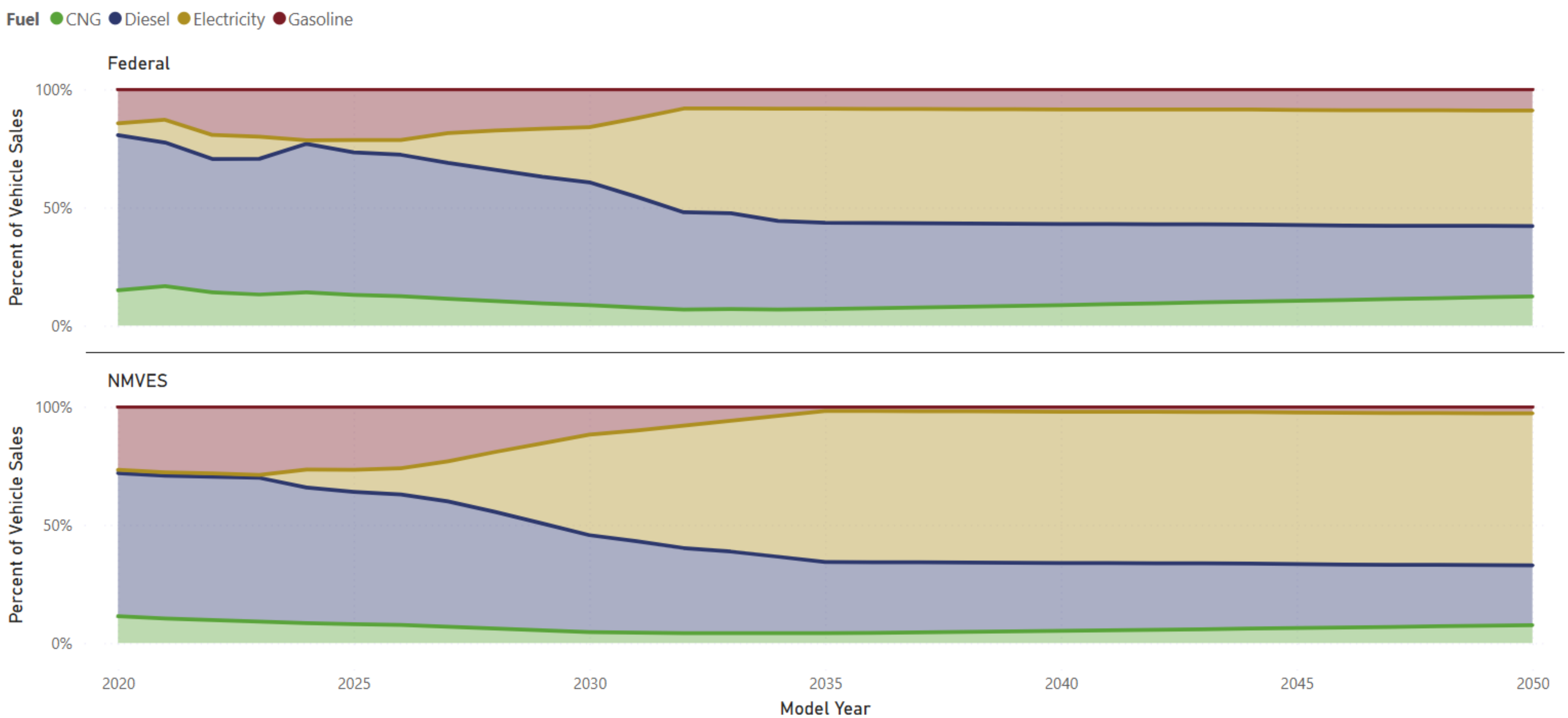

Figure B-5. Transit bus (MOVES sourceTypeID 42) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

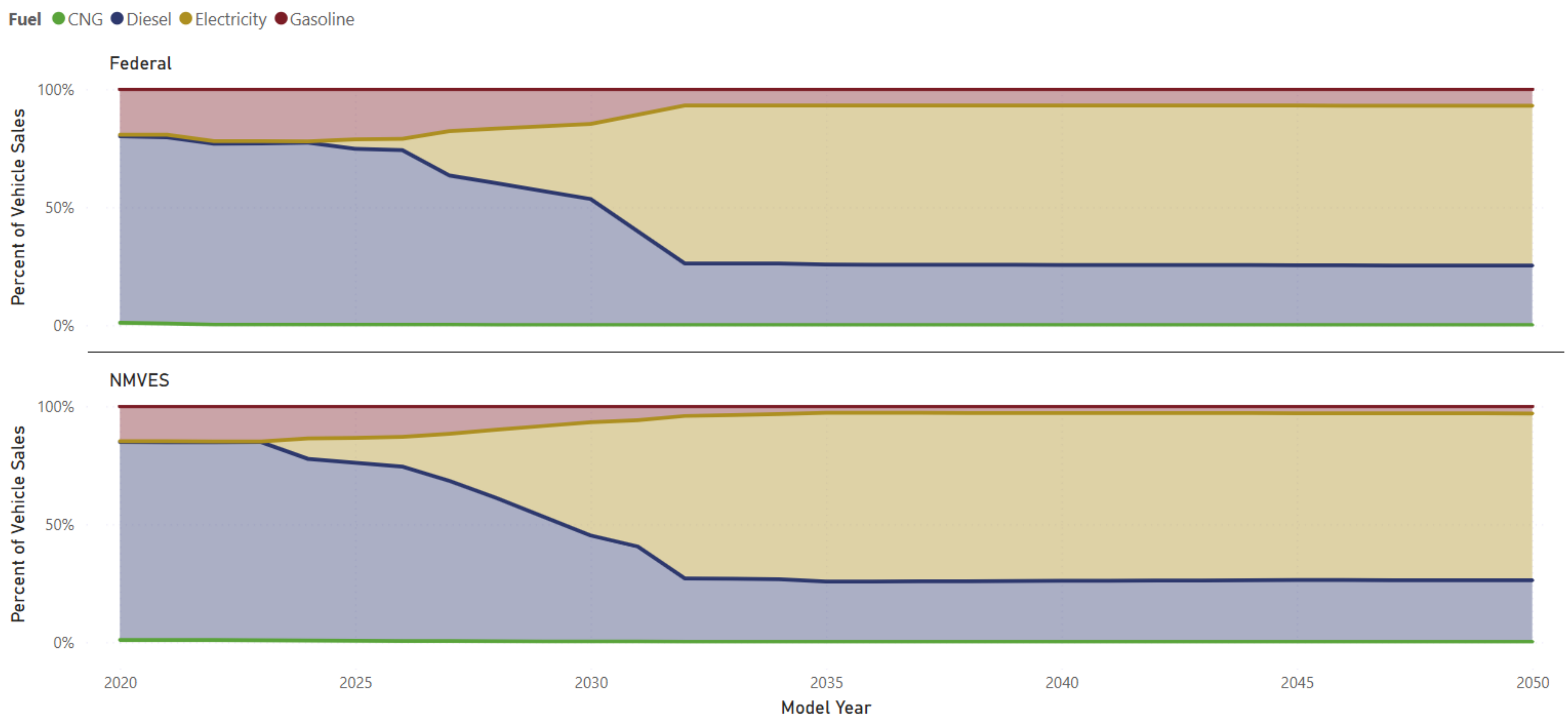

Figure B-6. School bus (MOVES sourceTypeID 43) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

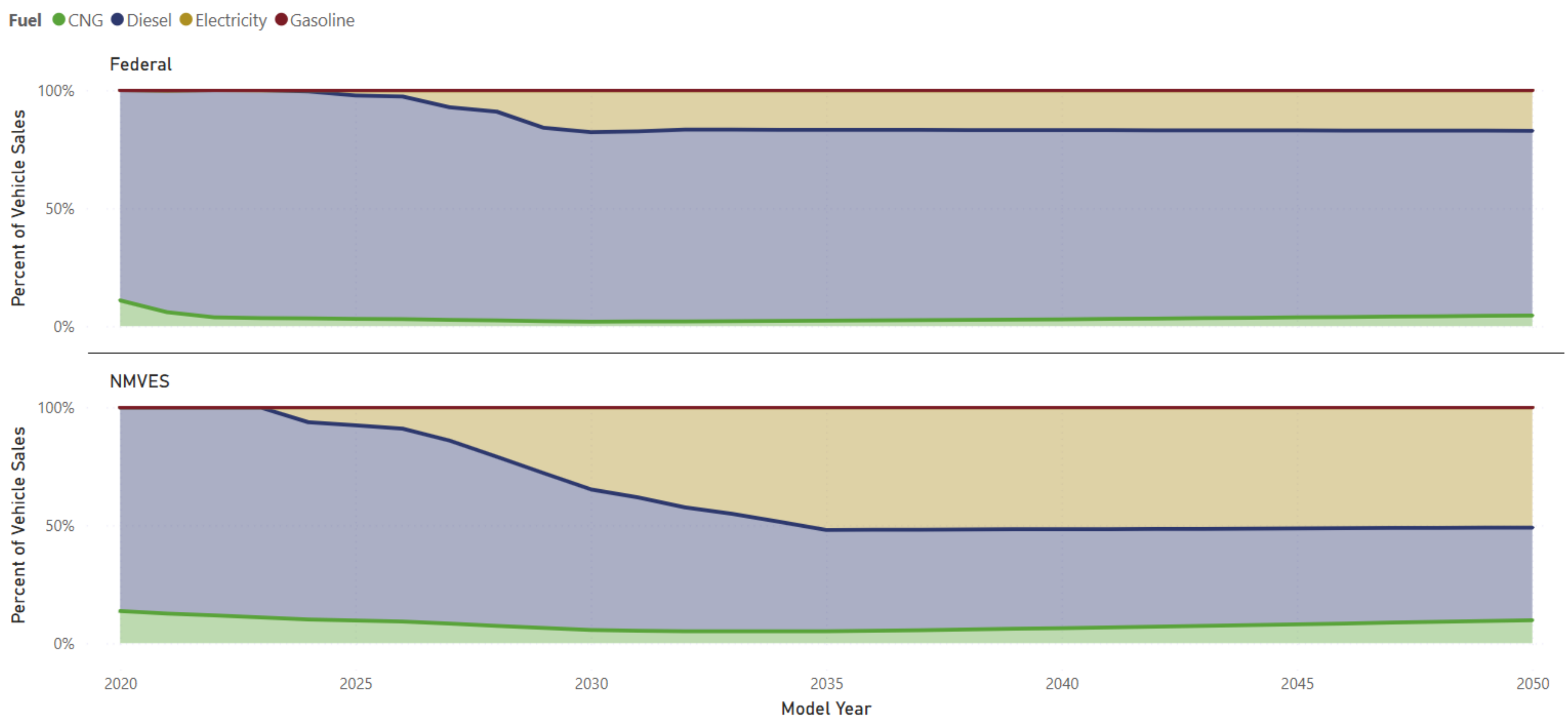

Figure B-7. Refuse truck (MOVES sourceTypeID 51) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

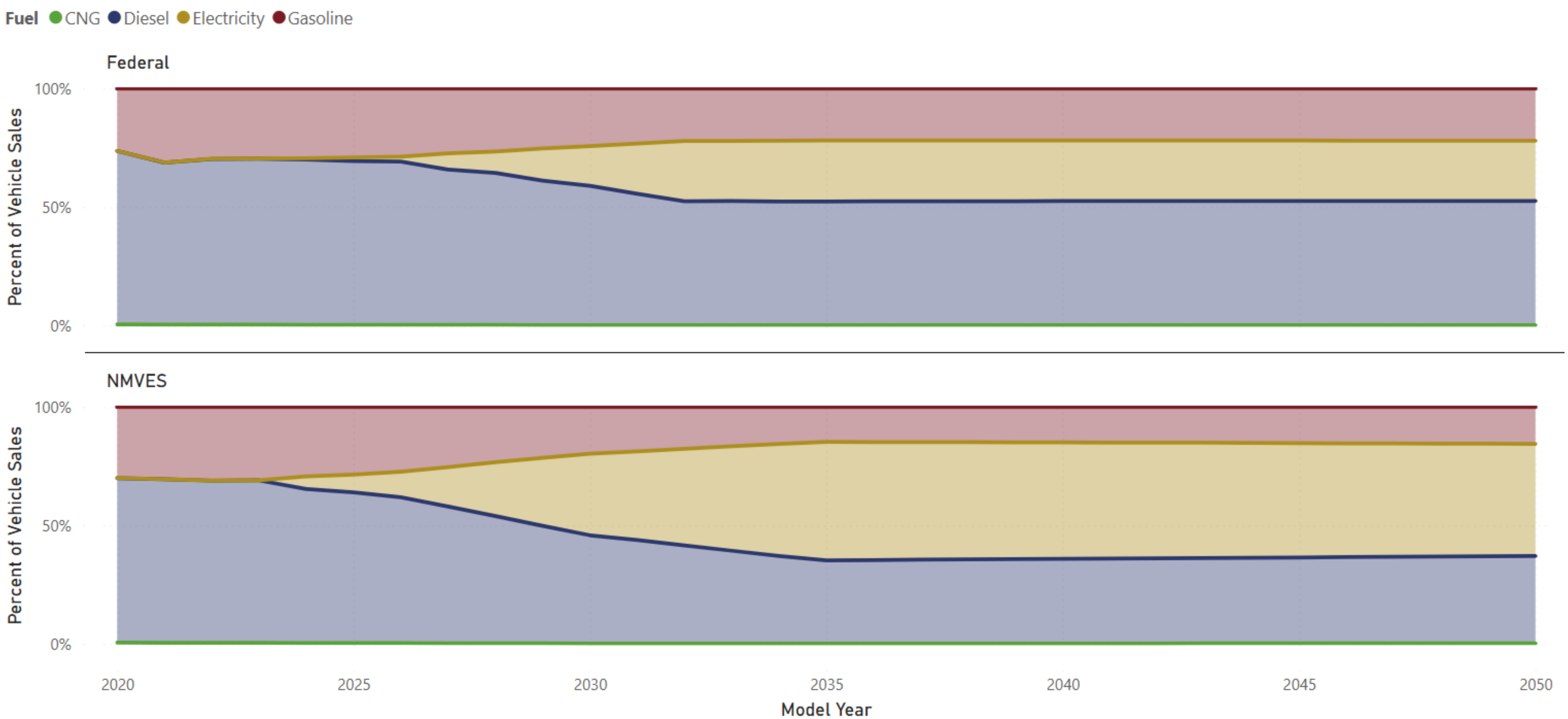

Figure B-8. Short-haul single unit truck (MOVES sourceTypeID 52) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

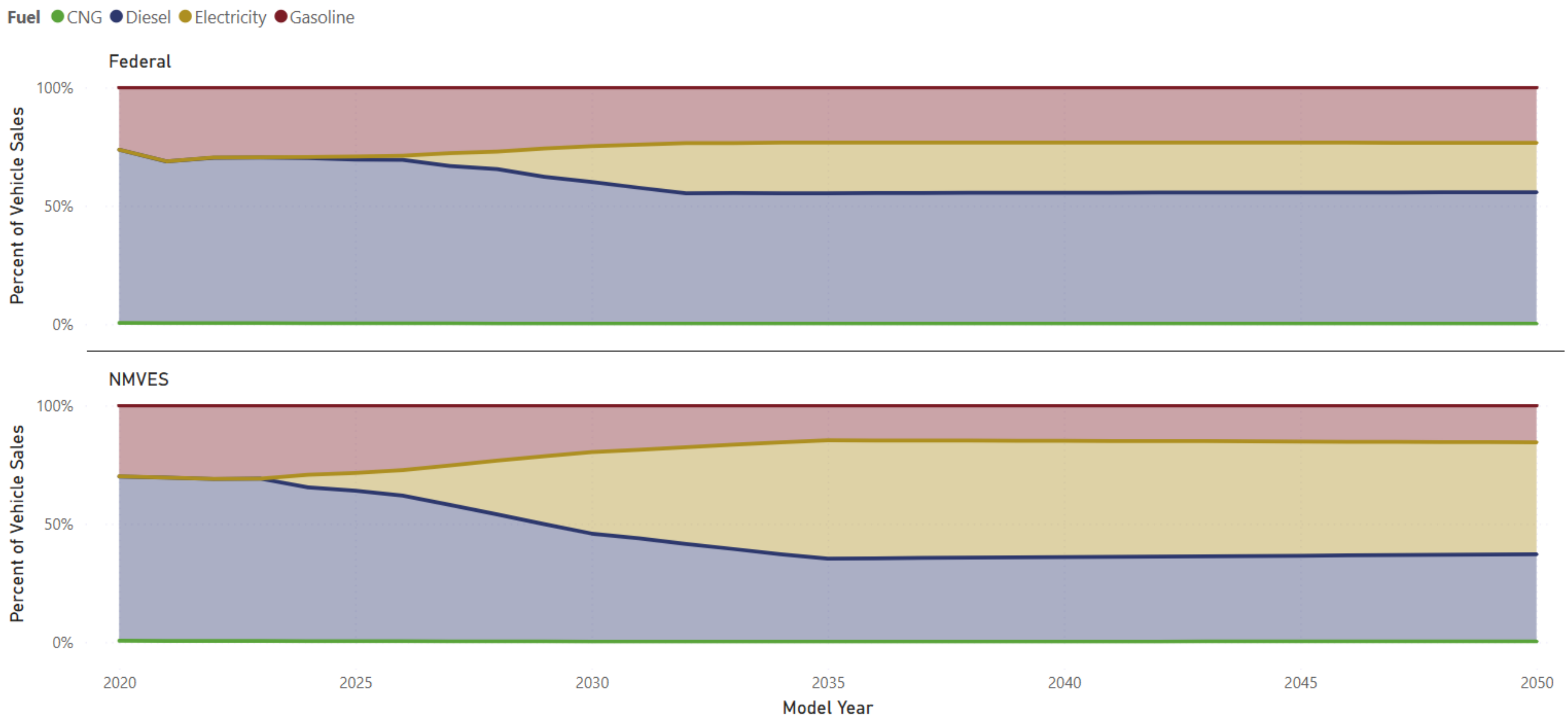

Figure B-9. Long-haul single unit truck (MOVES sourceTypeID 53) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

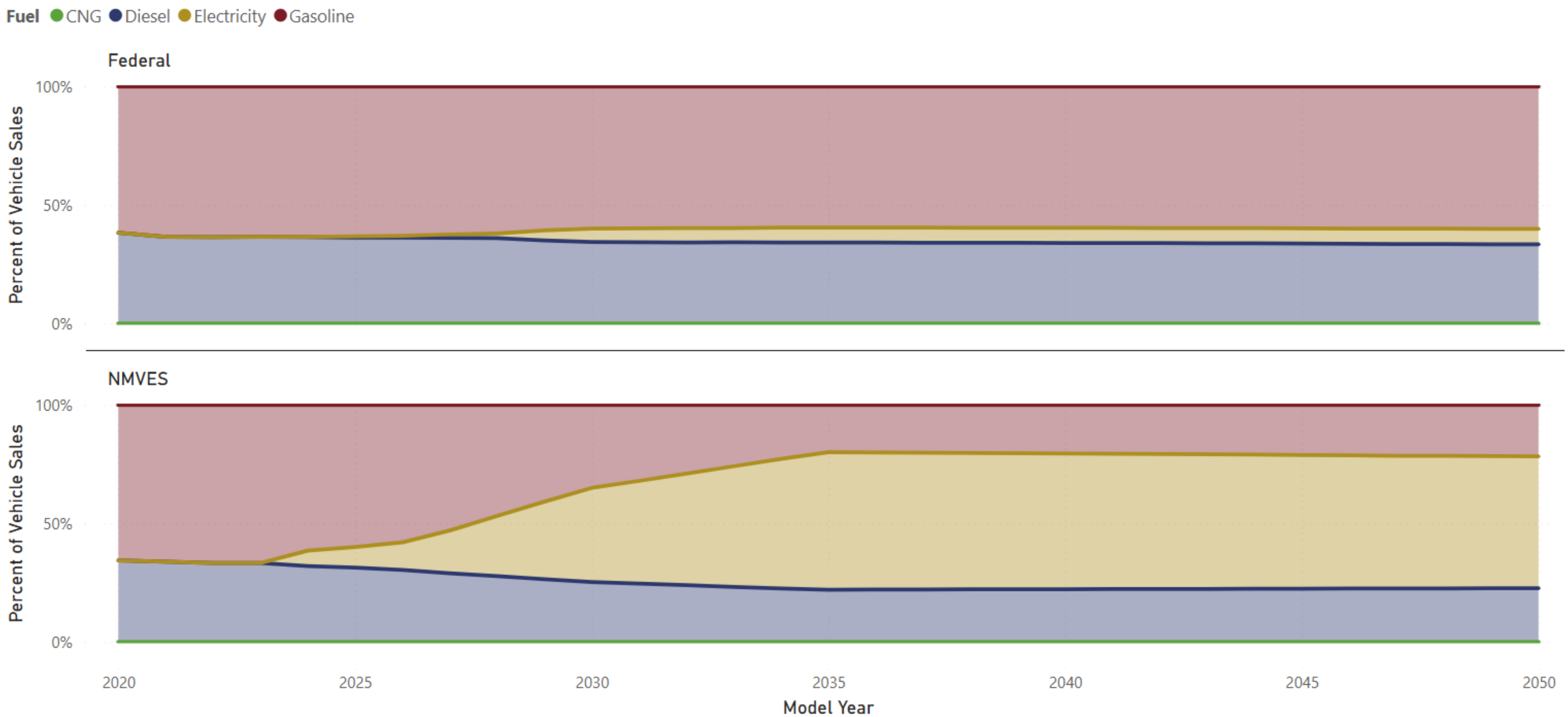

Figure B-10. Motor home (MOVES sourceTypeID 53) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

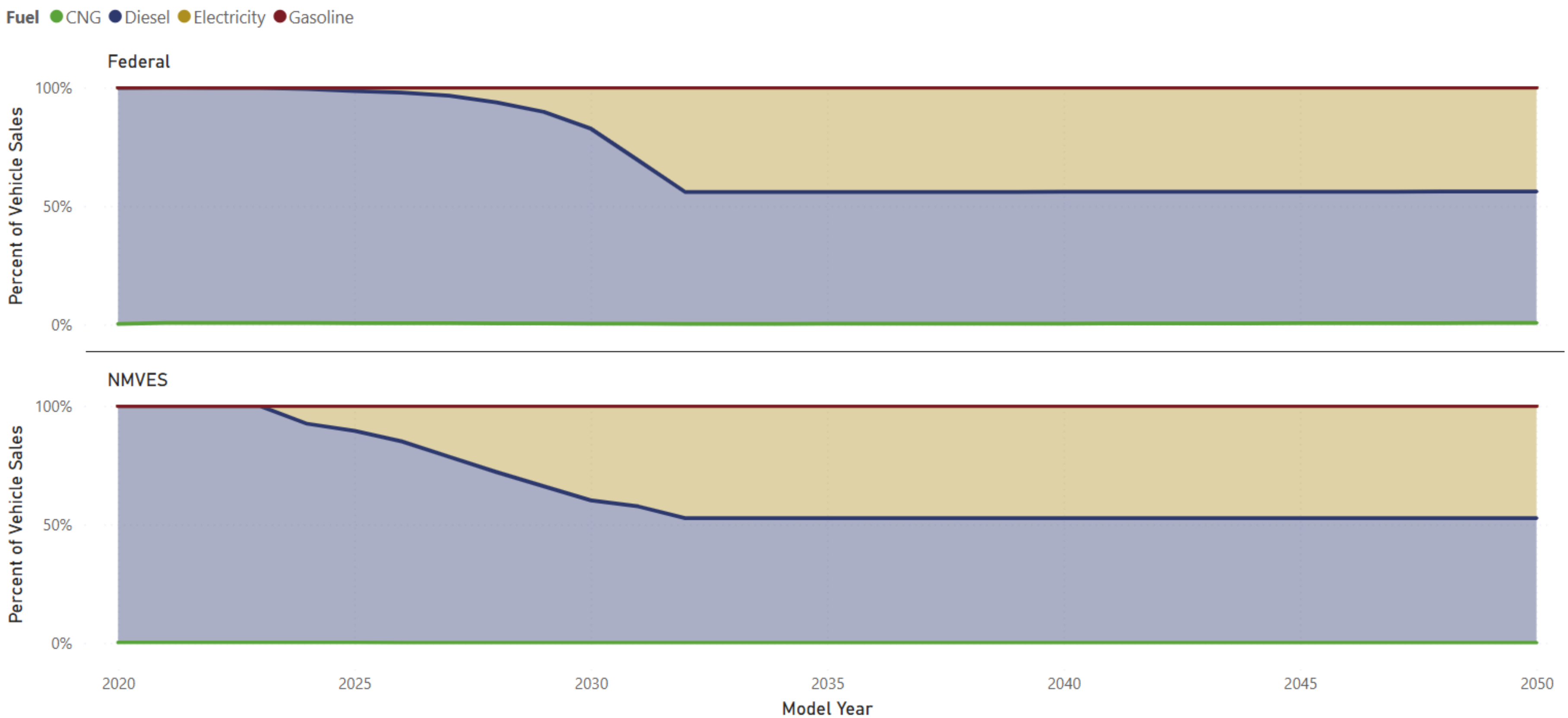

Figure B-11. Short-haul combination truck (MOVES sourceTypeID 61) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

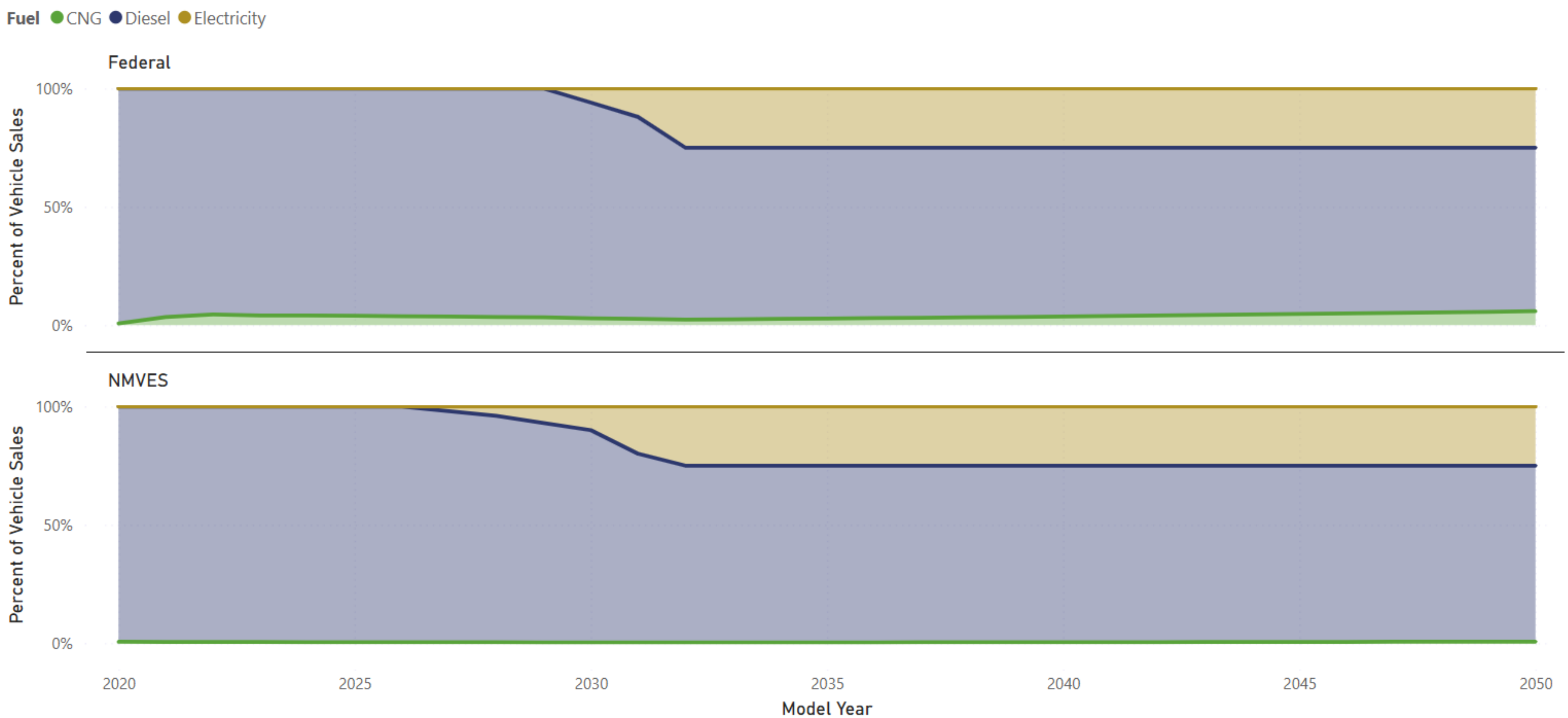

Figure B-12. Long-haul combination truck (MOVES sourceTypeID 62) fuel penetrations for (1) current federal standards and (2) NMVES (based on California's standards) over time

Table B-1. Onroad New Mexico county runspecs for all pollutants (non-evaporative only)

Category	Variable	Input
Description		"New Mexico CTFP - <xxx> County (20<xx>) - <NMVES or Federal> Reference"
Scale	Model	Onroad
	Domain/Scale	County
	Calculation Type	Inventory
Time Spans	Years	[2020, 2030, 2035, 2040, 2050]
	Months	All Selected
	Days	All Selected
	Hours	All Selected
Geographic Bounds	States	New Mexico
	Counties (FIPS code)	[Bernalillo (35001), Catron (35003), Chaves (35005), Cibola (35006), Colfax (35007), Curry (35009), De Baca (35011), Dona Ana (35013), Eddy (35015), Grant (35017), Guadalupe (35019), Harding (35021), Hidalgo (35023), Lea (35025), Lincoln (35027), Los Alamos (35028), Luna (35029), McKinley (35031), Mora (35033), Otero (35035), Quay (35037), Rio Arriba (35039), Roosevelt (35041), San Juan (35043), San Miguel (35045), Sandoval (35047), Santa Fe (35049), Sierra (35051), Socorro (35053), Taos (35055), Torrance (35057), Union (35059), Valencia (35061)]
Vehicles/Equipment	Onroad Vehicles	All Allowable Fuel/Source Type Combinations Selected
Pollutants and Processes (selected)	Total Gaseous Hydrocarbons (THC)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Non-Methane Hydrocarbons (NMHC)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Volatile Organic Compounds (VOCs)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss
	Methane (CH_4)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Carbon Monoxide (CO)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start

Category	Variable	Input
		Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Nitrogen Oxides (NO_x)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Nitrous Oxide (N_2O)	Running Exhaust, Start Exhaust
	Primary Exhaust $PM_{2.5}$ – Total	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Primary Exhaust $PM_{2.5}$ – Species	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Primary $PM_{2.5}$ – Brakewear Particulate	Brakewear
	Primary $PM_{2.5}$ – Tirewear Particulate	Tirewear
	Sulfur Dioxide (SO_2)	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
	Total Energy Consumption	Running Exhaust, Start Exhaust, Extended Idle Exhaust, Other Hotelling Exhaust
	Atmospheric CO_2	Running Exhaust, Start Exhaust, Extended Idle Exhaust, Other Hotelling Exhaust
	CO_2 Equivalent	Running Exhaust, Crankcase Running Exhaust, Start Exhaust, Crankcase Start Exhaust, Extended Idle Exhaust, Crankcase Extended Idle Exhaust, Other Hotelling Exhaust
Road Type	Available Road Types	All Selected
General Output	Output Database	"<yyyymmdd>_c350xx_ctfp_nmves_ref_out"
	Units	Mass: Grams, Energy: Kilojoules, Distance: Miles
	Activity	Distance Traveled, Source Hours Operating, Population
Output Emissions Details	Output Aggregation	Year, County
	For All Vehicle/Equipment Categories	Fuel Type, Emission Process
	Onroad	Source Use Type, Regulatory Class
Create Input Database	Database	"c350<xx>y20<xx>_<yyyymmdd>_nmves_ref"
Advanced Features	Preaggregation Options	Year, County

Table B-2. Onroad New Mexico county runspecs for VOC evaporative effects only

Category	Variable	Input
Description		"New Mexico CTFP - <xxx> County (20<xx>) – VOC Evap Effects"
Scale	Model	Onroad
	Domain/Scale	County
	Calculation Type	Inventory
Time Spans	Years	[2020, 2030, 2035, 2040, 2050]
	Months	January, July
	Days	All Selected
	Hours	All Selected
Geographic Bounds	States	New Mexico
	Counties (FIPS code)	[Bernalillo (35001), Catron (35003), Chaves (35005), Cibola (35006), Colfax (35007), Curry (35009), De Baca (35011), Dona Ana (35013), Eddy (35015), Grant (35017), Guadalupe (35019), Harding (35021), Hidalgo (35023), Lea (35025), Lincoln (35027), Los Alamos (35028), Luna (35029), McKinley (35031), Mora (35033), Otero (35035), Quay (35037), Rio Arriba (35039), Roosevelt (35041), San Juan (35043), San Miguel (35045), Sandoval (35047), Santa Fe (35049), Sierra (35051), Socorro (35053), Taos (35055), Torrance (35057), Union (35059), Valencia (35061)]
Vehicles/Equipment	Onroad Vehicles	All Allowable Fuel/Source Type Combinations Selected
Pollutants and Processes (selected)	Volatile Organic Compounds (VOCs)	Evap Permeation, Evap Fuel Vapor Venting, Evap Fuel Leaks
	Total Energy Consumption	Running Exhaust, Start Exhaust, Extended Idle Exhaust, Other Hotelling Exhaust
Road Type	Available Road Types	All Selected
General Output	Output Database	"<yyyymmdd>_c350xx_nm_ctfp_voc_out"
	Units	Mass: Grams, Energy: Kilojoules, Distance: Miles
	Activity	Distance Traveled, Source Hours Operating, Population
Output Emissions Details	Output Aggregation	Month, County
	For All Vehicle/Equipment Categories	Fuel Type, Emission Process
	Onroad	Source Use Type, Regulatory Class
Create Input Database	Database	"c350<xx>y20<xx>_<yyyymmdd>_nmves_ref"
Advanced Features	Preaggregation Options	Hour, County

Table B-3. Nonroad New Mexico county runspecs for all pollutants and processes

Category	Variable	Input
Description		"New Mexico CTFP – 20<xx> - Nonroad"
	Model	Nonroad
Scale	Domain/Scale	County
	Calculation Type	Inventory
	Years	[2020, 2030, 2035, 2040, 2050]
Time Spans	Months	All Selected
	Days	All Selected
	Hours	-
	States	New Mexico
Geographic Bounds	Counties (FIPS code)	[Bernalillo (35001), Catron (35003), Chaves (35005), Cibola (35006), Colfax (35007), Curry (35009), De Baca (35011), Dona Ana (35013), Eddy (35015), Grant (35017), Guadalupe (35019), Harding (35021), Hidalgo (35023), Lea (35025), Lincoln (35027), Los Alamos (35028), Luna (35029), McKinley (35031), Mora (35033), Otero (35035), Quay (35037), Rio Arriba (35039), Roosevelt (35041), San Juan (35043), San Miguel (35045), Sandoval (35047), Santa Fe (35049), Sierra (35051), Socorro (35053), Taos (35055), Torrance (35057), Union (35059), Valencia (35061)]
Vehicles/Equipment	Nonroad Equipment	All Allowable Fuel/Source Type Combinations Selected
Pollutants and Processes (selected)	Total Gaseous Hydrocarbons (THC)	Running Exhaust, Crankcase Running Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss, Evap Tank Permeation, Evap Hose Permeation, Diurnal Vapor Venting, Hot Soak Fuel Vapor Venting, Running Loss Fuel Vapor Venting
	Non-Methane Hydrocarbons (NMHC)	Running Exhaust, Crankcase Running Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss, Evap Tank Permeation, Evap Hose Permeation, Diurnal Vapor Venting, Hot Soak Fuel Vapor Venting, Running Loss Fuel Vapor Venting
	Volatile Organic Compounds (VOCs)	Running Exhaust, Crankcase Running Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss, Evap Tank Permeation, Evap Hose Permeation, Diurnal Vapor Venting, Hot Soak Fuel Vapor Venting, Running Loss Fuel Vapor Venting
	Methane (CH_4)	Running Exhaust, Crankcase Running Exhaust, Refueling Displacement Vapor Loss, Refueling Spillage Loss, Evap Tank Permeation, Evap Hose Permeation, Diurnal Vapor Venting, Hot Soak Fuel Vapor Venting, Running Loss Fuel Vapor Venting
	Carbon Monoxide (CO)	Running Exhaust
	Nitrogen Oxides (NO_x)	Running Exhaust

Category	Variable	Input
	Primary Exhaust $PM_{2.5}$ – Total	Running Exhaust
	Primary Exhaust PM10 – Total	Running Exhaust
	Sulfur Dioxide (SO_2)	Running Exhaust
	Brake Specific Fuel Consumption (BSFC)	Running Exhaust
	Atmospheric CO_2	Running Exhaust
Road Type	Available Road Types	-
	Output Database	“<yyyymmdd>_c35_ctfp_nonroad_out”
General Output	Units	Mass: Grams, Energy: Kilojoules, Distance: Miles
	Output Aggregation	24-Hour Day, County
Output Emissions Details	For All Vehicle/Equipment Categories	Fuel Type, Emission Process, SCC
	Nonroad	Sector
Create Input Database	Database	-
Advanced Features	Preaggregation Options	Day, County

Table B-4. NMVES fuel volumes forecast for final rules after BRG modifications (no CTFP implementation)

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	939,852,773	69,549,793	813,320,074	19,356,448	0	3,189,677	10,275	15,873,896	0	7,746,500
2026	934,191,905	69,134,073	794,313,340	18,904,101	0	9,033,105	64,853	16,209,014	0	8,014,948
2027	924,025,289	68,385,161	774,777,456	18,439,161	0	16,542,981	130,474	16,534,566	0	8,283,396
2028	909,853,295	67,340,050	754,817,713	17,964,133	0	25,601,940	207,123	16,850,881	0	8,551,844
2029	890,451,571	65,908,204	734,530,153	17,481,303	0	36,693,447	296,025	17,158,278	0	8,820,292
2030	936,074,901	69,287,513	714,264,283	16,998,989	0	50,181,725	434,824	17,457,065	0	9,088,741
2031	888,146,851	65,737,864	708,683,934	16,866,181	0	64,463,446	1,960,094	17,561,568	0	9,463,520
2032	841,480,224	62,281,633	703,097,272	16,733,222	0	78,664,846	3,467,086	17,666,466	0	9,838,299
2033	796,420,903	58,944,391	697,505,804	16,600,149	0	92,647,682	4,956,462	17,771,778	0	10,213,079
2034	752,512,254	55,692,367	691,910,925	16,466,995	0	106,560,011	6,428,843	17,877,518	0	10,587,858
2035	709,691,362	52,520,903	686,313,926	16,333,791	0	120,411,117	7,884,809	17,983,700	0	10,962,638
2036	673,050,723	49,807,879	682,574,410	16,244,793	0	134,877,173	8,929,562	18,032,087	0	11,425,623
2037	637,967,444	47,210,136	678,800,229	16,154,970	0	149,384,034	9,964,391	18,082,402	0	11,888,607
2038	604,016,478	44,696,238	674,994,230	16,064,390	0	164,061,214	10,989,678	18,134,627	0	12,351,592
2039	571,125,713	42,260,848	671,159,082	15,973,116	0	178,910,597	12,005,768	18,188,742	0	12,814,577
2040	539,229,647	39,899,117	667,297,292	15,881,208	0	193,934,151	13,012,973	18,244,728	0	13,277,562
2041	511,506,949	37,847,585	661,712,478	15,748,293	0	205,500,003	13,919,346	18,469,764	0	13,781,495
2042	484,891,884	35,878,010	656,107,327	15,614,895	0	217,149,575	14,822,704	18,694,661	0	14,285,428
2043	459,293,975	33,983,698	650,482,391	15,481,025	0	228,883,384	15,723,204	18,919,423	0	14,789,361
2044	434,633,483	32,158,749	644,838,211	15,346,698	0	240,701,954	16,620,993	19,144,051	0	15,293,295
2045	410,839,745	30,397,936	639,175,310	15,211,925	0	252,605,824	17,516,202	19,368,549	0	15,797,228
2046	387,849,826	28,696,603	633,494,201	15,076,718	0	264,595,541	18,408,952	19,592,918	0	16,301,161
2047	365,607,414	27,050,584	627,795,381	14,941,090	0	276,671,665	19,299,355	19,817,161	0	16,805,094
2048	344,061,899	25,456,135	622,079,336	14,805,052	0	288,834,767	20,187,512	20,041,281	0	17,309,027
2049	323,167,619	23,909,877	616,346,542	14,668,616	0	301,085,425	21,073,518	20,265,279	0	17,812,960
2050	302,883,215	22,408,751	610,597,462	14,531,792	0	313,424,232	21,957,460	20,489,158	0	18,316,894

Table B-5. NMVES fuel volumes forecast from initial MOVES runs prior to BRG modifications (no CTFP implementation)

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	803,072,833	59,432,771	781,916,241	18,609,059	0	36,032,435	296,979	14,120,998	0	7,746,500
2026	806,285,198	59,672,509	765,448,960	18,217,149	0	42,779,772	349,418	14,265,262	0	8,014,948
2027	808,729,984	59,855,452	749,445,515	17,836,278	0	49,778,289	399,866	14,409,547	0	8,283,396
2028	811,508,395	60,063,027	733,884,348	17,465,933	0	56,657,219	448,436	14,553,852	0	8,551,844
2029	813,405,593	60,205,405	718,745,351	17,105,636	0	63,852,370	495,229	14,698,176	0	8,820,292
2030	880,659,495	65,183,179	704,009,739	16,754,939	0	72,273,602	593,633	14,842,520	0	9,088,741
2031	824,060,272	60,992,278	690,424,583	16,431,621	0	91,498,913	3,157,792	14,834,120	0	9,463,520
2032	769,278,835	56,935,936	677,011,110	16,112,390	0	110,455,257	5,672,142	14,829,153	0	9,838,299
2033	716,540,382	53,030,799	663,765,191	15,797,146	0	129,042,432	8,138,447	14,827,529	0	10,213,079
2034	665,439,614	49,246,892	650,682,829	15,485,795	0	147,385,519	10,558,372	14,829,157	0	10,587,858
2035	615,890,996	45,577,885	637,760,152	15,178,245	0	165,497,136	12,933,492	14,833,951	0	10,962,638
2036	578,656,928	42,821,350	630,804,478	15,012,705	0	181,673,707	14,203,520	14,961,298	0	11,425,623
2037	543,109,669	40,189,655	623,922,862	14,848,927	0	197,823,916	15,453,058	15,090,291	0	11,888,607
2038	508,894,605	37,656,574	617,113,957	14,686,880	0	214,046,801	16,682,936	15,220,882	0	12,351,592
2039	475,927,246	35,215,853	610,376,463	14,526,532	0	230,344,728	17,893,920	15,353,024	0	12,814,577
2040	444,130,751	32,861,805	603,709,113	14,367,854	0	246,720,067	19,086,717	15,486,674	0	13,277,562
2041	421,175,336	31,163,056	601,926,933	14,325,439	0	256,219,824	19,667,340	15,783,417	0	13,781,495
2042	399,243,858	29,540,067	600,156,275	14,283,299	0	265,745,970	20,244,058	16,080,035	0	14,285,428
2043	378,254,866	27,986,809	598,396,943	14,241,428	0	275,298,747	20,816,959	16,376,530	0	14,789,361
2044	358,136,439	26,497,965	596,648,748	14,199,822	0	284,878,401	21,386,133	16,672,900	0	15,293,295
2045	338,824,728	25,068,809	594,911,508	14,158,477	0	294,485,178	21,951,671	16,969,146	0	15,797,228
2046	320,262,761	23,695,127	593,185,049	14,117,389	0	304,119,325	22,513,659	17,265,269	0	16,301,161
2047	302,399,475	22,373,142	591,469,202	14,076,553	0	313,781,092	23,072,183	17,561,270	0	16,805,094
2048	285,188,897	21,099,452	589,763,804	14,035,965	0	323,470,729	23,627,328	17,857,148	0	17,309,027
2049	268,589,479	19,870,984	588,068,698	13,995,623	0	333,188,490	24,179,175	18,152,903	0	17,812,960
2050	252,563,532	18,684,949	586,383,734	13,955,522	0	342,934,629	24,727,804	18,448,537	0	18,316,894

Table B-6. Federal baseline fuel volumes forecast for final rules after BRG modifications (no CTFP implementation)

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	940,409,857	69,591,330	807,804,701	19,225,186	0	4,079,587	0	17,339,680	0	7,746,500
2026	938,032,269	69,418,312	790,337,116	18,809,470	0	8,338,911	0	17,940,062	0	8,014,948
2027	931,557,346	68,942,298	773,407,936	18,406,567	0	13,789,117	0	18,518,877	0	8,283,396
2028	922,128,385	68,247,824	756,992,739	18,015,897	0	20,114,088	0	19,076,915	0	8,551,844
2029	907,639,530	67,179,172	740,996,817	17,635,205	0	28,126,370	38,223	19,614,934	0	8,820,292
2030	960,783,641	71,114,508	725,568,375	17,268,019	0	37,758,525	62,612	20,133,661	0	9,088,741
2031	932,289,651	69,002,743	722,620,318	17,197,857	0	45,367,608	165,374	20,512,258	0	9,463,520
2032	908,358,918	67,228,527	719,793,915	17,130,591	0	51,593,610	238,712	20,888,721	0	9,838,299
2033	863,353,808	63,896,104	716,868,091	17,060,958	0	65,659,976	313,982	21,263,075	0	10,213,079
2034	812,418,547	60,125,294	713,930,119	16,991,037	0	82,277,008	389,009	21,635,346	0	10,587,858
2035	777,227,091	57,518,753	710,971,081	16,920,614	0	93,567,204	463,793	22,005,558	0	10,962,638
2036	747,215,393	55,296,273	710,139,480	16,900,822	0	105,014,982	555,521	22,268,605	0	11,425,623
2037	719,022,957	53,208,428	709,262,307	16,879,946	0	116,304,613	647,269	22,530,904	0	11,888,607
2038	691,886,291	51,198,757	708,342,203	16,858,048	0	127,690,383	739,008	22,792,471	0	12,351,592
2039	665,737,154	49,262,208	707,381,669	16,835,188	0	139,173,257	830,716	23,053,318	0	12,814,577
2040	640,513,574	47,394,194	706,383,075	16,811,422	0	150,754,253	922,367	23,313,461	0	13,277,562
2041	616,759,185	45,636,338	702,700,133	16,723,771	0	160,052,572	1,028,291	23,876,606	0	13,781,495
2042	594,094,748	43,959,123	698,992,969	16,635,543	0	169,394,897	1,134,677	24,440,003	0	14,285,428
2043	572,431,613	42,355,993	695,262,164	16,546,752	0	178,781,332	1,241,512	25,003,640	0	14,789,361
2044	551,691,710	40,821,170	691,508,281	16,457,413	0	188,211,985	1,348,784	25,567,502	0	15,293,295
2045	531,805,916	39,349,543	687,731,865	16,367,537	0	197,686,970	1,456,481	26,131,574	0	15,797,228
2046	512,712,720	37,936,560	683,933,440	16,277,137	0	207,206,410	1,564,591	26,695,845	0	16,301,161
2047	494,357,132	36,578,153	680,113,515	16,186,225	0	216,770,432	1,673,104	27,260,300	0	16,805,094
2048	476,689,782	35,270,670	676,272,580	16,094,814	0	226,379,168	1,782,007	27,824,927	0	17,309,027
2049	459,666,168	34,010,818	672,411,110	16,002,913	0	236,032,758	1,891,289	28,389,714	0	17,812,960
2050	443,246,033	32,795,620	668,529,559	15,910,535	0	245,731,346	2,000,941	28,954,649	0	18,316,894

Table B-7. Federal baseline fuel volumes forecast from initial MOVES runs prior to BRG modifications (no CTFP implementation)

Year	Gasoline	Ethanol	Diesel	BD	RD	Electricity	H_2	CNG	RNG	Propane
2025	1,007,592,539	74,559,090	820,026,066	19,516,046	0	517,453	0	17,339,680	0	7,746,500
2026	998,921,429	73,920,702	802,172,514	19,091,144	0	2,590,921	0	17,940,062	0	8,014,948
2027	982,976,900	72,744,467	783,679,565	18,651,025	0	6,765,716	0	18,518,877	0	8,283,396
2028	960,647,158	71,096,058	764,653,658	18,198,221	0	13,361,972	0	19,076,915	0	8,551,844
2029	930,241,413	68,850,447	745,121,155	17,733,361	0	23,504,235	0	19,614,934	0	8,820,292
2030	965,105,910	71,434,114	725,603,036	17,268,844	0	37,918,192	0	20,133,661	0	9,088,741
2031	939,059,835	69,503,358	722,671,196	17,199,068	0	45,691,213	165,374	20,512,258	0	9,463,520
2032	917,683,553	67,918,028	719,862,395	17,132,221	0	52,098,996	238,712	20,888,721	0	9,838,299
2033	873,244,669	64,627,474	716,943,629	17,062,756	0	66,372,432	313,982	21,263,075	0	10,213,079
2034	822,219,295	60,850,001	714,009,058	16,992,915	0	83,224,585	389,009	21,635,346	0	10,587,858
2035	787,967,792	58,312,964	711,059,989	16,922,730	0	94,786,075	463,793	22,005,558	0	10,962,638
2036	758,840,923	56,155,912	710,237,091	16,903,145	0	106,555,044	555,521	22,268,605	0	11,425,623
2037	731,435,977	54,126,297	709,368,174	16,882,466	0	118,199,048	647,269	22,530,904	0	11,888,607
2038	704,984,372	52,167,282	708,455,889	16,860,754	0	129,977,114	739,008	22,792,471	0	12,351,592
2039	679,423,639	50,274,242	707,502,744	16,838,070	0	141,890,780	830,716	23,053,318	0	12,814,577
2040	654,697,106	48,442,982	706,511,118	16,814,470	0	153,941,648	922,367	23,313,461	0	13,277,562
2041	631,261,262	46,708,680	702,834,897	16,726,978	0	163,641,358	1,028,291	23,876,606	0	13,781,495
2042	608,859,737	45,050,906	699,134,242	16,638,905	0	173,410,095	1,134,677	24,440,003	0	14,285,428
2043	587,406,783	43,463,317	695,409,739	16,550,265	0	183,248,265	1,241,512	25,003,640	0	14,789,361
2044	566,826,980	41,940,333	691,661,958	16,461,070	0	193,156,285	1,348,784	25,567,502	0	15,293,295
2045	547,053,627	40,477,020	687,891,449	16,371,335	0	203,134,578	1,456,481	26,131,574	0	15,797,228
2046	528,027,438	39,068,992	684,098,742	16,281,071	0	213,183,582	1,564,591	26,695,845	0	16,301,161
2047	509,695,476	37,712,332	680,284,350	16,190,291	0	223,303,738	1,673,104	27,260,300	0	16,805,094
2048	492,010,266	36,403,528	676,448,770	16,099,007	0	233,495,502	1,782,007	27,824,927	0	17,309,027
2049	474,929,063	35,139,418	672,592,479	16,007,230	0	243,759,335	1,891,289	28,389,714	0	17,812,960
2050	458,413,240	33,917,145	668,715,936	15,914,971	0	254,095,707	2,000,941	28,954,649	0	18,316,894

C. Avoided Health Damages

C.1 Running COBRA

ERG used COBRA's default 2028 data for the emissions baseline and the 2028 Source Receptor (S-R) Matrix. ERG selected the New Mexico statewide tier as the emissions source location. Given that this analysis was not at the county level, ERG did not run COBRA for a particular county. In most cases, the emission changes were a reduction in tons. However, in the few cases when emissions increased for a particular pollutant, ERG input these as an increases in emissions.

When running COBRA, ERG selected the default 2 percent discount rate, which aligns with the Circular No. A-4 recommendation.[84] COBRA uses a discount rate to express future economic values in present terms. This accounts for present dollars being worth more now than in the future due to the potential for investment.[85]

C.1.1 COBRA Results by Health Outcome

Table C-1. Cumulative total health benefits by health outcome in 2024 USD

Health Outcome	**Scenario: CTFP-Only** Cumulative (2026–2035)	**Scenario: NMVES + CTFP** Cumulative (2026–2040)
\$ Total health benefits (low estimate)	\$10,995,856	\$38,190,099
\$ Total health benefits (high estimate)	\$20,792,795	\$51,542,167
\$ Total mortality (low estimate)	\$10,553,101	\$35,201,667
\$ Total mortality (high estimate)	\$20,350,041	\$48,553,735
\$ PM mortality, all causes (low)	\$8,870,305	\$12,233,097
\$ PM mortality, all causes (high)	\$18,667,245	\$25,585,164
\$ PM infant mortality	\$18,313	\$24,212
\$ Total O_3 mortality	\$1,664,482	\$22,944,358
\$ O_3 mortality (short-term exposure)	\$71,401	\$983,616
\$ O_3 mortality (long-term exposure)	\$1,593,082	\$21,960,741
\$ Total asthma symptoms	\$42,481	\$527,768
\$ PM asthma symptoms, albuterol use	\$181	\$244
\$ O_3 asthma symptoms, chest tightness	\$11,654	\$145,336
\$ O_3 asthma symptoms, cough	\$13,746	\$171,439
\$ O_3 asthma symptoms, shortness of breath	\$5,881	\$73,346
\$ O_3 asthma symptoms, wheeze	\$11,018	\$137,402
\$ Total incidence, asthma	\$149,350	\$737,511
\$ PM incidence, asthma	\$101,441	\$135,371
\$ O_3 incidence, asthma	\$47,909	\$602,138
\$ Total incidence, hay fever/rhinitis	\$15,998	\$81,202
\$ PM incidence, hay fever/rhinitis	\$10,817	\$14,532
\$ O_3 incidence, hay fever/rhinitis	\$5,056	\$65,044

[84] U.S. Environmental Protection Agency, "COBRA Questions and Answers," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-questions-and-answers.

[85] U.S. Environmental Protection Agency, "COBRA Questions and Answers," accessed May 23, 2025, https://www.epa.gov/cobra/cobra-questions-and-answers.

Health Outcome	**Scenario: CTFP-Only** Cumulative (2026–2035)	**Scenario: NMVES + CTFP** Cumulative (2026–2040)
\$ Total ER visits, respiratory	\$950	\$5,594
\$ PM ER visits, respiratory	\$580	\$781
\$ O_3 ER visits, respiratory	\$370	\$4,814
\$ Total hospital admits, all respiratory	\$1,987	\$4,803
\$ PM hospital admits, all respiratory	\$1,815	\$2,456
\$ O_3 hospital admits, all respiratory	\$172	\$2,347
\$ PM nonfatal heart attacks	\$31,327	\$42,758
\$ PM minor restricted activity days	\$49,394	\$66,038
\$ PM work loss days	\$21,350	\$28,540
\$ PM incidence, lung cancer	\$2,096	\$2,886
\$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	\$1,686	\$2,312
\$ PM Hospital Admissions Alzheimer's Disease	\$4,055	\$5,596
\$ PM Hospital Admissions Parkinson's Disease	\$833	\$1,127
\$ PM incidence, stroke	\$2,598	\$3,506
\$ PM incidence, out-of-hospital cardiac arrest	\$547	\$737
\$ PM ER visits, all cardiac outcomes	\$348	\$475
\$ O_3 ER visits, asthma	\$1	\$13
\$ O_3 school loss days, all causes	\$112,028	\$1,437,538

Table C-2. CTFP-only annual statewide health impacts by category (2026–2030) in 2024 USD

Health Outcome	2026	2027	2028	2029	2030
$ Total health benefits (low estimate)	$1,057,152	$1,175,689	$1,351,048	$1,800,124	$1,648,187
$ Total health benefits (high estimate)	$2,149,363	$2,293,274	$2,538,385	$3,349,942	$3,050,428
$ Total mortality (low estimate)	$1,021,636	$1,129,814	$1,292,337	$1,721,739	$1,577,418
$ Total mortality (high estimate)	$2,113,847	$2,247,399	$2,479,675	$3,271,557	$2,979,659
$ PM mortality, all causes (low)	$962,016	$992,852	$1,063,472	$1,397,922	$1,274,042
$ PM mortality, all causes (high)	$2,054,227	$2,110,437	$2,250,808	$2,947,739	$2,676,283
$ PM infant mortality	$2,232	$2,225	$2,304	$2,929	$2,585
$ Total O_3 mortality	$57,386	$134,736	$226,563	$320,888	$300,790
$ O_3 mortality (short-term exposure)	$2,463	$5,782	$9,721	$13,767	$12,903
$ O_3 mortality (long-term exposure)	$54,924	$128,955	$216,842	$307,122	$287,888
$ Total asthma symptoms	$1,641	$3,715	$6,059	$8,354	$7,622
$ PM, albuterol use	$22	$22	$23	$29	$26
$ O_3, chest tightness	$446	$1,018	$1,663	$2,294	$2,093
$ O_3, cough	$527	$1,200	$1,962	$2,706	$2,469
$ O_3, shortness of breath	$225	$514	$839	$1,157	$1,056
$ O_3, wheeze	$422	$962	$1,572	$2,169	$1,978
$ Total incidence, asthma	$14,054	$16,392	$19,506	$25,644	$22,954
$ PM incidence, asthma	$12,218	$12,207	$12,668	$16,213	$14,349
$ O_3 incidence, asthma	$1,836	$4,184	$6,838	$9,431	$8,605
$ Total incidence, hay fever/rhinitis	$1,475	$1,732	$2,075	$2,741	$2,466
$ PM incidence, hay fever/rhinitis	$1,280	$1,285	$1,341	$1,724	$1,534
$ O_3 incidence, hay fever/rhinitis	$195	$447	$734	$1,017	$932
$ Total ER visits, respiratory	$84	$104	$127	$169	$153
$ PM ER visits, respiratory	$71	$71	$74	$94	$84
$ O_3 ER visits, respiratory	$14	$33	$53	$75	$69
$ Total hospital admits, all respiratory	$225	$235	$255	$330	$295
$ PM hospital admits, all respiratory	$219	$220	$231	$296	$264
$ O_3 hospital admits, all respiratory	$6	$14	$25	$34	$32
$ PM nonfatal heart attacks	$3,662	$3,720	$3,924	$5,091	$4,577
$ PM minor restricted activity days	$6,028	$6,041	$6,290	$8,080	$7,176
$ PM work loss days	$2,613	$2,617	$2,721	$3,494	$3,101
$ PM incidence, lung cancer	$242	$247	$261	$339	$306
$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	$196	$200	$211	$274	$246
$ PM Hospital Admissions Alzheimer's Disease	$465	$476	$505	$656	$593
$ PM Hospital Admissions Parkinson's Disease	$100	$101	$106	$135	$121
$ PM incidence, stroke	$317	$318	$332	$423	$376
$ PM incidence, out-of-hospital cardiac arrest	$67	$67	$70	$89	$79
$ PM ER visits, all cardiac outcomes	$41	$42	$44	$56	$50
$ O_3 ER visits, asthma	$0	$0	$0	$0	$0
$ O_3 school loss days, all causes	$4,304	$9,871	$16,225	$22,507	$20,654

Table C-3. CTFP-only annual statewide health impacts by category (2031–2035) in 2024 USD

Health Outcome	2031	2032	2033	2034	2035
\$ Total health benefits (low estimate)	\$1,468,852	\$1,273,946	\$754,678	\$358,145	\$108,034
\$ Total health benefits (high estimate)	\$2,714,056	\$2,351,338	\$1,414,186	\$695,799	\$236,023
\$ Total mortality (low estimate)	\$1,407,443	\$1,222,138	\$726,573	\$347,111	\$106,895
\$ Total mortality (high estimate)	\$2,652,646	\$2,299,530	\$1,386,081	\$684,765	\$234,885
\$ PM mortality, all causes (low)	\$1,139,313	\$992,387	\$611,377	\$314,941	\$121,984
\$ PM mortality, all causes (high)	\$2,384,517	\$2,069,779	\$1,270,886	\$652,595	\$249,973
\$ PM infant mortality	\$2,240	\$1,891	\$1,131	\$565	\$210
\$ Total O_3 mortality	\$265,890	\$227,860	\$114,064	\$31,603	-\$15,299
\$ O_3 mortality (short-term exposure)	\$11,404	\$9,772	\$4,891	\$1,355	-\$656
\$ O_3 mortality (long-term exposure)	\$254,485	\$218,088	\$109,173	\$30,248	-\$14,643
\$ Total asthma symptoms	\$6,562	\$5,480	\$2,676	\$726	-\$355
\$ PM, albuterol use	\$23	\$19	\$11	\$6	\$2
\$ O_3, chest tightness	\$1,802	\$1,505	\$734	\$199	-\$98
\$ O_3, cough	\$2,125	\$1,774	\$866	\$234	-\$116
\$ O_3, shortness of breath	\$909	\$760	\$371	\$100	-\$49
\$ O_3, wheeze	\$1,704	\$1,423	\$694	\$188	-\$93
\$ Total incidence, asthma	\$19,872	\$16,740	\$9,344	\$3,988	\$857
\$ PM incidence, asthma	\$12,466	\$10,555	\$6,326	\$3,172	\$1,266
\$ O_3 incidence, asthma	\$7,407	\$6,185	\$3,018	\$816	-\$409
\$ Total incidence, hay fever/rhinitis	\$2,145	\$1,816	\$1,018	\$436	\$94
\$ PM incidence, hay fever/rhinitis	\$1,340	\$1,140	\$687	\$346	\$139
\$ O_3 incidence, hay fever/rhinitis	\$806	\$676	\$331	\$90	-\$45
\$ Total ER visits, respiratory	\$132	\$112	\$63	\$26	\$4
\$ PM ER visits, respiratory	\$74	\$63	\$38	\$19	\$8
\$ O_3 ER visits, respiratory	\$59	\$49	\$25	\$6	-\$3
\$ Total hospital admits, all respiratory	\$258	\$220	\$130	\$64	\$23
\$ PM hospital admits, all respiratory	\$231	\$197	\$119	\$59	\$25
\$ O_3 hospital admits, all respiratory	\$28	\$24	\$11	\$3	-\$2
\$ PM nonfatal heart attacks	\$4,037	\$3,473	\$2,113	\$1,075	\$439
\$ PM minor restricted activity days	\$6,256	\$5,316	\$3,197	\$1,609	\$638
\$ PM work loss days	\$2,700	\$2,292	\$1,378	\$693	\$277
\$ PM incidence, lung cancer	\$272	\$234	\$142	\$73	\$30
\$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	\$217	\$188	\$115	\$58	\$24
\$ PM Hospital Admissions Alzheimer's Disease	\$526	\$455	\$278	\$142	\$58
\$ PM Hospital Admissions Parkinson's Disease	\$106	\$90	\$54	\$28	\$11
\$ PM incidence, stroke	\$329	\$280	\$168	\$85	\$34
\$ PM incidence, out-of-hospital cardiac arrest	\$70	\$58	\$36	\$17	\$7
\$ PM ER visits, all cardiac outcomes	\$45	\$38	\$24	\$12	\$5
\$ O_3 ER visits, asthma	\$0	\$0	\$0	\$0	\$0
\$ O_3 school loss days, all causes	\$17,882	\$15,017	\$7,371	\$2,004	-\$1,007

Table C-4. CTFP + NMVES annual statewide health impacts by category (2026–2030) in 2024 USD

Health Outcome	2026	2027	2028	2029	2030
\$ Total health benefits (low estimate)	\$1,057,152	\$1,677,763	\$1,960,638	\$2,519,313	\$2,476,231
\$ Total health benefits (high estimate)	\$2,149,363	\$2,877,135	\$3,250,299	\$4,192,996	\$4,021,059
\$ Total mortality (low estimate)	\$1,021,636	\$1,578,916	\$1,839,350	\$2,369,025	\$2,324,505
\$ Total mortality (high estimate)	\$2,113,847	\$2,778,288	\$3,129,010	\$4,042,708	\$3,869,333
\$ PM mortality, all causes (low)	\$962,016	\$1,065,342	\$1,154,927	\$1,509,518	\$1,403,481
\$ PM mortality, all causes (high)	\$2,054,227	\$2,264,714	\$2,444,588	\$3,183,201	\$2,948,309
\$ PM infant mortality	\$2,232	\$2,389	\$2,503	\$3,165	\$2,849
\$ Total O_3 mortality	\$57,386	\$511,186	\$681,918	\$856,342	\$918,174
\$ O_3 mortality (short-term exposure)	\$2,463	\$21,936	\$29,258	\$36,738	\$39,385
\$ O_3 mortality (long-term exposure)	\$54,924	\$489,250	\$652,660	\$819,604	\$878,789
\$ Total asthma symptoms	\$1,641	\$14,034	\$18,193	\$22,232	\$23,194
\$ PM, albuterol use	\$22	\$23	\$25	\$31	\$29
\$ O_3, chest tightness	\$446	\$3,860	\$5,005	\$6,116	\$6,383
\$ O_3, cough	\$527	\$4,554	\$5,904	\$7,215	\$7,529
\$ O_3, shortness of breath	\$225	\$1,949	\$2,526	\$3,086	\$3,221
\$ O_3, wheeze	\$422	\$3,650	\$4,732	\$5,782	\$6,034
\$ Total incidence, asthma	\$14,054	\$28,968	\$34,334	\$42,645	\$42,033
\$ PM incidence, asthma	\$12,218	\$13,094	\$13,753	\$17,498	\$15,794
\$ O_3 incidence, asthma	\$1,836	\$15,874	\$20,581	\$25,148	\$26,239
\$ Total incidence, hay fever/rhinitis	\$1,475	\$3,075	\$3,664	\$4,572	\$4,530
\$ PM incidence, hay fever/rhinitis	\$1,280	\$1,379	\$1,455	\$1,861	\$1,688
\$ O_3 incidence, hay fever/rhinitis	\$195	\$1,695	\$2,209	\$2,711	\$2,842
\$ Total ER visits, respiratory	\$84	\$200	\$241	\$300	\$300
\$ PM ER visits, respiratory	\$71	\$76	\$80	\$102	\$92
\$ O_3 ER visits, respiratory	\$14	\$124	\$161	\$198	\$208
\$ Total hospital admits, all respiratory	\$225	\$292	\$324	\$411	\$387
\$ PM hospital admits, all respiratory	\$219	\$237	\$250	\$320	\$291
\$ O_3 hospital admits, all respiratory	\$6	\$56	\$74	\$91	\$97
\$ PM nonfatal heart attacks	\$3,662	\$3,990	\$4,259	\$5,494	\$5,038
\$ PM minor restricted activity days	\$6,028	\$6,477	\$6,824	\$8,715	\$7,892
\$ PM work loss days	\$2,613	\$2,805	\$2,953	\$3,768	\$3,410
\$ PM incidence, lung cancer	\$242	\$265	\$284	\$367	\$337
\$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	\$196	\$214	\$229	\$295	\$272
\$ PM Hospital Admissions Alzheimer's Disease	\$465	\$511	\$548	\$709	\$654
\$ PM Hospital Admissions Parkinson's Disease	\$100	\$109	\$115	\$147	\$133
\$ PM incidence, stroke	\$317	\$341	\$361	\$458	\$415
\$ PM incidence, out-of-hospital cardiac arrest	\$67	\$72	\$76	\$96	\$87
\$ PM ER visits, all cardiac outcomes	\$41	\$45	\$47	\$61	\$55
\$ O_3 ER visits, asthma	\$0	\$0	\$0	\$1	\$1
\$ O_3 school loss days, all causes	\$4,304	\$37,448	\$48,835	\$60,016	\$62,985

Table C-5. CTFP + NMVES annual statewide health impacts by category (2031–2035) in 2024 USD

Health Outcome	2031	2032	2033	2034	2035
\$ Total health benefits (low estimate)	\$2,620,440	\$2,750,404	\$2,566,239	\$2,514,028	\$2,665,917
\$ Total health benefits (high estimate)	\$4,043,311	\$4,040,128	\$3,474,869	\$3,139,200	\$3,119,450
\$ Total mortality (low estimate)	\$2,447,225	\$2,557,045	\$2,367,133	\$2,302,885	\$2,419,454
\$ Total mortality (high estimate)	\$3,870,097	\$3,846,769	\$3,275,762	\$2,928,056	\$2,872,985
\$ PM mortality, all causes (low)	\$1,301,728	\$1,187,806	\$842,157	\$582,967	\$432,110
\$ PM mortality, all causes (high)	\$2,724,600	\$2,477,530	\$1,750,786	\$1,208,140	\$885,642
\$ PM infant mortality	\$2,560	\$2,266	\$1,560	\$1,050	\$748
\$ Total O_3 mortality	\$1,142,936	\$1,366,973	\$1,523,416	\$1,718,868	\$1,986,594
\$ O_3 mortality (short-term exposure)	\$49,021	\$58,624	\$65,327	\$73,701	\$85,160
\$ O_3 mortality (long-term exposure)	\$1,093,915	\$1,308,349	\$1,458,089	\$1,645,167	\$1,901,434
\$ Total asthma symptoms	\$28,103	\$32,737	\$35,551	\$39,109	\$46,265
\$ PM, albuterol use	\$26	\$23	\$16	\$11	\$8
\$ O_3, chest tightness	\$7,736	\$9,013	\$9,790	\$10,772	\$12,744
\$ O_3, cough	\$9,124	\$10,632	\$11,549	\$12,707	\$15,032
\$ O_3, shortness of breath	\$3,904	\$4,549	\$4,940	\$5,437	\$6,432
\$ O_3, wheeze	\$7,313	\$8,521	\$9,256	\$10,184	\$12,049
\$ Total incidence, asthma	\$46,023	\$49,659	\$48,923	\$50,106	\$57,363
\$ PM incidence, asthma	\$14,226	\$12,612	\$8,687	\$5,839	\$4,442
\$ O_3 incidence, asthma	\$31,798	\$37,046	\$40,235	\$44,266	\$52,920
\$ Total incidence, hay fever/rhinitis	\$4,989	\$5,412	\$5,362	\$5,522	\$6,398
\$ PM incidence, hay fever/rhinitis	\$1,528	\$1,362	\$943	\$638	\$490
\$ O_3 incidence, hay fever/rhinitis	\$3,460	\$4,050	\$4,419	\$4,884	\$5,907
\$ Total ER visits, respiratory	\$337	\$372	\$376	\$394	\$461
\$ PM ER visits, respiratory	\$84	\$75	\$52	\$35	\$27
\$ O_3 ER visits, respiratory	\$253	\$297	\$325	\$359	\$435
\$ Total hospital admits, all respiratory	\$383	\$377	\$320	\$285	\$298
\$ PM hospital admits, all respiratory	\$263	\$236	\$164	\$111	\$86
\$ O_3 hospital admits, all respiratory	\$119	\$141	\$156	\$174	\$213
\$ PM nonfatal heart attacks	\$4,608	\$4,150	\$2,903	\$1,981	\$1,542
\$ PM minor restricted activity days	\$7,131	\$6,341	\$4,378	\$2,947	\$2,219
\$ PM work loss days	\$3,078	\$2,735	\$1,886	\$1,269	\$961
\$ PM incidence, lung cancer	\$311	\$281	\$197	\$135	\$106
\$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	\$249	\$224	\$158	\$108	\$84
\$ PM Hospital Admissions Alzheimer's Disease	\$602	\$545	\$383	\$264	\$207
\$ PM Hospital Admissions Parkinson's Disease	\$121	\$108	\$75	\$51	\$39
\$ PM incidence, stroke	\$376	\$335	\$233	\$158	\$122
\$ PM incidence, out-of-hospital cardiac arrest	\$79	\$71	\$49	\$33	\$26
\$ PM ER visits, all cardiac outcomes	\$51	\$46	\$32	\$22	\$17
\$ O_3 ER visits, asthma	\$1	\$1	\$1	\$1	\$1
\$ O_3 school loss days, all causes	\$76,775	\$89,967	\$98,282	\$108,760	\$130,354

Table C-6. CTFP + NMVES annual statewide health impacts by category (2036–2040) in 2024 USD

Health Outcome	2036	2037	2038	2039	2040
$ Total health benefits (low estimate)	$2,722,761	$2,889,335	$3,054,389	$3,216,983	$3,498,505
$ Total health benefits (high estimate)	$3,063,169	$3,244,754	$3,424,334	$3,600,880	$3,901,223
$ Total mortality (low estimate)	$2,466,184	$2,621,815	$2,776,497	$2,929,350	$3,180,648
$ Total mortality (high estimate)	$2,806,591	$2,977,233	$3,146,442	$3,313,249	$3,583,366
$ PM mortality, all causes (low)	$325,385	$340,847	$355,904	$370,465	$398,442
$ PM mortality, all causes (high)	$665,791	$696,266	$725,847	$754,362	$801,159
$ PM infant mortality	$552	$566	$577	$587	$607
$ Total O_3 mortality	$2,140,248	$2,280,403	$2,420,017	$2,558,298	$2,781,600
$ O_3 mortality (short-term exposure)	$91,740	$97,740	$103,717	$109,636	$119,172
$ O_3 mortality (long-term exposure)	$2,048,508	$2,182,663	$2,316,301	$2,448,662	$2,662,427
$ Total asthma symptoms	$48,738	$50,793	$52,735	$54,553	$59,889
$ PM, albuterol use	$6	$6	$6	$6	$7
$ O_3, chest tightness	$13,426	$13,992	$14,527	$15,027	$16,498
$ O_3, cough	$15,837	$16,505	$17,136	$17,727	$19,461
$ O_3, shortness of breath	$6,775	$7,061	$7,332	$7,584	$8,326
$ O_3, wheeze	$12,693	$13,229	$13,734	$14,207	$15,597
$ Total incidence, asthma	$59,035	$61,491	$63,813	$65,988	$73,078
$ PM incidence, asthma	$3,255	$3,331	$3,399	$3,458	$3,765
$ O_3 incidence, asthma	$55,780	$58,160	$60,415	$62,529	$69,312
$ Total incidence, hay fever/rhinitis	$6,591	$6,869	$7,133	$7,382	$8,229
$ PM incidence, hay fever/rhinitis	$360	$368	$376	$383	$419
$ O_3 incidence, hay fever/rhinitis	$6,231	$6,500	$6,758	$6,999	$7,809
$ Total ER visits, respiratory	$481	$503	$525	$546	$612
$ PM ER visits, respiratory	$19	$20	$20	$22	$24
$ O_3 ER visits, respiratory	$460	$483	$504	$525	$588
$ Total hospital admits, all respiratory	$290	$304	$319	$332	$373
$ PM hospital admits, all respiratory	$64	$66	$67	$69	$76
$ O_3 hospital admits, all respiratory	$227	$240	$251	$263	$297
$ PM nonfatal heart attacks	$1,143	$1,184	$1,222	$1,258	$1,394
$ PM minor restricted activity days	$1,632	$1,682	$1,728	$1,770	$1,923
$ PM work loss days	$706	$727	$746	$764	$834
$ PM incidence, lung cancer	$79	$82	$85	$88	$97
$ PM Hospital Admissions cardio cerebro and peripheral vascular disease	$63	$65	$68	$70	$77
$ PM Hospital Admissions Alzheimer's Disease	$155	$161	$167	$172	$191
$ PM Hospital Admissions Parkinson's Disease	$29	$30	$31	$32	$35
$ PM incidence, stroke	$90	$92	$94	$96	$106
$ PM incidence, out-of-hospital cardiac arrest	$18	$19	$19	$20	$23
$ PM ER visits, all cardiac outcomes	$12	$13	$13	$14	$15
$ O_3 ER visits, asthma	$1	$1	$1	$1	$2
$ O_3 school loss days, all causes	$137,513	$143,503	$149,192	$154,548	$170,981

Table C-7. CTFP-only annual statewide avoided incidence by category (2026–2030)

Health Outcome	2026	2027	2028	2029	2030
Total mortality (low estimate)	0.0614	0.0679	0.0777	0.1035	0.0948
Total mortality (high estimate)	0.1271	0.1351	0.1490	0.1966	0.1791
PM mortality, all causes (low)	0.0578	0.0597	0.0639	0.0840	0.0766
PM mortality, all causes (high)	0.1235	0.1269	0.1353	0.1772	0.1609
PM infant mortality	0.0001	0.0001	0.0001	0.0002	0.0001
Total O_3 mortality	0.0034	0.0081	0.0136	0.0193	0.0181
O_3 mortality (short-term exposure)	0.0001	0.0003	0.0006	0.0008	0.0008
O_3 mortality (long-term exposure)	0.0033	0.0078	0.0130	0.0185	0.0173
Total asthma symptoms	31.9847	36.8720	43.4820	57.2732	51.4438
PM asthma symptoms, albuterol use	28.3013	28.4730	29.7548	38.3406	34.1687
O_3 asthma symptoms, chest tightness	1.0148	2.3140	3.7820	5.2161	4.7595
O_3 asthma symptoms, cough	1.1970	2.7296	4.4612	6.1528	5.6142
O_3 asthma symptoms, shortness of breath	0.5121	1.1678	1.9086	2.6324	2.4019
O_3 asthma symptoms, wheeze	0.9594	2.1877	3.5755	4.9313	4.4996
Total incidence, asthma	0.1783	0.2079	0.2474	0.3253	0.2911
PM incidence, asthma	0.1550	0.1548	0.1607	0.2056	0.1820
O_3 incidence, asthma	0.0233	0.0531	0.0867	0.1196	0.1091
Total incidence, hay fever/rhinitis	1.1274	1.3239	1.5854	2.0948	1.8844
PM incidence, hay fever/rhinitis	0.9783	0.9824	1.0246	1.3178	1.1722
O_3 incidence, hay fever/rhinitis	0.1491	0.3416	0.5608	0.7770	0.7122
Total ER visits, respiratory	0.0443	0.0541	0.0667	0.0886	0.0799
PM ER visits, respiratory	0.0368	0.0370	0.0386	0.0496	0.0442
O_3 ER visits, respiratory	0.0075	0.0171	0.0281	0.0390	0.0357
Total hospital admits, all respiratory	0.0080	0.0084	0.0092	0.0119	0.0107
PM hospital admits, all respiratory	0.0077	0.0077	0.0080	0.0103	0.0092
O_3 hospital admits, all respiratory	0.0003	0.0007	0.0012	0.0016	0.0015
PM nonfatal heart attacks	0.0371	0.0377	0.0397	0.0515	0.0463
PM minor restricted activity days	42.0650	42.1619	43.8958	56.3878	50.0766
PM work loss days	7.1579	7.1682	7.4566	9.5721	8.4935
PM incidence, lung cancer	0.0046	0.0046	0.0049	0.0064	0.0057
PM Hospital Admissions cardio cerebro and peripheral vascular disease	0.0058	0.0059	0.0062	0.0081	0.0073
PM Hospital Admissions Alzheimer's Disease	0.0178	0.0181	0.0193	0.0250	0.0226
PM Hospital Admissions Parkinson's Disease	0.0036	0.0036	0.0038	0.0048	0.0043
PM incidence, stroke	0.0043	0.0043	0.0045	0.0057	0.0051
PM incidence, out-of-hospital cardiac arrest	0.0009	0.0009	0.0010	0.0012	0.0011
PM ER visits, all cardiac outcomes	0.0162	0.0165	0.0173	0.0223	0.0200
O_3 ER visits, asthma	0.0000	0.0001	0.0001	0.0002	0.0002
O_3 school loss days, all causes	2.1961	5.0367	8.2793	11.4847	10.5394

Table C-8. CTFP-only annual statewide avoided incidence by category (2031–2035)

Health Outcome	2031	2032	2033	2034	2035
Total mortality (low estimate)	0.0846	0.0735	0.0437	0.0209	0.0060
Total mortality (high estimate)	0.1594	0.1382	0.0833	0.0412	0.0132
PM mortality, all causes (low)	0.0685	0.0597	0.0367	0.0189	0.0068
PM mortality, all causes (high)	0.1433	0.1244	0.0764	0.0392	0.0140
PM infant mortality	0.0001	0.0001	0.0001	0.0000	0.0000
Total O_3 mortality	0.0160	0.0137	0.0069	0.0019	-0.0009
O_3 mortality (short-term exposure)	0.0007	0.0006	0.0003	0.0001	0.0000
O_3 mortality (long-term exposure)	0.0153	0.0131	0.0066	0.0018	-0.0008
Total asthma symptoms	44.7619	37.9048	21.4411	9.4041	2.1225
PM asthma symptoms, albuterol use	29.8903	25.4864	15.3804	7.7661	2.8799
O_3 asthma symptoms, chest tightness	4.0973	3.4214	1.6698	0.4513	-0.2087
O_3 asthma symptoms, cough	4.8331	4.0358	1.9696	0.5323	-0.2462
O_3 asthma symptoms, shortness of breath	2.0677	1.7266	0.8427	0.2277	-0.1053
O_3 asthma symptoms, wheeze	3.8736	3.2346	1.5786	0.4266	-0.1973
Total incidence, asthma	0.2521	0.2123	0.1185	0.0506	0.0100
PM incidence, asthma	0.1581	0.1339	0.0802	0.0402	0.0148
O_3 incidence, asthma	0.0939	0.0784	0.0383	0.0103	-0.0048
Total incidence, hay fever/rhinitis	1.6394	1.3877	0.7780	0.3332	0.0659
PM incidence, hay fever/rhinitis	1.0235	0.8711	0.5247	0.2644	0.0979
O_3 incidence, hay fever/rhinitis	0.6159	0.5166	0.2533	0.0688	-0.0319
Total ER visits, respiratory	0.0695	0.0588	0.0325	0.0134	0.0021
PM ER visits, respiratory	0.0386	0.0328	0.0198	0.0100	0.0037
O_3 ER visits, respiratory	0.0309	0.0260	0.0127	0.0035	-0.0016
Total hospital admits, all respiratory	0.0093	0.0079	0.0046	0.0022	0.0007
PM hospital admits, all respiratory	0.0080	0.0068	0.0041	0.0021	0.0008
O_3 hospital admits, all respiratory	0.0013	0.0011	0.0006	0.0002	-0.0001
PM nonfatal heart attacks	0.0409	0.0352	0.0214	0.0109	0.0041
PM minor restricted activity days	43.6530	37.0919	22.3081	11.2268	4.1504
PM work loss days	7.3976	6.2803	3.7739	1.8976	0.7009
PM incidence, lung cancer	0.0051	0.0044	0.0027	0.0014	0.0005
PM Hospital Admissions cardio cerebro and peripheral vascular disease	0.0065	0.0056	0.0034	0.0017	0.0006
PM Hospital Admissions Alzheimer's Disease	0.0201	0.0173	0.0106	0.0054	0.0020
PM Hospital Admissions Parkinson's Disease	0.0038	0.0032	0.0019	0.0010	0.0004
PM incidence, stroke	0.0044	0.0038	0.0023	0.0011	0.0004
PM incidence, out-of-hospital cardiac arrest	0.0010	0.0008	0.0005	0.0002	0.0001
PM ER visits, all cardiac outcomes	0.0176	0.0151	0.0092	0.0047	0.0017
O_3 ER visits, asthma	0.0002	0.0001	0.0001	0.0000	0.0000
O_3 school loss days, all causes	9.1249	7.6633	3.7614	1.0224	-0.4755

Table C-9. CTFP + NMVES annual statewide avoided incidence by category (2026–2030)

Health Outcome	2026	2027	2028	2029	2030
Total mortality (low estimate)	0.0614	0.0949	0.1106	0.1424	0.1397
Total mortality (high estimate)	0.1271	0.1670	0.1881	0.2430	0.2326
PM mortality, all causes (low)	0.0578	0.0640	0.0694	0.0907	0.0844
PM mortality, all causes (high)	0.1235	0.1361	0.1469	0.1913	0.1772
PM infant mortality	0.0001	0.0001	0.0001	0.0002	0.0002
Total O_3 mortality	0.0034	0.0307	0.0410	0.0515	0.0552
O_3 mortality (short-term exposure)	0.0001	0.0013	0.0018	0.0022	0.0024
O_3 mortality (long-term exposure)	0.0033	0.0294	0.0392	0.0493	0.0528
Total asthma symptoms	31.9847	62.4103	73.6228	91.8670	90.2956
PM asthma symptoms, albuterol use	28.3013	30.5460	32.3062	41.3802	37.6130
O_3 asthma symptoms, chest tightness	1.0148	8.7789	11.3831	13.9095	14.5145
O_3 asthma symptoms, cough	1.1970	10.3555	13.4273	16.4075	17.1211
O_3 asthma symptoms, shortness of breath	0.5121	4.4304	5.7446	7.0196	7.3249
O_3 asthma symptoms, wheeze	0.9594	8.2996	10.7616	13.1501	13.7220
Total incidence, asthma	0.1783	0.3674	0.4355	0.5409	0.5331
PM incidence, asthma	0.1550	0.1661	0.1744	0.2219	0.2003
O_3 incidence, asthma	0.0233	0.2013	0.2611	0.3190	0.3328
Total incidence, hay fever/rhinitis	1.1274	2.3497	2.8003	3.4941	3.4621
PM incidence, hay fever/rhinitis	0.9783	1.0538	1.1124	1.4223	1.2903
O_3 incidence, hay fever/rhinitis	0.1491	1.2958	1.6878	2.0718	2.1718
Total ER visits, respiratory	0.0443	0.1046	0.1265	0.1575	0.1577
PM ER visits, respiratory	0.0368	0.0397	0.0419	0.0535	0.0486
O_3 ER visits, respiratory	0.0075	0.0649	0.0846	0.1039	0.1091
Total hospital admits, all respiratory	0.0080	0.0109	0.0122	0.0155	0.0147
PM hospital admits, all respiratory	0.0077	0.0083	0.0087	0.0111	0.0101
O_3 hospital admits, all respiratory	0.0003	0.0027	0.0035	0.0043	0.0046
PM nonfatal heart attacks	0.0371	0.0404	0.0431	0.0556	0.0510
PM minor restricted activity days	42.0650	45.2024	47.6266	60.8186	55.0805
PM work loss days	7.1579	7.6849	8.0901	10.3238	9.3417
PM incidence, lung cancer	0.0046	0.0050	0.0053	0.0069	0.0063
PM Hospital Admissions cardio cerebro and peripheral vascular disease	0.0058	0.0063	0.0068	0.0088	0.0080
PM Hospital Admissions Alzheimer's Disease	0.0178	0.0195	0.0209	0.0270	0.0249
PM Hospital Admissions Parkinson's Disease	0.0036	0.0039	0.0041	0.0052	0.0048
PM incidence, stroke	0.0043	0.0046	0.0049	0.0062	0.0056
PM incidence, out-of-hospital cardiac arrest	0.0009	0.0010	0.0010	0.0013	0.0012
PM ER visits, all cardiac outcomes	0.0162	0.0177	0.0188	0.0241	0.0221
O_3 ER visits, asthma	0.0000	0.0003	0.0004	0.0005	0.0006
O_3 school loss days, all causes	2.1961	19.1091	24.9197	30.6254	32.1404

Table C-10. CTFP + NMVES annual statewide avoided incidence by category (2031–2035)

Health Outcome	2031	2032	2033	2034	2035
Total mortality (low estimate)	0.1471	0.1537	0.1423	0.1384	0.1357
Total mortality (high estimate)	0.2326	0.2312	0.1969	0.1760	0.1611
PM mortality, all causes (low)	0.0782	0.0714	0.0506	0.0350	0.0242
PM mortality, all causes (high)	0.1638	0.1489	0.1052	0.0726	0.0497
PM infant mortality	0.0001	0.0001	0.0001	0.0001	0.0000
Total O_3 mortality	0.0687	0.0822	0.0916	0.1033	0.1114
O_3 mortality (short-term exposure)	0.0029	0.0035	0.0039	0.0044	0.0048
O_3 mortality (long-term exposure)	0.0658	0.0786	0.0876	0.0989	0.1066
Total asthma symptoms	97.9645	104.8534	101.9344	103.2140	108.2422
PM asthma symptoms, albuterol use	34.1134	30.4556	21.1232	14.2974	10.1079
O_3 asthma symptoms, chest tightness	17.5915	20.4972	22.2641	24.4971	27.0366
O_3 asthma symptoms, cough	20.7508	24.1783	26.2626	28.8968	31.8925
O_3 asthma symptoms, shortness of breath	8.8778	10.3442	11.2359	12.3629	13.6445
O_3 asthma symptoms, wheeze	16.6311	19.3781	21.0486	23.1598	25.5607
Total incidence, asthma	0.5838	0.6299	0.6205	0.6355	0.6716
PM incidence, asthma	0.1804	0.1600	0.1102	0.0741	0.0520
O_3 incidence, asthma	0.4033	0.4699	0.5103	0.5615	0.6196
Total incidence, hay fever/rhinitis	3.8122	4.1357	4.0975	4.2194	4.4818
PM incidence, hay fever/rhinitis	1.1681	1.0409	0.7206	0.4868	0.3436
O_3 incidence, hay fever/rhinitis	2.6441	3.0948	3.3769	3.7325	4.1383
Total ER visits, respiratory	0.1769	0.1950	0.1973	0.2065	0.2218
PM ER visits, respiratory	0.0440	0.0393	0.0272	0.0184	0.0130
O_3 ER visits, respiratory	0.1329	0.1557	0.1701	0.1882	0.2088
Total hospital admits, all respiratory	0.0148	0.0148	0.0130	0.0120	0.0119
PM hospital admits, all respiratory	0.0091	0.0081	0.0056	0.0038	0.0027
O_3 hospital admits, all respiratory	0.0057	0.0067	0.0074	0.0083	0.0093
PM nonfatal heart attacks	0.0467	0.0420	0.0294	0.0201	0.0143
PM minor restricted activity days	49.7613	44.2501	30.5493	20.5656	14.4481
PM work loss days	8.4321	7.4916	5.1673	3.4753	2.4391
PM incidence, lung cancer	0.0058	0.0052	0.0037	0.0025	0.0018
PM Hospital Admissions cardio cerebro and peripheral vascular disease	0.0074	0.0067	0.0047	0.0032	0.0023
PM Hospital Admissions Alzheimer's Disease	0.0229	0.0208	0.0146	0.0101	0.0072
PM Hospital Admissions Parkinson's Disease	0.0043	0.0039	0.0027	0.0018	0.0013
PM incidence, stroke	0.0051	0.0045	0.0031	0.0021	0.0015
PM incidence, out-of-hospital cardiac arrest	0.0011	0.0010	0.0007	0.0005	0.0003
PM ER visits, all cardiac outcomes	0.0201	0.0181	0.0126	0.0086	0.0061
O_3 ER visits, asthma	0.0007	0.0008	0.0009	0.0010	0.0011
O_3 school loss days, all causes	39.1770	45.9094	50.1524	55.4985	61.6026

Table C-11. CTFP + NMVES annual statewide avoided incidence by category (2036–2040)

Health Outcome	2036	2037	2038	2039	2040
Total mortality (low estimate)	0.1383	0.1470	0.1557	0.1643	0.1671
Total mortality (high estimate)	0.1574	0.1669	0.1764	0.1858	0.1883
PM mortality, all causes (low)	0.0182	0.0191	0.0200	0.0208	0.0209
PM mortality, all causes (high)	0.0373	0.0390	0.0407	0.0423	0.0421
PM infant mortality	0.0000	0.0000	0.0000	0.0000	0.0000
Total O_3 mortality	0.1200	0.1279	0.1357	0.1435	0.1462
O_3 mortality (short-term exposure)	0.0051	0.0055	0.0058	0.0061	0.0063
O_3 mortality (long-term exposure)	0.1149	0.1224	0.1299	0.1373	0.1399
Total asthma symptoms	110.8002	115.3399	119.6227	123.6238	127.0495
PM asthma symptoms, albuterol use	7.4142	7.5956	7.7589	7.9032	7.9991
O_3 asthma symptoms, chest tightness	28.4835	29.6842	30.8191	31.8817	32.7990
O_3 asthma symptoms, cough	33.5992	35.0156	36.3545	37.6079	38.6900
O_3 asthma symptoms, shortness of breath	14.3747	14.9807	15.5535	16.0897	16.5527
O_3 asthma symptoms, wheeze	26.9286	28.0638	29.1368	30.1413	31.0086
Total incidence, asthma	0.6912	0.7200	0.7472	0.7726	0.7945
PM incidence, asthma	0.0381	0.0390	0.0398	0.0405	0.0409
O_3 incidence, asthma	0.6531	0.6810	0.7074	0.7321	0.7536
Total incidence, hay fever/rhinitis	4.6166	4.8120	4.9971	5.1709	5.3212
PM incidence, hay fever/rhinitis	0.2519	0.2580	0.2634	0.2682	0.2714
O_3 incidence, hay fever/rhinitis	4.3647	4.5540	4.7337	4.9027	5.0498
Total ER visits, respiratory	0.2308	0.2418	0.2523	0.2624	0.2713
PM ER visits, respiratory	0.0096	0.0098	0.0101	0.0103	0.0105
O_3 ER visits, respiratory	0.2213	0.2319	0.2422	0.2520	0.2608
Total hospital admits, all respiratory	0.0118	0.0124	0.0130	0.0135	0.0141
PM hospital admits, all respiratory	0.0019	0.0020	0.0020	0.0021	0.0021
O_3 hospital admits, all respiratory	0.0099	0.0104	0.0110	0.0115	0.0119
PM nonfatal heart attacks	0.0106	0.0110	0.0113	0.0117	0.0119
PM minor restricted activity days	10.6246	10.9480	11.2487	11.5251	11.7333
PM work loss days	1.7915	1.8442	1.8929	1.9374	1.9704
PM incidence, lung cancer	0.0013	0.0014	0.0014	0.0015	0.0015
PM Hospital Admissions cardio cerebro and peripheral vascular disease	0.0017	0.0018	0.0018	0.0019	0.0019
PM Hospital Admissions Alzheimer's Disease	0.0054	0.0056	0.0058	0.0060	0.0062
PM Hospital Admissions Parkinson's Disease	0.0010	0.0010	0.0010	0.0010	0.0010
PM incidence, stroke	0.0011	0.0011	0.0012	0.0012	0.0012
PM incidence, out-of-hospital cardiac arrest	0.0002	0.0002	0.0003	0.0003	0.0003
PM ER visits, all cardiac outcomes	0.0046	0.0047	0.0049	0.0050	0.0051
O_3 ER visits, asthma	0.0011	0.0012	0.0012	0.0013	0.0013
O_3 school loss days, all causes	64.9857	67.8163	70.5050	73.0359	75.2417

D. Macroeconomic Impacts

D.1 Business Consumer Proportions

As stated in economic impacts analysis, Section 6.2.3 ERG modeled changes in business expenditures as changes in revenue, depending on each industry's reliance on gasoline or diesel. Table D-1 presents the share of demand for each fuel type across different sectors. These estimates are based on data from the NEI.[86]

Table D-1. Business consumers by vehicle type

Industry	Gasoline	Diesel
Agricultural equipment	0.994%	0.024%
Commercial equipment	0.409%	0.507%
Construction equipment	8.217%	0.254%
Industrial equipment	0.606%	0.059%
Lawn and garden equipment	0.167%	1.604%
Logging equipment	0.002%	0.000%
Recreational equipment	0.010%	0.300%
Underground mining equipment	0.014%	0.000%
Combination long-haul truck	35.185%	0.000%
Combination short-haul truck	30.610%	0.271%
Motor home	0.186%	0.387%
Other buses	0.219%	0.000%
Refuse truck	0.178%	0.002%
School bus	1.562%	0.065%
Single unit long-haul truck	2.060%	0.943%
Single unit short-haul truck	13.578%	4.132%
Transit bus	0.327%	0.139%
Light commercial truck	0.630%	4.833%
Passenger car	0.188%	29.101%
Passenger truck	4.857%	56.111%
Motorcycle	0.000%	1.268%
Total	**100.0%**	**100.0%**

D.2 Updates to the NMVES Analysis

As part of the data shared with BRG, ERG updated its previous NMVES macroeconomic analysis of the ACC II and ACT. ERG updated vehicle population and VMT by adjusting the baseline of the

[86] U.S. Environmental Protection Agency, “2020 National Emissions Inventory (NEI) Data,” accessed May 29, 2025, https://www.epa.gov/air-emissions-inventories/2020-national-emissions-inventory-nei-data.

NMVES analysis to the federal baseline, shown in Figure 4-1, which resulted in macroeconomic changes for vehicle costs, sales taxes, fuel costs, and maintenance costs.

THE INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION

Washington Clean Fuels Standard – Carbon Intensity Model Peer Review

Prepared by the International Council on Clean Transportation under contract for the Washington Department of Ecology

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Overall Impressions and Summary of Recommendations

This peer review was conducted in support of Washington State Department of Ecology's rulemaking for a new rule, Chapter 173-424 WAC, Clean Fuels Program Rule. As part of this peer review, the International Council on Clean Transportation (ICCT) assessed the public documents shared at the March 15, 2022 stakeholder meeting developed by Life Cycle Associates. These documents included a draft carbon intensity model to inform the development of the Clean Fuels Program (CFP) and the accompanying calculations and supporting documentation. For this peer review, ICCT assessed the methodology and results of the draft carbon intensity model, Washington Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies Model (WA-GREET), itself an update of a similar model used in California (CA-GREET). In doing so, ICCT reviewed the calculations within the model for internal consistency as well as consistency with other life-cycle models, compared the data sources & assumptions to public data and the scientific literature, as well as assessed the recommendations of the modelers for the inclusion of indirect land-use change (ILUC) emissions outside of the model.

Overall, we find that the life-cycle fuel model updates developed by Life Cycle Associates (LC Associates) largely follow the existing precedent set by the California Air Resources Board (CARB) in its comprehensive life-cycle assessment (LCA) established in the California Low-Carbon Fuel Standard (LCFS). The changes made within WA-GREET to tailor it to Washington state-specific data on fossil fuel consumption and electricity production are largely aligned with existing life-cycle assessment practices and are consistent with the intended scope of the Washington Clean Fuels Program (WA CFP). We present a high-level summary of five key fuel pathways' emissions in Figure 1, illustrating the difference in their carbon intensity calculated for Washington in WA-GREET against values calculated for California's LCFS using CA-GREET. The most impactful changes in the Washington analysis are the inclusion of a Washington state-average carbon intensity for electricity (resulting in a 20% decrease in electricity grid carbon intensity relative to California), and the proposed use of a different ILUC emission factor for corn ethanol (a 17.5% decline in default corn ethanol carbon intensity relative to California). Changes to the crude oil carbon intensity were much smaller, with less than 1% difference compared to California petroleum products. Throughout this peer review, we document that there are several assumptions made in the analysis or omissions based on data gaps that affect the emissions estimates for petroleum products and electricity, and offer several recommendations on addressing those data gaps and developing more accurate estimates.

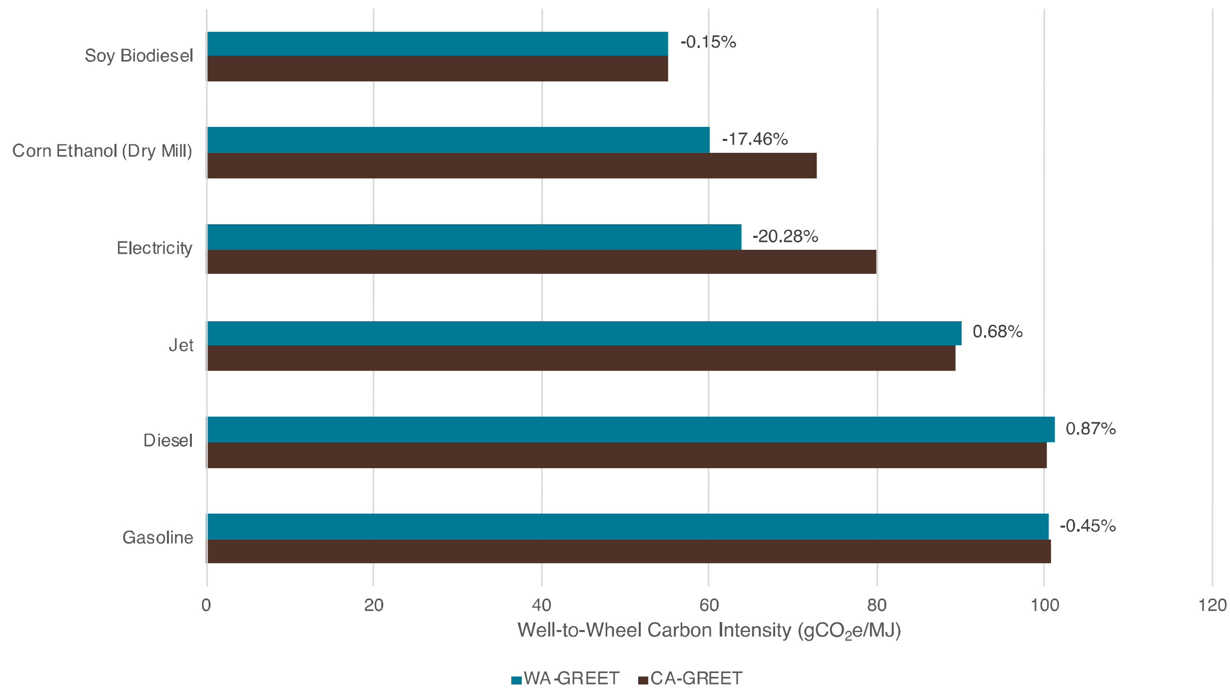

Figure 1: Comparison of well-to-wheel carbon intensities for a selection of fuel pathways for WA-GREET and CA-GREET

We also note several areas in which LC Associates did not develop model updates that may warrant updates prior to implementation of the WA CFP in order to reflect the latest scientific understanding of fuel production and climate change. This includes expanding the analysis of crude oil upstream emissions and refinery emissions to address data gaps and reflect state-specific fuels and practices. This will affect the emissions attributable to petroleum products used as a transportation fuel, as well as the emissions attributable to electricity and multiple fuel pathways using petroleum as a process fuel. We also recommend that WA-GREET incorporates updated global warming potential (GWP) values based on the IPCC's Fifth Assessment Report (AR5) to reflect an updated understanding of the climate impacts of different non-CO_2 greenhouse gases (GHGs).

Indirect land-use change (ILUC) emissions are an important consideration within policy making and must be calculated outside of a process-based attributional LCA model such as WA-GREET. These emissions estimates are based on economic modeling and come with a degree of epistemic uncertainty in addition to decision uncertainty. ILUC estimates may be limited by data gaps for key parameters as well as structural choices relating to model design, scenario design and risk tolerance. We note several methodological issues associated with the emission factor chosen for corn ethanol in the LC Associates report, based on model design and the emission factor model for land conversion. Therefore, we recommend using the full set of CARB's existing ILUC estimates for the WA CFP in the near-term, as well as further work to assess land-use change emissions for the WA CFP context. We also recommend against including a zero-ILUC value for cover cropped carinata, as there is not a definition of cover cropping in the proposed CFP nor a system for verifying that feedstocks are in fact being grown as a cover crop.

Over the next several sections of this peer review, we evaluate the major changes made to the WA-GREET and accompanying documentation. We first assess the methodology used for the changes and evaluate the data sources used and then document the impact of these changes on the calculated carbon intensity for relevant fuels. Where necessary, we provide recommendations to improve the rigor of the analysis and address data gaps.

Fossil Fuel Carbon Intensity

Crude oil mix

The calculation of average carbon intensity (CI) of WA's crude oil in 2017 is calculated primarily on two parameters: (1) the crude oil mix in WA, i.e., the volumetric distribution of the types of crude oil that comes from different location origins; and (2) crude oil CI of each source, which includes the GHG emissions during crude oil extraction and processing, as well as emissions from transporting the oil to WA. Based on the two parameters, a volumetric weighted average CI can be calculated to represent crude oil being used in WA. This crude oil CI is then used for the calculation of WA's petroleum product CIs in 2017, specifically gasoline, diesel, and jet fuel.

In addition to petroleum that is refined within the state, WA also imports refined petroleum products from Montana and Utah. A similar approach is adopted to estimate the volumetric-weighted average CI for crude oils in those two states, and consequently state specific petroleum CIs. The CIs, each of gasoline, diesel, and jet fuel, from the three states are then weight-averaged for a final gasoline, diesel, or jet fuel CI in WA, which serves as the baseline for the CFP.

This section identifies potential improvements that could be made regarding the methodology used to assess the mix of crude oils consumed in Washington as well as the calculation of the total well-to-wheel CI of petroleum products estimated.

In the peer review process, we evaluated the mix of crude oils provided by Washington State Department of Commerce and find that the estimation of total volumes and development of the weighted average mix matched the underlying data. The data was sufficient to determine country-level crude oil source data and identify suitable matches in California's previous crude oil life-cycle analysis. Data gaps on field level crude import data is not something that LC Associates can resolve, but nonetheless can cause difficulties when developing a comprehensive assessment of crude oil mix in WA. In the longer-term, a better understanding of the crude oil mix and its impact on Washington's fuel emissions can be achieved through regular reporting of the crude oil imports into Washington, similar to the annual reporting for California's LCFS.[1]

Crude oil from Canada can be categorized into conventional oil or oil sands and CI of each vary significantly. However, the state-level import data by oil type in Montana and Utah does not distinguish by source and thus is estimated. According to WA's crude oil carbon intensity analysis spreadsheet, the estimated distribution of conventional and oil sands from Canada in the two states are based on two sets of assumptions. First, it assumes the imported oil is from Alberta, based on Washington's own imports. Second, the distribution is based on the split

[1] https://ww2.arb.ca.gov/resources/documents/lcfs-crude-oil-life-cycle-assessment

between conventional (16%) and oil sands (84%) per oil production in Alberta. There are two caveats using this split. First, there is no clarification if this split is based on the year 2017. Second, the oil produced is not necessarily proportional to the share of oil exported – it is possible that Alberta gives a preference to one type of oil for exports. The accuracy of distribution assumption would have a significant impact on final crude oil CI in the two states, especially for Montana where 93% of its oil is from Canada. Therefore, we recommend that LC Associates conducts additional research and collects more representative distribution data in Montana and Utah. Past studies and reports may provide some data information on the split of Canada's conventional oil and oil sands for PADD 4 in general, which might be more applicable than the current approach. A possible source is the Canadian Association of Petroleum Producers (CAPP), such as the annual Crude Oil Forecast, Markets and Transportation report.[2]

Crude oil carbon intensity

Crude oil extracted from different oil fields can have differing upstream GHG emissions due to variations in the energy and emissions associated with different extraction and processing techniques. To assess the upstream CI of different sources of crude oil, LC Associates retrieved CI of each of its oil origin from an existing life-cycle assessment developed by the California Air Resources Board (CARB) for California's Low Carbon Fuel Standard (LCFS), which is based on modeling performed using the Oil Production Greenhouse Gas Emission Estimator (OPGEE 2.0) model.[3] To develop the weighted CI for Washington's crude oil, the modelers made two adjustments. First, the CI values developed for the California LCFS have finer granularity in terms of the regional oil fields than WA and thus the modelers use weighted average were taken (e.g., averaging multiple fields' CI's in Saudi Arabia). Second, the modelers adjust the transportation emissions for crude oil to account for the change in distance between California and Washington. This section identifies potential improvements in these two adjustments.

Even within a single country or region, different crude oil fields can have very different carbon intensities for extraction and processing. While Washington does not provide detailed data on the specific oil fields that supply oil to WA, the California LCFS on the other hand provides CI and import values that are differentiated into oil fields for each country or U.S. state. Table 2 shows an example of how data fitting for oil from Brazil was carried out with the current approach. Specifically, WA only has the total amount of oil imported from Brazil, while LCFS provides import volume and CI by oil field in Brazil. In order to get a single Brazil CI for WA, the CI of each oil field in LCFS is weighted by its corresponding import volume in California. Such a data fitting approach is done for almost all oil origins that export to WA, except for Canada, Brunei, and Papua New Guinea. A potential problem with this approach is that the weighted average of the by oil field mix imported in California does not be able to represent the distribution in WA and thus the calculated average of imports in Washington is inaccurate.

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[2] CAPP's 2017 Crude Oil Forecast, Markets and Transportation report http://www.oscaalberta.ca/wp-content/uploads/2017/06/CAPP-2017-Crude-Oil-Forecast.pdf
[3] https://ww2.arb.ca.gov/resources/documents/lcfs-crude-oil-life-cycle-assessment

Table 1. An example of how CI from LCFS is fitted into Washington with current approach, using oil imports from Brazil as an example.

Data available in WA		Data available in LCFS	2017 import volume by oil field (thousand bbl per year)	Carbon intensity	Carbon intensity in WA	
2017 total volume imported from Brazil	5,855 thousand bbl per year	Brazil – Iracema (Cernambi)	3,457.3	5.54	Brazil	5.86
		Brazil – Lula	7,652	6.24	Weighted average based on oil field volume and CI in LCFS	
		Brazil – Ostra	1,608.7	5.65		
		Brazil – Peregrino	600.4	4.16		
		Brazil – Polvo	298.9	4.31		

An alternative approach when lacking the actual oil field volumetric data is to match fuels to CI's based on oil properties. For example, the Crude Imports dataset from EIA differentiates the import volume from each country into five crude oil grades: light sweet, light sour, medium, heavy sweet, and heavy sour.[4] The categorization of light vs heavy is based on the oil's API gravity number. The higher API, the lighter the oil. The categorization of sour vs sweet is based on the sulphur content in the oil. High sulphur means sour and low means sweet. Other datasets on crude oil might provide oil categorization for oil fields that are on the LCFS list and relevant for WA, or might provide the oil property information (i.e., API and sulphur content) on oil fields, such as the one from Eurostat.[5] By matching the oil fields with the import volume by oil grade from EIA, the oil field CI values can be weight-averaged based on WA specific volume information rather than California's information. Table 3 illustrates this alternative approach, again using oils from Brazil as an example. In this alternative approach, only oils from Iracema, Lula, and Peregrino oil fields are taken into account for CI fitting, as these are the ones that match with the imports information from EIA. The new CI of Brazil's oil into WA is thus estimated to be 5.76, compared to 5.86 per currently used approach—a minor difference. This alternative approach might be able to estimate country or state level crude oil CI values that are more representative of the cases in WA. Nonetheless, neither the currently adopted approach nor the proposed alternative approach can provide truly accurate field-level crude oil CIs for WA. In the longer term, particularly if a crude oil carbon intensity is revaluated later on in the lifetime of the CFP, WA could consider implementing a reporting system to track imports by oil field to develop more accurate crude oil CI's for the CFP.

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4 https://www.eia.gov/petroleum/imports/browser/#/?d=000004000480&dt=RS&e=2021&f=a&gg=i&o=0000000000000000000000000&od=d&ot=CTY&s=2017&vs=PET_IMPORTS.CTY_AO-RS_WA-LSW.A

5 https://ec.europa.eu/eurostat/documents/38154/42198/ESTAT-ENERGY-COIR-July-2020.xlsx/ff082ff5-918b-0d3a-21d7-18550f1ed49d

Table 2. An alternative approach to fit crude oil CI from LCFS into Washington, using oil imports from Brazil as an example.

2017 import volume by oil grade from EIA (thousand bbl per year)			Oil grade produced by oil field	Carbon intensity from LCFS	Fitted carbon intensity of Brazil's oil for WA	
Brazil – heavy sour	818	Brazil – Iracema (Cernambi)	Medium	5.54	Current approach	Alternative approach
Brazil – medium	5037	Brazil – Lula	Medium sweet	6.24	5.86	5.76
		Brazil – Ostra	Heavy sweet	5.65		
		Brazil – Peregrino	Heavy sour	4.16	Weighted average based on oil field volume and CI in LCFS	Weighted average based on WA's imported oil grade volume and CI in LCFS
		Brazil – Polvo	API of 20 but no information on sulphur content (i.e., heavy but unknow sweet or sour)	4.31		

The LCFS crude oil CI list does not provide information for oils imported from Brunei and Papua New Guinea, while the two countries make up 0.5% of the oil imports in WA. Therefore, these two countries, thus their oil volumes, are completely omitted when calculating the WA state average crude oil CI from different origins. In other words, the weighted average CI is calculated based on the remaining 99.5% alone. Because the contribution of petroleum of these two countries is a small share of the total, the current approach likely only makes a minor impact on the final crude oil CI. However, for comprehensiveness, a literature review on crude oil CI in these two countries could be conducted. For example, one previous study that used OPGEE 2.0 to estimate country level crude oil CI estimates emissions from crude oil produced from these two countries.[6] Alternatively, an OPGEE assessment could be developed to estimate the CI for crude oil produced in these two regions.

Regarding crude oil CIs for Montana and Utah, the supplemental documentation does not provide the data source for the CI of crude oil produced in Wyoming, which is used when calculating the weighted average CI for both Montana and Utah. Although the spreadsheet indicated that CI value is from OPGEE, it is hard-coded and not shown in the LCFS's CI list in the spreadsheet. It is also not clear regarding how to get the simple averaged CI value of all Utah sources of crude oil, which is used when calculating the weighted average CI for Utah. The LCFS's CI list in the spreadsheet only provides one single CI value for Utah, which is 6.92 and differs from the hard-coded average Utah-sourced crude oil CI, which is 6.03. We recommend updating the supplemental documentation to provide additional information on crude oil CI sourced from Wyoming and Utah.

Crude oil produced in Montana contributes to less than 2% of the crude oil refined in Montana. However, there is not a corresponding CI estimate for Montana crude oil in California's LCFS data. Therefore, this source is omitted when calculating the weighted average CI in Montana. This omission has a minor impact, as the share of Montana-sourced oil is only approximately 0.1% of WA crude oil consumption, based on the assumption that Montana supplies 6% of

[6] https://www.science.org/doi/10.1126/science.aar6859

Washington's petroleum. For comprehensiveness, the OPGEE model could be used to estimate a carbon intensity for crude oil extracted in Montana.

Crude oil transportation emissions

The crude oil CI's developed by CARB include emissions during crude oil transportation using a variety of modes. However, these emissions are applicable for oils imported to California, while the transportation distance of oils from the same origin to California and to WA are necessarily different distances thus it is necessary to adjust the CIs. To summarize the approach used to adjust transportation distances, the emissions for the distribution of crude oil are estimated by multiplying the transport distance for the crude oil by a mode-specific (cargo ship, rail, or pipeline) emission factor for transportation. Depending on the source of crude oil, these adjustments either increase or decrease the transportation emissions for that crude oil, based on the oil field's distance to Los Angeles vs. Seattle. If the distance from the crude oil source to Seattle is shorter, the emissions are reduced, whereas if it is further, the transportation emissions increase.

Though the methodology used to adjust transport distances for crude oils is sound, we recommend additional detail to document the approach in the supplementary documentation. Additional detail is necessary regarding the transportation of oils from Canada. The OPGEE2.0 assumed oils from Canada to be first transmitted through pipeline from Edmonton to Vancouver, which are then transported to the Los Angeles, California through vessel. In the case of Canadian oils to WA, the pipeline transmission from Edmonton to Vancouver would remain, while the needed distance adjustment is switching from vessel transport between Vancouver and LA to vessel or pipeline or rail transport between Vancouver and Seattle. However, such a description is not well documented in the spreadsheet, nor in the supplementary, which could lead to confusions and misinterpretations.

Currently, there is no distance adjustment for crude oils used in Montana and Utah. This means the California's OPGEE2.0 CI values are used directly. However, better estimates could be done for the oils in these two states. For Montana, it only needs to consider crude oil transported from Wyoming and Canada. First, a search on whether there was oil pipeline in 2017 between Wyoming and Montana. If no pipeline, then rail transport is highly likely and locations of oil refineries in Montana and locations of oil fields in Wyoming could be identified for an estimate of rail transport distance between the two states. The transport from Wyoming to California is likely found from the OPGEE dataset that is being used for the CI of oil sourced from Wyoming. Based on these sets of information, a distance adjustment for oils from Wyoming could be done. Regarding the adjustments for oils from Canada, it is likely to have rail transport from Canada to Montana, as in 2017, there appeared to be no existing pipeline between western Canada and Montana, according to the 2017 CAPP report.[7] A similar distance adjustment approach could be taken per rail transport from Canada to WA.

For Utah, the state report that provided volume information also specified pipeline imports of oils from Colorado, Wyoming, and Canada. Therefore, pipeline distance adjustment for the three origins could be conducted following similar approaches as for WA adjustments. We

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[7] http://www.oscaalberta.ca/wp-content/uploads/2017/06/CAPP-2017-Crude-Oil-Forecast.pdf

recommend that LC Associates incorporate transport distance adjustments for crude oils refined in Montana and Utah, consistent with the updates for crude oils refined in Washington.

The WA's crude oil carbon intensity analysis spreadsheet notes that emission factors for crude oil by transportation mode are retrieved from OPGEE 2.0 but does not explain how these emission factors differ from CA-GREET 3.0. Using emission factors from OPGEE 2.0 is internally consistent with the approach to calculate upstream crude oil emissions within OPGEE 2.0.[8] To better understand the impact of this choice, Table 4 compares the emission factors of different transportation modes in WA's crude oil calculation spreadsheet (sourced from OPGEE 2.0) and WA-GREET. Using the emission factors from WA-GREET in place of OPGEE would change the average crude oil CI in WA from 12.57 gCO2e/MJ to 12.63 gCO2e/MJ, a 0.6% difference.

Table 3. Transportation emissions factors in OPGEE 2.0 and WA-GREET

Transportation mode	WA crude oil carbon intensity analysis spreadsheet (sourced from OPGEE 2.0)		WA-GREET		Percentage difference
	g/MMBtu-mi	g/MJ-mi	gCO_2e/MMBtu-mi	gCO_2e/MJ-mi	
Ocean tank	0.124	0.00012	0.204395	0.000194	65%
Barge	1.696	0.00161	0.60723	0.000576	-64%
Pipeline	0.49	0.00046	1.85608	0.001759	279%
Rail	1.252	0.00119	0.738804	0.0007	-41%
Truck	4.257	0.00404	3.400397	0.003223	-20%

Refining carbon intensity

The weighted-average crude oil CI in each of WA, Montana, and Utah is then used to estimate the CI of petroleum products, particularly gasoline, diesel, and jet fuel, that are produced within the three states. Ultimately, the CI of each petroleum product is weighted by volume share of the three states for a WA average CI. These weight-average CIs serve as the baselines for policy targets of GHG emission reductions. The estimation of petroleum CI depends largely on refinery assumptions. Particularly, previous studies found that the properties of crude oil, the configuration of the refinery, as well as the finished product slate all affect the energy intensity and the consequent GHG emissions from petroleum production.[9]

The upstream emissions for the weighted crude average mix are combined with refinery and combustion emissions to develop a well-to-wake emission factor for gasoline, diesel, and jet fuel in the "Petroleum" tab in WA-GREET. In the current approach, for gasoline and low-sulfur diesel in WA, the refining assumptions, such as the energy efficiency and share of process fuels, are

[8] We note that it would be helpful to clarify the unit of emission factors in the spreadsheet if it is grams of CO_2 equivalent (it is currently g/MMBtu/mi)
[9] https://pubs.acs.org/doi/full/10.1021/es5010347

using the U.S. average values. Comparing these assumed values to CA-GREET 3.0, the gasoline assumptions are different, while the assumptions for low-sulfur diesel are the same.

The refinery assumptions for each type of the petroleum product are estimated using the methodology by Elgowainy et al. (2014).[10] Specifically, an overall energy efficiency at the refinery level is first estimated. This efficiency is then adjusted for each petroleum product through energy allocation based on the energy intensity of the process units and their contributions to the product yields, for example, fluid catalytic cracking, catalytic reformer, hydrocracker, and alkylation units that contribute to gasoline. Similarly, the process fuel is also energy-allocated among products at the process unit level. Through this process, the product-specific energy efficiency and process energy can be derived with a production-weighted average.

To understand whether using U.S. average or California's assumptions are comparable for the refineries in WA, we collect the refinery capacity information in WA, California, and the U.S. from EIA, shown in Table 5.[11] Though we do not have detailed information on the refinery configurations for Washington's refineries, we draw upon EIA data to on the installed capacity by volume to infer its average configuration. The comparison of refinery capacity between Washington, California illustrated in Table 5 suggests that WA and California have similar profile for refinery operations; these values are also close to the U.S. average. Therefore, using California's or U.S. average assumptions for refining parameters likely yield a similar estimate. We note that the underlying assumptions and calculations of the petroleum CI values in Montana and Utah are also not included in WA-GREET and these values are instead hard-coded in the petroleum sheet. We therefore recommend that these calculations are included within the model for transparency.

Table 4. Refinery Capacity in Washington, California, and the United States in 2017

Refinery type breakdown (vol%)	Washington	California	U.S. average
Vacuum distillation	24%	22%	21%
Thermal cracking	7%	9%	7%
Catalytic cracking – Fresh	12%	13%	14%
Catalytic cracking – Recycled	0.2%	0.3%	0.2%
Catalytic hydro-cracking	5%	9%	6%
Catalytic reforming	12%	7%	9%
Hydrotreating/ Desulfurization	38%	39%	42%
Fuels solvent deasphalting	2%	1%	1%

Although we find that LC Associates' current approach largely aligns with existing practices in California, we note that transparency and accuracy of the crude oil CI could be improved through a dedicated refinery LCA. Concurrent with our recommendation for use of OPGEE to assess the LCA emissions for the specific crude oils used in Washington, a dedicated refinery LCA model could be used to assess the emissions attributable to petroleum products in

[10] https://pubs.acs.org/doi/full/10.1021/es5010347#notes-1
[11] https://www.eia.gov/dnav/pet/pet_pnp_cap1_dcu_nus_a.htm

Washington specifically. For example, the open-source Petroleum Refinery Life Cycle Inventory Model (PRELIM) model could be used to combine fine resolution data on imported crudes with in-state refinery specifications.[12] In the long run, particularly if the fossil fuel baseline for petroleum fuels is subject to revision, this level of additional analysis could enhance the accuracy of the fossil fuel baseline emissions estimates.

Inclusion of fossil jet fuel

We first note that the draft CFP rule does not obligate conventional fossil aviation fuel as a deficit generating fuel and these fuels are except from the program. However, the draft rule does specify that alternative jet fuels are to be compared to benchmarks established within the program—though it does not specify a benchmark value for conventional jet fuel. The draft WA-GREET model developed by LC Associates includes a separate fossil jet fuel baseline estimated for the WA crude oil mix of 89.98 gCO_2e/MJ.

The estimated fossil jet fuel baseline is calculated by inputting the previously-derived WA upstream crude oil upstream CI and calculating downstream emissions on a consistent basis with the calculations in CA-GREET 3.0. The input assumes a WA-only crude mix, and does not take into account domestic imports from Utah and Montana, which had been done for diesel and gasoline. We note there is no documentation to describe the approach to estimating the refinery emissions attributable to jet fuel; this value appears to be based on the existing CA-GREET 3.0 analysis, changing the source of crude oil. Table 6 summarizes the differences in key assumptions for jet fuel between U.S. average and WA-GREET.

[12] https://www.ucalgary.ca/energy-technology-assessment/open-source-models/prelim

Table 5. Differences in refinery assumptions for jet fuel between GREET 2021 and WA-GREET

	Jet fuel	
	WA-GREET (sourced from CA-GREET 3.0)	GREET 2021
Energy efficiency	94.9%	95.4%
Share of residual oil	22%	25.1%
Share of natural gas	71.8%	60.1%
Share of electricity	4.1%	4%
Share of hydrogen	1.7%	10.7%
Share of butane	NA	
Share of blendstock	NA	
Share of N-butane	0.27%	0.1%
Share of GTL	0.09%	0%

Though fossil jet fuel is not obligated in the CFP, we recommend the inclusion of a fossil jet baseline in the policy, as jet fuel has meaningfully different WtW emissions from road fuels. In practice, this means that displacing jet fuel has different climate outcomes than displacing diesel or gasoline, as it is estimated to have approximately 10gCO_2e/MJ lower WtW emissions than either road fuel. The WA-GREET emissions estimate for fossil jet is consistent with estimates of the jet WtW emissions conducted for California's LCFS (89.37 gCO_2e/MJ) and the international Civil Aviation Organization (89 gCO_2e/MJ).[13] Therefore, we recommend that the WA-GREET benchmark for fossil jet fuel is included within the WA CFP similar to the inclusion of a fossil jet fuel baseline for the opt-in aviation fuel pathway within the California LCFS, so as to ensure the accurate crediting of alternative aviation fuels. As in California, though the benchmarks for different fossil fuels would start at different levels, they would converge over the lifetime of the program as the overall CI target declines. Further, we recommend that the documentation is updated to reflect the methodology used to calculate the upstream refining emissions for WA jet fuel, as well as to ensure consistency with the methodology to calculate the crude oil mix and refinery emissions of road fuels in the program.

Electricity Grid Carbon Intensity

One of the major changes necessary to adapt the GREET life-cycle model used for California's LCFS to Washington is to model the electricity grid carbon intensity of Washington. This change is not only used directly to estimate emissions from electric vehicle charging, but also to

[13] https://www.sciencedirect.com/science/article/pii/S1364032121006833

estimate the emissions for other fuels pathways that utilize electricity as an input. In general, LC Associates follows much of the same methodology as CARB does for California to estimate the average state-wide emissions intensity for Washington's electricity grid. The largest change in methodology is the introduction of a new grid electricity region integrated into the model, labeled WAMX, that represents the average electricity mix of electricity produced and consumed in Washington. This electricity mix is derived from a disclosure report published by the WA Department of Commerce (herein referred to as "Commerce") for the year 2018.[14] In 2018, hydropower made up the largest share of reported electricity production (59%) followed by coal (10%) and natural gas (7%). That year, a significant share of electricity was also attributed to "unspecified" sources defined as "electricity obtained in a transaction where the seller does not identify a specific generating source" (p. 3).[15] LC Associates does not document the rationale for selecting the 2018 electricity data rather than the most recently published (2020) or baseline year (2017) electricity mix assumptions.

In the WA-GREET model, electricity mix shares reported in percentages are combined with life-cycle emission factors reported in grams of carbon dioxide equivalent (CO_2e) per kilowatt-hour of electricity to estimate the GHG emissions associated with producing a unit of electricity. To integrate WA fuel mix assumptions into the GREET model, LC Associates allocated electricity production data among fuel sources that already have an existing emission factor in GREET. This includes allocating "landfill gas", and "unspecified" electricity toward the natural gas category and "waste" (i.e., waste-to-energy) and "other biogenic" electricity toward the residual oil category. Together, these sources comprise 13.2% of the WA electricity mix. The results of this reallocation in percentage fuel shares delivered to WA state end-users are presented in Table 7.

[14] Greg Nothstein and Michael Furze, "Washington State Electric Utility Fuel Mix Disclosure Reports for Calendar Year 2018" (Washington State Department of Commerce, November 7, 2019).
[15] Ibid

Table 6. Average fuel mix delivered to WA state end-users

Source	2018 WA fuel mix (Commerce)	Reallocated WA fuel mix (LC Associates)
Hydro	59.16%	59.16%
Unspecified	12.93%	N/A
Coal	10.22%	10.22%
Natural Gas	7.33%	20.46%
Nuclear	4.75%	4.75%
Wind	4.58%	4.58%
Solar	0.28%	0.28%
Biomass	0.45%	0.45%
Biogas (landfill gas)	0.20%	N/A
Other Biogenic	0.05%	N/A
Waste	0.04%	N/A
Petroleum	0.02%	0.10%
Geothermal	0.004%	0.004%

We recommend that LC Associates update the model assumptions for two reasons:
1) estimated fuel mix shares in the reallocated scenario do not align with historical data and
2) LC Associates' reallocation methodology is not consistent with methodology previously adopted by Commerce to assign fuel mix shares to "unspecified" electricity generation. We further recommend that LC Associates could further refine their allocation shares by modifying the GREET model to include emission factors for landfill gas and incinerated waste electricity.

Because unspecified electricity is the second largest source of electricity in the original grid mix, the decision to allocate it all to natural gas is potentially significant; the result is a sharp increase in the assumed share of natural gas in the electricity grid. In energy terms, Commerce estimated that the quantity of natural gas electricity delivered to Washington end-users in 2018 was 6.86 TWh while LCA estimated that this value increases to 19.14 TWh following reallocation. To measure the annual state fuel mix, Commerce obtains documents from the Energy Information Authority (EIA) and Environmental Protection Agency (EPA) to aggregate electricity produced at specific generation facilities in addition to data on "unspecified power purchases" for which the electricity source is unknown. Until 2019, Commerce was statutorily required to assign fuel shares to unspecified power generation consistent with methodology outlined in 19.29A.060 RCW Section 4.[16] Section 4 directs electricity retail suppliers to allocate "unspecified" power purchases among generation sources based on the grid makeup of the bulk power market, the Northwest Power Pool. More specifically, retail suppliers are directed to

[16] Washington State 56th Legislature, "Electricity Products - Fuel Mix Disclosure," Pub. L. No. RCW 19.29A.060, § 4, Chapter 213 (2000), https://lawfilesext.leg.wa.gov/biennium/1999-00/Pdf/Bills/Session%20Laws/House/2565.SL.pdf?cite=2000%20c%20213%20%C2%A7%204.

calculate their product fuel mix as the "weighted average of the megawatt-hours from declared resources and the megawatt-hours from the net system power mix for the previous calendar year according to the proportion of declared resources and net system power contained in the electricity product." In 2019, House Bill 1428 revoked this requirement and instead directed Commerce to report "unspecified" power as a separate category.[17] This bill change simplifies the reporting process and requires no product reallocation.

We compare disclosed natural gas production before House Bill 1428 was passed to natural gas production estimated between 2018-2020 using the reallocation methodology adopted by LCA (Figure 2). We find that between 2017-2018, generation estimates increased 86%, a sharp increase from previous trends. We review project data to confirm that no new natural gas capacity was built in the Northwest Power Pool market after 2017[18] to rule out the possibility that this upswing is attributed to new natural gas power capacity. However, because natural gas power plants can be easily dispatched, the quantity of natural gas electricity supplied to the grid can fluctuate year over year.

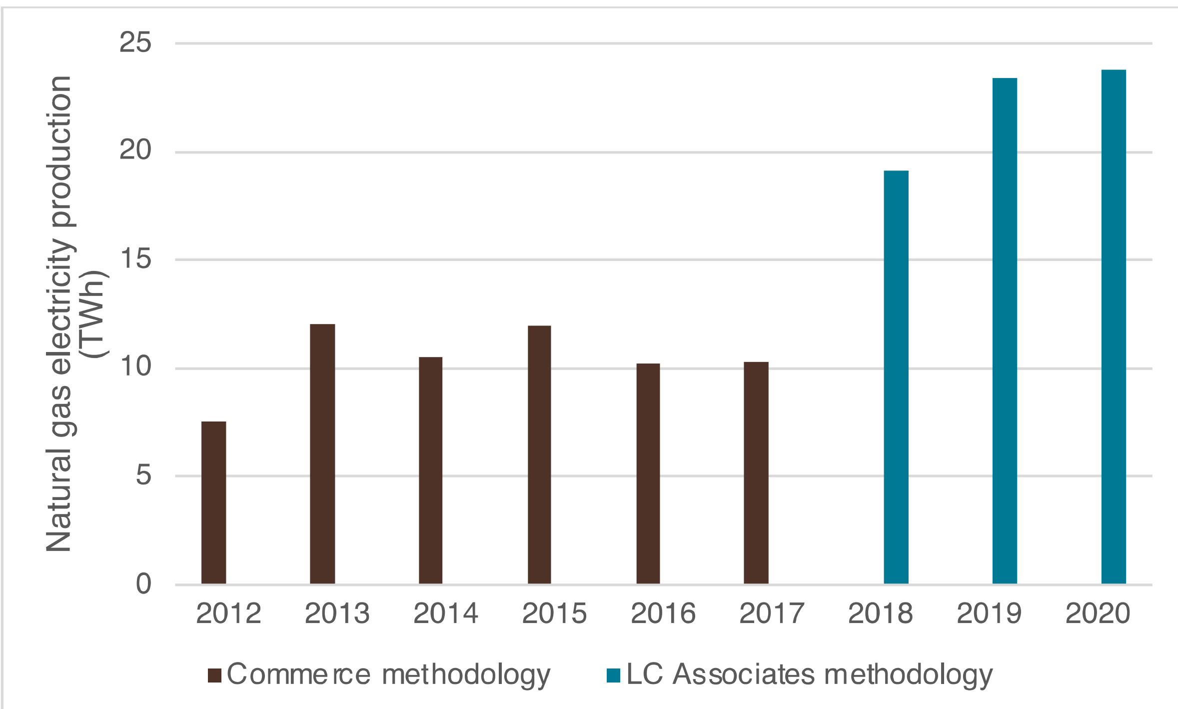

Figure 2: Estimated quantity of natural gas electricity delivered to WA state end-users (2012-2020)

[17] Washington State 66th Legislature, "Electricity Product Attributes - Disclosure," Pub. L. No. RCW 19.29A.060, Chapter 222 15 (2019).
[18] Northwest Power and Conservation Council, "Map of Power Generation in the Northwest," accessed March 30, 2022, https://www.nwcouncil.org/energy/energy-topics/power-supply/map-of-power-generation-in-the-northwest/.

LC Associates' allocation methodology is a coarser approach than the methodology adopted by Commerce and assumes that all undeclared electricity is sourced from natural gas power plants. Presumably, this is because unspecified power purchases are typically made via short-term transactions in bulk power markets when localized electricity generators cannot meet real-time energy demand.[19] Although natural gas "peaker" plants are dispatchable and commonly used for periods of high electricity demand, they are not the only power generation source used for this purpose. An economic dispatch curve of electricity generated within the Western Interconnection region indicates that biomass units are the most likely to be sourced from during periods of maximum demand, followed by natural gas, and coal generating units.[20] Hydroelectric power can also be dispatched very quickly to meet excess electricity demand.[21] Renewable energy generation sources may also be a source of unspecified power; however, since they typically bundled with a renewable electricity credit (REC), electricity generated at these facilities is less likely to be unclaimed.[22] Finally, unspecified power is not limited to spot market purchases; thus, any resource on the bulk power market may be drawn from for this fuel category.

We follow Commerce's previous allocation methodology to provide a more precise estimate of fuel mix allocation within Washington in 2018. We compare these results to the fuel mix estimated by LCA and the fuel mix estimated by Commerce in 2017 (Table 8). Using this methodology, the share of natural gas electricity in the grid mix drops from 20.5% to 10.4% and is more closely aligned with previous disclosure reports.[23] This re-allocation has a minor impact on the average electricity emissions, reducing them by approximately 6 gCO_2e/kWh.

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[19] Nothstein and Furze, "Washington State Electric Utility Fuel Mix Disclosure Reports for Calendar Year 2018."

[20] Alan Jenn, "Electricity Dispatch Model," UC Davis Plug-In Hybrid & Electric Vehicle Research Center, accessed March 31, 2022, https://phev.ucdavis.edu/project/electricity-dispatch-model/.

[21] U.S. Department of the Interior Bureau of Reclamation Power Resources Office, "Hydroelectric Power," July 2005, https://www.usbr.gov/power/edu/pamphlet.pdf.

[22] Michael Nyberg, "2019 Total System Electric Generation," California Energy Commission (California Energy Commission, current-date), https://www.energy.ca.gov/data-reports/energy-almanac/california-electricity-data/2020-total-system-electric-generation/2019.

[23] Nothstein and Furze, "Washington State Electric Utility Fuel Mix Disclosure Reports for Calendar Year 2018"; Greg Nothstein and Michael Furze, "Washington State Electric Utility Fuel Mix Disclosure Reports for Calendar Year 2017" (Washington State Department of Commerce, November 2018).

Table 7. Comparison of LC Associates and ICCT fuel allocation methodology

Source	2017 Electricity Mix (Commerce)	2018 Electricity Mix (LC Associates)	2018 Electricity Mix (ICCT)
Hydro	67.7%	59.2%	64.8%
Unspecified	0.0%	N/A	-
Coal	13.4%	10.2%	13.6%
Natural Gas	10.8%	20.5%	10.4%
Nuclear	4.2%	4.8%	5.1%
Wind	2.8%	4.6%	4.6%
Solar	0.0%	0.3%	0.3%
Biomass	0.6%	0.5%	0.7%
Biogas (landfill gas)	0.1%	N/A	0.2%
Other Biogenic	0.0%	N/A	0.05%
Waste	0.2%	N/A	0.04%
Petroleum	0.1%	0.1%	0.19%
Geothermal	0.0%	0.0%	0.004%

Emission factor assumptions for secondary generation pathways

Because the fuel mix categorization listed in annual Commerce reports is not directly translatable to the GREET model, LC Associates assigned all unspecified power purchases toward resources with existing emission factors (EFs) in GREET. This includes attributing natural gas emissions to landfill gas electricity generation and residual oil emissions to the "other biogenic", "petroleum", and "waste" electricity categories. All other generation sources (together comprising 64% of the total grid mix) are lumped within an "other" fuel category and assigned an emission factor of 0.0034 gCO2e/MJ. This small quantity of emissions is attributed to fugitive carbon dioxide emissions from geothermal power plants.[24] Although LC Associates did not explicitly state their reasoning in supporting documentation, these allocations are presumably based on the assumption that landfill gas has similar emission factors to natural gas and other biogenic, petroleum and WTE have similar emission factors to the residual oil electricity pathway. We review the literature and find that there are significant differences among life-cycle EFs for the waste-to-energy and residual oil pathways and smaller differences among the EFs for landfill gas and natural gas.

Producing electricity from the incineration of waste (i.e., waste-to-energy [WTE]) is common practice in urban areas. Within Washington, the Spokane Waste-to-Energy Plant provides a

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[24] J. L. Sullivan et al., "Life-Cycle Analysis Results of Geothermal Systems in Comparison to Other Power Systems.," October 11, 2010, https://doi.org/10.2172/993694.

small share of electricity to the grid region managed by Avista utilities.[25] Avista does not publicly disclose facility-specific electricity data; however, its overall resource mix indicates that its percentage production share is less than 1%.[26] The other commercial WTE facility located within the NWPP is in Marion County, Oregon. The life-cycle emissions impact of incinerating waste is largely dependent upon its material composition, specifically its energy-weighted share of biogenic waste. The combustion emissions of the biogenic share of waste are typically treated as zero whereas the non-biogenic portion (e.g. plastics) have a carbon intensity that is comparable to petroleum-based products. ECY reports that 99.9% of incinerated waste at the Spokane facility is classified as municipal/commercial and the remainder as "medical waste" and "special waste".[27] Further, a recent survey of the state's municipal solid waste (MSW) stream found that approximately 53% of the post-recycle waste stream is composed of organic material. As recycling practices improve over time, we expect that the biogenic share of MSW will increase, followed by a decrease in its associated electricity EF.

Pfadt-Trilling et al. conducted a life-cycle analysis of electricity generated via MSW incineration using data from a WTE facility located in New York. [28] This study used a system expansion approach that quantified avoided emissions relative to a business-as-usual case scenario. Pfadt-Trilling found that the WTE electricity pathway has an emission factor (EF) of 0.082 kg CO_2e/kWh when system expansion is used and an EF of 0.775 kg CO_2e/kWh when avoided emissions are unaccounted for. We convert these factors to gCO2e/MJ assuming a calorific value of 10 MJ/kg for MSW[29] and conversion efficiency of 0.693 kWh per kg of MSW incinerated taken directly from the life-cycle study. The converted EFs range between 5.7 and 53.7 gCO2e/MJ. For comparison, the WA-GREET model reports an EF of 80.9 gCO_2e/MJ for electricity produced from residual oil. Thus, LC Associates' assumption that incinerated waste electricity has an EF equivalent to electricity derived from residual oil is likely to vastly overstate this pathway's emissions impact.

Like Pfadt-Trilling, ECY could conduct a case-specific analysis of the Spokane WTE facility to estimate an EF for "waste" electricity to be incorporated into the WA-GREET model. For WTE produced at other facilities on the bulk power market, a regional average emissions factor may be more appropriate. Washington has a higher recycling rate than New York state, so we would expect the case-specific EF to be higher than the Pfadt-Trilling et al. study. In that study, the authors assume a waste composition of 60% biomass and 40% non-biomass materials in the waste stream, relative to the 53% biogenic waste share measured by ECY.

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[25] "Waste to Energy Plant," Spokane City, March 31, 2022, https://my.spokanecity.org/solidwaste/waste-to-energy/.
[26] Avista utilities, "About Our Energy Mix," accessed March 31, 2022, https://www.myavista.com/about-us/about-our-energy-mix.
[27] Washington State Department of Ecology, "Solid Waste & Recycling Data," 2022, https://ecology.wa.gov/Research-Data/Data-resources/Solid-waste-recycling-data.
[28] Alyssa R. Pfadt-Trilling, Timothy A. Volk, and Marie-Odile P. Fortier, "Climate Change Impacts of Electricity Generated at a Waste-to-Energy Facility," Environmental Science & Technology 55, no. 3 (February 2, 2021): 1436–45, https://doi.org/10.1021/acs.est.0c03477.
[29] IEA Bioenergy, "Municipal Solid Waste and Its Role in Sustainability," 2003, https://www.ieabioenergy.com/wp-content/uploads/2013/10/40_IEAPositionPaperMSW.pdf.

We also review the EF of landfill gas-generated electricity relative to the EF of natural gas. WA-GREET already includes CI's for electricity combusted from biogas, which has a higher methane content and heating value than landfill gas. Landfill gas can be cleaned and upgraded into biogas that is burned in reciprocating engines. Thus, we determine that the EF for biogas electricity reported in GREET (65.96 gCO2e/MJ) is appropriate to adopt for landfill gas-generated electricity. This value is roughly 17% higher than the EF estimated for utility-scale natural gas. For natural gas burned in stationary reciprocating engines, the EFs are nearly equivalent.

If new fuel categories for landfill gas and WTE were introduced in WA-GREET and the electricity mix shares were updated to align with Commerce's previous allocation methodology, this would change the emission factor for WAMX electricity by approximately 5.9 gCO2e/kWh (or about 3.1%). Because electricity only makes up a portion of life-cycle emissions for most fuels (with electric vehicle charging as a notable exception) and the shares of these sub-categories within the electricity mix are so low, these changes are minor to the CI estimates for most finished fuels. For example, the CI for tallow biodiesel decreases from 39.78 gCO2e/MJ in the default model to 39.76 gCO2e/MJ in the updated model, or a reduction of 0.05%. This change is slightly more apparent for corn ethanol where life-cycle emissions decrease by 0.12% between the default and updated models. For fuels produced outside of Washington, changes to the WAMX emission factor on a fuel's final CI are inconsequential. The inclusion of these pathways and correct attribution of emission factors in the model increases in relevance for its impact on the estimate of utility-specific electricity grid emissions, which may incorporate larger shares of some waste-derived electricity.

In summary, to improve the accuracy of the WAMX emission factor, we recommend that LC Associates 1) use more recent data, and 2) break out the "unspecified" electricity into sub-categories based on the methodology pursuant with 19.29A.060 RCW, and 3) match remaining sources of electricity emissions to more accurate, technology-specific emission factors either in GREET or in the literature. To streamline modifications to the model, fuel types can be assigned to an existing electricity category in GREET. This includes grouping landfill gas and incinerated waste within the "Others" electricity category and grouping non-biogenic electricity within the "Residual oil" electricity category. Consistent with Recommendation 3, we recommend that ECY also explore the model's capability to set path dependencies for attributes (e.g., water consumption, emission factors) from fuel sources such as landfill gas and incinerated waste not currently built into GREET. The latter changes would require a more in-depth set of modifications but improve the accuracy of final fuel pathway CI estimates, particularly for individual utilities.

Choice of GWP factors

Atmospheric scientists estimate the global warming potential (GWP) of greenhouse gases to standardize the climate-forcing potential of GHGs relative to carbon dioxide. GWP measures the amount of energy a mass unit of emissions will absorb over a specified period of time relative to the energy absorbed by carbon dioxide.[30] The Intergovernmental Panel on Climate Change (IPCC) regularly updates GWP measurements in Assessment Reports; GWP values are then later adopted by regulatory agencies. IPCC's GWP estimates are considered "best practice" for emissions modeling. The most recent Assessment Report (AR6) was released in late 2021,[31] preceded by AR5 in 2014 and AR4 in 2007.

GWP values from AR4 were selected for the CA-GREET 3.0 model; these values were then subsequently adopted for WA-GREET. CA-GREET 3.0 was developed in 2018 and based on underlying modeling assumptions from the 2016 ANL GREET model.[32] The GWP values used the reference model were already outdated, leading to a continuation of outdated assumptions over time. Over the last 15 years, the science on radiative forcing and indirect emissions effects of gases has evolved, especially regarding the short-term climate-forcing impacts of methane release. In AR6, scientists updated their estimates for the indirect chemical effects of methane and nitrous oxide emissions as well as revised their atmospheric lifetimes. These changes led to a slight reduction in GWP estimates from the previous report (AR5).[33] An overview of GWP values published by IPCC for 100-year warming periods is provided in Table 9, summarizing the estimates from AR4 through AR6.

Table 8. Global warming potential (GWP) of primary greenhouse gases across IPCC assessment reports

	GWP100		
Greenhouse gas	**AR4**	**AR5**	**AR6**
CO2	1	1	1
CH4	25	30	27.9
N2O	298	265	273

We recommend that LC Associates update WA-GREET to utilize AR5 GWP factors. This would serve to align ECY and the CFP with the latest climate science, but also align the program with updated reporting guidelines under the Paris Agreement that require the United States to shift to use of AR5 100-year GWP values (without feedbacks) for national inventory reporting in 2024.[34]

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[30] OAR US EPA, "Understanding Global Warming Potentials," Overviews and Factsheets, January 12, 2016, https://www.epa.gov/ghgemissions/understanding-global-warming-potentials.
[31] IPCC, "Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change" (Intergovernmental Panel on Climate Change, 2021), https://www.ipcc.ch/report/ar6/wg1/.
[32] CARB, "LCFS Life Cycle Analysis Models and Documentation," accessed April 5, 2022, https://ww2.arb.ca.gov/resources/documents/lcfs-life-cycle-analysis-models-and-documentation.
[33] IPCC, "Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change."
[34] https://unfccc.int/process-and-meetings/transparency-and-reporting/reporting-and-review-under-the-paris-agreement

This would also align WA-GREET with the forthcoming OPGEE 3.0 release, which will be transitioning to using AR5 GWP values.

Tier 1 Calculators

As part of this peer review, ICCT also reviewed a set of 8 "Tier 1" calculators developed for the WA CFP and based on the draft WA-GREET model. The purpose of these calculators is to provide a simplified method for fuel producers to input their facility-specific data to estimate their emissions in lieu of a detailed life-cycle assessment. These calculators comprise a set of well-characterized commercialized fuel pathways, and are based on a set of extracted emission factors and data from WA-GREET. As part of this peer review, ICCT assessed the Tier 1 emissions calculators for consistency with the base model and separately provided recommendations to LC Associates on small modifications to the Tier 1 calculators to address minor data transcription errors. Overall, we found that these calculators matched the calculations in WA-GREET and provided users sufficient flexibility to provide their own estimates of site-specific emissions for their fuels. Major changes to the life-cycle assessment methodologies of these pathways, such as the use of different chemicals with different upstream emissions intensities as discussed by one commenter, may warrant additional analysis and may require a Tier 2 application.[35]

Proposed indirect land-use change emission factors

Life Cycle Associates recommends that Washington Department of Ecology (ECY) adopts many of the ILUC values calculated in a 2014 study commissioned by the California Air Resources Board (CARB) for their Low Carbon Fuel Standard (LCFS) program.[36] These include the ILUC values for soy, canola, and palm bio- and renewable diesel (i.e., biomass-based diesel [BBD]), and sugarcane ethanol, Life Cycle Associates also recommends that ECY selects the ILUC value for corn ethanol adopted under the Oregon Clean Fuels Program (CFP) based on modeling by Argonne National Laboratory (ANL);[37] the report also recommends that ECY adopt an equivalent ILUC value for sorghum ethanol. For these two pathways, land-use change estimates calculated in the GTAP-BIO-ADV economic model are supplemented with the Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) emission factor model to estimate ILUC emissions, measured in grams of carbon dioxide equivalent per Megajoule (gCO_2e/MJ) of fuel. The ILUC value for corn ethanol adopted by Oregon is approximately 60% lower than the equivalent ILUC value adopted by California. Finally, LC Associates recommends

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[35] https://scs-public.s3-us-gov-west-1.amazonaws.com/env_production/oid100/did1008/pid_202037/assets/merged/f70sirb_document.pdf?v=2MT63WQUR
[36] Katrina Sideco, "Detailed Analysis for Indirect Land Use Change" (CARB, 2014).
[37] State of Oregon Department of Environmental Quality, "Notice of Proposed Rulemaking: Clean Fuels Program Electricity 2021 Rulemaking," December 22, 2020, https://www.oregon.gov/deq/Regulations/rulemaking/RuleDocuments/CFPE2021Notice.pdf.

that ECY adopt a zero ILUC value for all cover crops, based on CARB's feedstock-specific determination for camelina BBD.[38]

Background

ILUC models provide an informed estimate of the net change in global land cover due to policy-driven biofuels demand. Researchers use ILUC models to identify how much and what type of land area is cleared in response to a unit increase in biofuel demand; modeling results are then paired with emission factor models to quantify the greenhouse gas (GHG) emissions impacts of clearing and cultivating that equivalent area of land. One drawback to ILUC models is that they are inherently uncertain and based on various input assumptions such as demand and supply elasticities and linkages across economic sectors (e.g., trade restrictions). Computable general equilibrium models such as GTAP model market effects across the entire economy, while partial equilibrium models model these linkages across the global agricultural and forestry sectors at a more granular level. General equilibrium models are wider in scope and have drawbacks in their ability to accurately model land as well as agricultural processes.[39] California and Oregon have adopted results from a version of the GTAP model (i.e., GTAP-BIO-ADV) in their LCFS and CFP programs while the U.S. EPA uses results from FAPRI-FASOM, a combination of two partial equilibrium models, for biofuels certified under the federal Renewable Fuel Standard (RFS) program. Other models, such as GLOBIOM and MIRAGE have been utilized by the European Commission and the International Civil Aviation Organization.

Both GTAP and CCLUB have been subject to significant critique from subject matter experts.[40] Some of these criticisms are based on the argument that input assumptions to the models are not reflective of real-world conditions across the global agriculture and forestry sectors. In other cases, analysts find that the underlying datasets making up the foundation of these models are not comprehensive, or that modifications made over time are not well substantiated. We

[38] Global Clean Eenrgy Holdings, Inc., "CARB Issues First-Of-Its-Kind LCFS Pathway for Sustainable Oils' Patented Camelina," GlobeNewswire News Room, February 5, 2015, https://www.globenewswire.com/news-release/2015/02/05/703358/12627/en/CARB-Issues-First-Of-Its-Kind-LCFS-Pathway-for-Sustainable-Oils-Patented-Camelina.html.
[39] Ehsanreza Sajedinia and Wallace E. Tyner, "Use of General Equilibrium Models in Evaluating Biofuels Policies," in World Scientific Studies in International Economics, by Peter Dixon, Joseph Francois, and Dominique van der Mensbrugghe, vol. 76 (WORLD SCIENTIFIC, 2021), 437–65, https://doi.org/10.1142/9789811233630_0014.
[40] Stephanie Searle, "Don't Throw out California's ILUC Factors Yet," ICCT Staff Blog (blog), March 9, 2018, https://theicct.org/dont-throw-out-californias-iluc-factors-yet/; Chris Malins, Richard Plevin, and Robert Edwards, "How Robust Are Reductions in Modeled Estimates from GTAP-BIO of the Indirect Land Use Change Induced by Conventional Biofuels?," Journal of Cleaner Production 258 (June 10, 2020): 120716, https://doi.org/10.1016/j.jclepro.2020.120716; Stephanie Searle and Chris Malins, "A Critique of Soil Carbon Assumptions Used in ILUC Modeling" (Washington, D.C.: International Council on Clean Transportation, June 13, 2016), https://theicct.org/publication/a-critique-of-soil-carbon-assumptions-used-in-iluc-modeling/. Comment on 'Carbon intensity of corn ethanol in the United States: state of the science', https://iopscience.iop.org/article/10.1088/1748-9326/ac2e35

summarize these critiques and provide recommendations for addressing these concerns within ECY's CFP program in the discussion below.

Limitations of CCLUB

CCLUB is an emissions factor model developed by ANL that can translate land use change (LUC) estimates reported in hectares for various types of land into GHG emissions reported in tonnes.[41] CCLUB uses emission factors from the CENTURY and COLE soil and forest biomass models as the default emission factors for the U.S., and emission factors calculated by Winrock et al. for the rest of the world.[42] The Winrock emission factor model was developed for U.S. EPA for its ILUC modeling for the Renewable Fuel Standard program. In contrast, California developed the AEZ-EF emissions factor model for use in its ILUC modeling.

Our assessment finds that CCLUB takes scientific liberties in its modeling of soil carbon changes and that its development process was far less transparent than the AEZ-EF model adopted by CARB. One of the major concerns with CCLUB is that the predicted change in soil carbon for certain land types modeled in CENTURY (part of CCLUB's modeling framework) contrast sharply with results from other emission factor models. Here, we delve into CCLUB's modeling of "cropland pasture", or land that has previously been cropped but is currently in a pasture state. Cropland pasture is not a standard land category in global land-use datasets; thus, measuring the impacts of cropping expansion onto this land type can be difficult to accurately quantify. The distinction between cropland and pasture is important, as soil can rebuild carbon stocks when it is left as pasture compared with soil carbon stock depletion during the conversion of pasture to cropland.

Malins et al. visualize how different emission factor models predict a change in soil carbon stocks following cropland pasture conversion, as shown below in Figure 3.[43] While Winrock et al. and the AEZ-EF model predict that the conversion of cropland-pasture to corn and soybean cropping results in soil carbon loss, the CENTURY model predicts the opposite effect – an increase in soil carbon.[44]

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[41] Jennifer B. Dunn et al., "Carbon Calculator for Land Use Change from Biofuels Production (CCLUB)," September 1, 2018, https://doi.org/10.2172/1480518.
[42] Dunn et al.
[43] Figure 6. Malins, Plevin, and Edwards, "How Robust Are Reductions in Modeled Estimates from GTAP-BIO of the Indirect Land Use Change Induced by Conventional Biofuels?"
[44] Figure 6. Malins, Plevin, and Edwards.

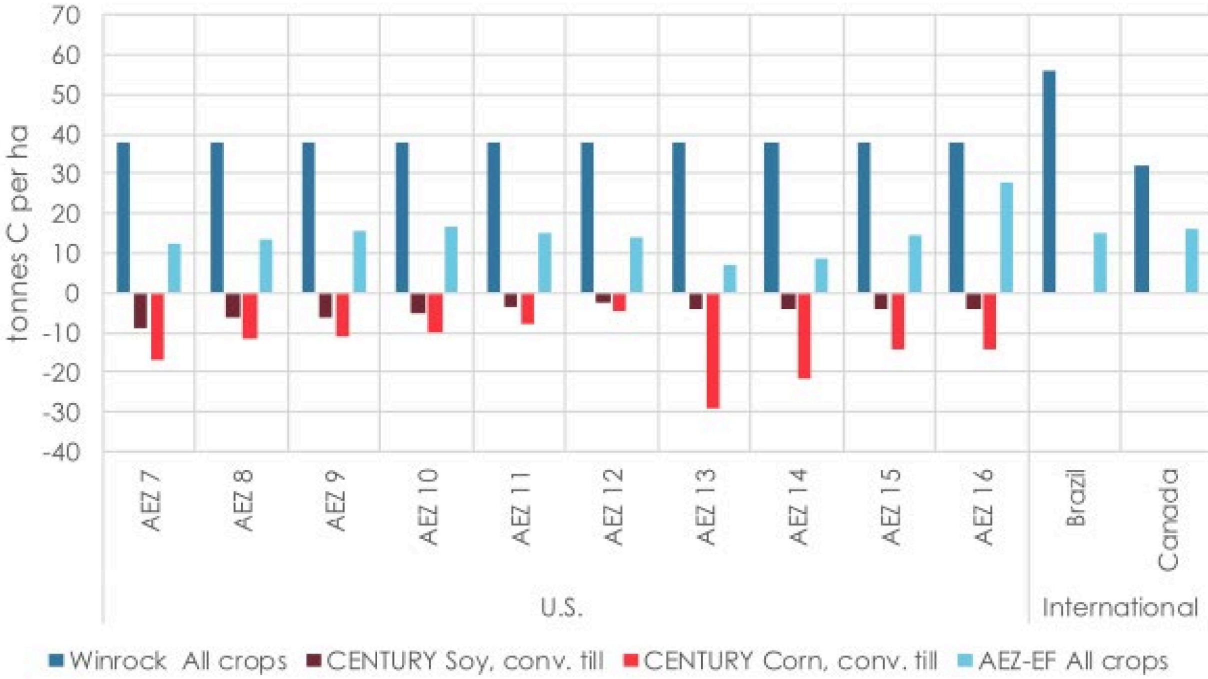

Figure 3: Carbon loss following cropland pasture conversion using Winrock, CENTURY and AEZ-EF emission factor models.

Reproduced from Malins et al. (2020).

One factor contributing to this counterintuitive finding is that CCLUB uses a very different interpretation of the "cropland-pasture" category than what is used in official statistics. The official definition of cropland-pasture in the United States Department of Agriculture's glossary is: "Cropland pasture—Generally is considered to be in long-term crop rotation. This category includes acres of crops hogged or grazed but not harvested and some land used for pasture that could have been cropped without additional improvement. Cropland pastured before or after crops were harvested was included as harvested cropland and not cropland pasture."[45] It is thus clear that cropland-pasture should currently be in a pastured state and not actively cropped. However, the CENTURY soil carbon stock values used in CCLUB are derived assuming cropland-pasture was in a cropped state for 35 years prior to conversion to corn production. This distinction is important; it is well-established in the scientific literature that the conversion of pasture results in large soil carbon losses while the conversion of cropland to corn is not a change in land use status at all. In a meta-analysis including 74 studies on the LUC effects on soil carbon stocks, Guo and Gifford estimate a 60% reduction in soil organic carbon (SOC) content from the conversion of pasture to cropland.[46] When CCLUB assumes cropland-

[45] USDA ERS, "Major Land Uses - Glossary," accessed April 5, 2022, https://www.ers.usda.gov/data-products/major-land-uses/glossary/.
[46] L. B. Guo and R. M. Gifford, "Soil Carbon Stocks and Land Use Change: A Meta Analysis: SOIL CARBON STOCKS and LAND USE CHANGE," Global Change Biology 8, no. 4 (April 2002): 345–60, https://doi.org/10.1046/j.1354-1013.2002.00486.x.

pasture has been cropped for the past 35 years, it very likely is modeling the same level of soil carbon stocks that can be expected on permanent cropland, since soil carbon changes generally equilibrate within 10 or 20 years following land conversion.[47] Thus, while it is clear from USDA's definition that the conversion of cropland-pasture to cropland resembles the conversion of regular pasture – and thus can be expected to result in large soil carbon losses – by assuming cropland-pasture is actually cropland instead of pasture, CCLUB omits this carbon loss term entirely, and unjustifiably.

Another contributing factor to the strange result of soil carbon gains upon conversion of cropland-pasture to corn in CCLUB is a misinterpretation of the scientific literature. CCLUB uses inputs on soil carbon responses from a meta-analysis conducted by Qin et al.[48] This analysis has been previously critiqued.[49] In that critique, we found that Qin et al. misinterpreted the soil carbon literature in three ways. Firstly, Qin et al. took results from scientific studies measuring changes in soil carbon on cropland over time (i.e., land that has not been converted from cropland-pasture but has been cropland all along) and applied it to the conversion of cropland-pasture to corn. Secondly, the scientific studies cited in Qin et al., when aggregated, clearly show that soil carbon increases over time in corn/soy rotations but declines over time in continuous corn fields. Qin et al. combined the results from continuous corn and corn/soy rotations and applied the resulting soil carbon increase specifically to the conversion of cropland-pasture to continuous corn. Thirdly, we found that the linear regression used in Qin et al. was heavily influenced by a large number of data points from short-term studies finding soil carbon increases, while those from long-term studies indicated a soil carbon loss over time. Soil carbon is notoriously difficult to measure with high measurement error, and measurements of long-term soil carbon changes are much more reliable than those of short-term changes. In conclusion, CCLUB's prediction of a net soil carbon increase from converting a hectare of cropland pasture to hectare of corn production results from inappropriate and incorrect interpretations of statistics and the scientific literature.

One alternative to CCLUB is the AEZ-EF model developed for the California LCFS.[50] AEZ-EF is a user-friendly model available in Excel. AEZ-EF contains thorough documentation and a clear set of assumptions that can be traced back to the scientific literature. Although AEZ-EF is a simpler model than CCLUB, its underlying assumptions are more consistent with the scientific literature. For example, while CCLUB calculates an increase in SOC from the conversion of cropland pasture to corn, AEZ-EF calculates cropland pasture conversion as the average of the SOC change between cropland conversion and pasture conversion, resulting in a net SOC loss.

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[47] Danuse Murty et al., "Does Conversion of Forest to Agricultural Land Change Soil Carbon and Nitrogen? A Review of the Literature," Global Change Biology 8, no. 2 (2002): 105–23, https://doi.org/10.1046/j.1354-1013.2001.00459.x.
[48] Zhangcai Qin et al., "Influence of Spatially Dependent, Modeled Soil Carbon Emission Factors on Life-Cycle Greenhouse Gas Emissions of Corn and Cellulosic Ethanol," GCB Bioenergy 8, no. 6 (2016): 1136–49, https://doi.org/10.1111/gcbb.12333.
[49] Searle and Malins, "A Critique of Soil Carbon Assumptions Used in ILUC Modeling."
[50] -Richard J Plevin et al., "Agro-Ecological Zone Emission Factor (AEZ-EF) Model: A Model of Greenhouse Gas Emissions from Land-Use Change for Use with AEZ-Based Economic Models," February 21, 2014.

Limitations of GTAP-BIO-ADV

GTAP is a widely used general equilibrium model for biofuels policy analysis and in other research fields. The version most often used for biofuels policy analysis is GTAP-BIO-ADV, developed by researchers at Purdue University. The development of this model version and studies published by Purdue researchers using it have been criticized as favoring changes in model structure and input assumptions that tend to reduce ILUC estimates, while avoiding changes that would increase them. Here, we summarize these critiques.

Conversion of unmanaged forests

One drawback of GTAP-BIO-ADV is its inability to model the effects of biofuel expansion on forested and pastured land that is currently out of economic use. The GTAP-BIO-ADV model does not include unmanaged forests and other land and thus structurally cannot model the conversion of these types of land to cropland. All cropland expansion in GTAP-BIO-ADV must be on managed land that has direct economic use. This limitation prevents the model from reflecting the land use change, and thus GHG emissions, that very likely occur from cropland expansion in reality. This likely overstates the "intensification of existing agricultural lands and overestimat[ing] conversions from agriculture to forestry when carbon sequestration incentives are applied".[51] This modeling decision is in contrast with other ILUC models including GCAM, IFPRI MIRAGE, and EPPA that account for conversion of unmanaged land.[52]

It has been demonstrated that it is possible to include unmanaged land in GTAP: a modified version of GTAP developed by Golub and Hertel included the ability to model unmanaged forest.[53] In this version, authors noted that modelers "must account for the possibility that currently inaccessible forestland will be brought into commercial production" (p. 470) to accurately capture the effects of global markets on land development. Despite this development, a separate team of Purdue researchers opted not to adopt this modeling change from Golub and Hertel in the GTAP-BIO-ADV model they developed for the California LCFS.

Due to the prevalence of unmanaged land globally, we expect that excluding this parameter will have a significant effect on final ILUC results – as of 2004, an estimated 75% of forested land in

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[51] Alla A. Golub et al., "Global Climate Policy Impacts on Livestock, Land Use, Livelihoods, and Food Security," Proceedings of the National Academy of Sciences 110, no. 52 (December 24, 2013): 20894–99, https://doi.org/10.1073/pnas.1108772109.
[52] David Laborde and Hugo Valin, "Modeling Land-Use Changes in a Global CGE: Assessing the EU Biofuel Mandates with the MIRAGE-BioF Model," Climate Change Economics 03, no. 03 (August 2012): 1250017, https://doi.org/10.1142/S2010007812500170; P. Kyle et al., "GCAM 3.0 Agriculture and Land Use: Data Sources and Methods" (Pacific Northwest National Laboratory, December 2011), https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-21025.pdf; Angelo Gurgel, John M Reilly, and Sergey Paltsev, "Potential Land Use Implications of a Global Biofuels Industry," 2007, 36.
[53] Alla Golub and Thomas W. Hertel, "Global Economic Integration and Land Use Change," Journal of Economic Integration 23, no. 3 (2008): 463–88.

North America and more than 90% of forested land in Oceania is classified as inaccessible.[54] Plevin ran a version of the GTAP model for the period 2020-2060 to underscore the significance of this model limitation.[55] In this analysis, GTAP predicts that increased biofuel demand results in no loss of non-commercial forested land and that approximately half of managed forest that is converted to cropland in the U.S. is offset by an increase in the land area of timber plantations globally. An equivalent modeling simulation run using the base scenario of GCAM did not yield the same results and instead predicted a net loss in non-commercial forested land area and a net zero change in commercial forest area.

Put plainly, GTAP predicts that when commercial forested land area is converted to cropland, this change is offset by newly planted forested area elsewhere. This is based on the assumption that a constraint on timber supply raises its price, which timber suppliers compensate for by planting more forested land area. In reality, we would expect that much of forest land expansion would occur on unmanaged forests with a lower economic value, minimizing the likelihood of any afforestation at all. Thus, we expect that GTAP modeling is likely to understate ILUC impacts since it predicts that any loss of forest area is, to a significant extent, offset by afforestation elsewhere. This has an important impact on estimated ILUC emissions because forest loss results in large losses of terrestrial carbon stocks.

Price-induced yield

The price-induced yield elasticity is an important input used in GTAP-BIO-ADV. This factor attempts to quantify the relationship between increased biofuel demand, rising crop prices, and agricultural intensification. Because higher demand for biofuels raises the price of agricultural commodities, the theory is that farmers will then find it economical to use methods such as increased fertilizer consumption and higher rates of irrigation to improve yield. Price-induced yield is quantified using a “yield elasticity to price” (i.e., YDEL) factor, defined as the percent change in yield corresponding with a percent change in the price of the commodity. For example, a YDEL factor of 0.25 means that a 1% increase in the price of corn would result in a 0.25% increase in the yield of planted corn. A YDEL factor of 1 corresponds with perfect elasticity. GTAP modelers have used a range of YDEL factors throughout different iterations of the model – a YDEL factor of 0.25 was adopted under the California LCFS program while YDEL factors range between 0.175 and 0.325 in the most recently published ILUC studies by Purdue.[56]

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[54] Brent Sohngen and Colleen Tennity, “Country Specific Global Forest Data Set v.1” (Department of Agricultural, Environmnetal, and Development Economics Ohio State University, November 30, 2004).

[55] Richard J. Plevin et al., “Choices in Land Representation Materially Affect Modeled Biofuel Carbon Intensity Estimates,” Journal of Cleaner Production 349 (May 2022): 131477, https://doi.org/10.1016/j.jclepro.2022.131477.

[56] Taheripour, F., Cui, H., Tyner, W.E., 2017a. An Exploration of agricultural land use change at the intensive and extensive margins: implications for biofuels induced land use change. In: Qin, Z., Mishra, U., Hastings, A. (Eds.), Bioenergy and Land Use Change. American Geophysical Union, pp. 19e37. Retrieved from (continued on next page)

The YDEL factors used in recent GTAP studies by Purdue researchers indicate a fairly high elasticity between agricultural intensification and price. Other assessments in the literature find little or no statistically significant relationship between crop prices and yields. In an expert assessment for a CARB working group, Babcock et al. concluded that the average YDEL for U.S. crops ranges between 0.05 and 0.2, although it could be justifiable to use a higher value in ILUC modeling in order to implicitly account for an increase in the practice of double cropping that might also occur in response to increased commodity price.[57] Berry and Schlenker (2011) used an instrumental variable analysis to determine that there is no significant causal impact of the price and yield of corn, soy, wheat, and rice on the yields of these crops globally and within the U.S. and Brazil.[58] The YDEL factor of 0.25 used in the modeling for the LCFS regulation is greater than the high-end range estimated by expert reviewers, and is only justified on the basis that it implicitly includes the yield effects of double cropping.[59] Relative to other assessments, the YDEL factor adopted by CARB may overestimate the rate of cropland intensification and underestimate the area of land cleared to allow for increased biofuel demand.

Throughout different studies using different iterations of the GTAP model, Taheripour et al. adopted different YDEL factors for geographic regions. Although authors note the importance of preserving “the original central” YDEL value (i.e. 0.25) supported by the literature, in the 2017 study,[60] they chose to adopt a higher YDEL for 10 out of 19 agro-economic zone (AEZ) regions, and reduce the YDEL for 6 of them. Areas where YDEL was increased account for approximately 50% of land use change captured in a previous version of the GTAP-BIO model [61] while areas where YDEL was reduced only account for 10% of modeled land area.[62] Additionally, the decision to assign a YDEL factor of 0.3 to the entire U.S. exceeds the central

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https://books.google.co.uk/books?hl¼en&lr¼&id¼vWk9DwAAQBAJ &oi¼fnd&pg¼PA19&dq¼AnþExplorationþofþagriculturalþ landþuseþchangeþatþtheþintensiveþandþextensiveþmargins&ots¼ DCLdhoHgYh&sig¼heg7uMycBk6hpQ4W0q0jQFl9Ugc.

[57] Babcock, Bruce, Angelo Gurgel, Mark Stowers, and K. Adili. "Final recommendations from the elasticity values subgroup." ARB LCFD Expert workgroup, California Environmental Protection Agency (2011).

[58] Steven Berry and Wolfram Schlenker, “Empirical Evidence on Crop Yield Elasticities,” August 5, 2011.

[59] Malins, Plevin, and Edwards, “How Robust Are Reductions in Modeled Estimates from GTAP-BIO of the Indirect Land Use Change Induced by Conventional Biofuels?”

[60] Taheripour, F., Cui, H., Tyner, W.E., 2017a. An Exploration of agricultural land use change at the intensive and extensive margins: implications for biofuels induced land use change. In: Qin, Z., Mishra, U., Hastings, A. (Eds.), Bioenergy and Land Use Change. American Geophysical Union, pp. 19e37.

[61] Thomas W. Hertel et al., “Effects of US Maize Ethanol on Global Land Use and Greenhouse Gas Emissions: Estimating Market-Mediated Responses,” BioScience 60, no. 3 (March 2010): 223–31, https://doi.org/10.1525/bio.2010.60.3.8.

[62] Hertel et al.

value (0.25) used in the California modeling. Some researchers suggest that these changes to YDEL are not well-substantiated or justified based on evidence.[63]

Double cropping

Along with maintaining high YDEL factors, recent studies using the GTAP model have explicitly added an additional yield intensification factor, reflecting changes in the practice of multiple cropping (growing more than one crop in a year) in response to commodity prices. These studies have justified this modeling change by arguing that multiple cropping rates have increased in some world regions in recent years, and that this will continue in response to increased commodity demand. High and increasing rates of double cropping identified by Taheripour et al. (2017), is not well substantiated in the literature. Although Taheripour et al. cite multiple studies to support this assumption, only one, Babcock and Iqbal (2014) draw a direct link between increased cropping intensity and biofuel policies.[64] Babcock and Iqbal's analysis relied on comparing harvested area to total cropland area using the FAOSTAT database. In some cases, that study assumed harvested area increases cannot represent new cropland, for example arguing that Indonesia is so densely populated that cropland expansion is not possible – an argument undermined by continued evidence of significant cropland expansion in that country.[65] Moreover, Babcock and Iqbal simply try to demonstrate that cropping intensity has increased over the same time period that biofuel production has increased and do not attempt to demonstrate any sort of causal linkage. Even if an increase in multiple cropping has occurred over this time period, it could be driven by other factors unrelated to biofuel policy such as business-as-usual technology progress; neither Babcock and Iqbal nor any other study have attempted to directly tie the two trends together. Because of the likely influence of external factors, Cui and Tyner emphasize that LUC modelers must first prove the relationship between cropping intensity and policy-driven biofuel expansion and that if no relationship is determined, the "biofuels-driven part of the cropping intensity change needs to be effectively isolated."[66]

Several other studies indicate that the prevalence of double cropping may not be so common and that data limitations may contribute to a skewed result. Borchers et al. estimate that between 1999 and 2012, double cropped land made up only 2% of total U.S. cropland and did not increase according to any long-term trend.[67] Researchers from the FAO caution against

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[63] Malins, Plevin, and Edwards, "How Robust Are Reductions in Modeled Estimates from GTAP-BIO of the Indirect Land Use Change Induced by Conventional Biofuels?"
[64] Bruce A Babcock and Zabid Iqbal, "Using Recent Land Use Changes to Validate Land Use Change Models" (Ames, Iowa: Center for Agricultural and Rural Development, Iowa State University, November 2014).
[65] Kemen G Austin et al., "What Causes Deforestation in Indonesia?," Environmental Research Letters 14, no. 2 (February 1, 2019): 024007, https://doi.org/10.1088/1748-9326/aaf6db.
[66] Hao (David) Cui and Wally Tyner, "Modeling Land Intensification Response in GTAP: Implications for Biofuels Induced Land Use Change," Presented at the 20th Annual Conference on Global Economic Analysis, West Lafayette, IN, USA, http://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=5287.
[67] Allison Borchers et al., "Multi-Cropping Practices: Recent Trends in Double-Cropping," May 2014.

extrapolating the same cropland:arable land ratio to future years due to inconsistency in data collection and reporting across datasets.[68] Additionally, by comparing cropland pasture data reported by USDA and total arable area reported by FAO, we find that FAO has likely included cropland pasture in its reported total arable land area over time. This misclassification would increase the ratio of cropland:arable land area (i.e., cropping intensity) in FAOSTAT data.[69] Babcock and Iqbal (2014) did not rely on FAO data for the U.S. due to data issues, but Taheripour (2017) did.

Despite weak evidence, Taheripour et al. apply a cropping intensity ratio of 4 hectares of additional double cropping for every hectare of cropland expansion in subsequent versions of the GTAP-BIO model.[70] This assumption exacerbates the effects of a high YDEL factor on land conversion assumptions. This is demonstrated in Taheripour et al. (2017), where adding the new double cropping assumption reduces U.S. pasture and forest conversion by a factor of 5 and global pasture and forest conversion by half in the corn ethanol scenario. A high YDEL assumes that agricultural land is used more efficiently, minimizing total land area conversion, while a high cropping intensity ratio assumes that a larger area of land is converted to double cropping rather than sourced from newly cleared land. Thus, we conclude that a high YDEL factor (higher than 0.2) can only be justified if double cropping is not explicitly included in the modeling to minimize the risk of underestimating ILUC emissions. Such as high value is not justified if double cropping effects are modeled independent of YDEL.

Classification of cropland pasture

Another area of concern with the GTAP-BIO-ADV model is that the nesting structure results in cropland pasture being preferentially converted to conventional cropland in response to increased biofuel demand. This modeling structure change reflects an assumption that cropland expansion occurs more on cropland pasture than on other types of land, such as permanent pasture or forest, but this finding is not substantiated by evidence. Although cropland pasture rates reported in the USDA census have rapidly decreased over time (and thus could in theory reflect a strong trend of cropland pasture conversion to new cropland), USDA experts have stated that this is likely a matter of data misclassification rather than real-world trends. Bigelow and Borchers report that this decline is attributed to methodological changes in data collection including reclassifying a portion of "cropland pasture" to "permanent grassland pasture and range."[71]

The GTAP-BIO-ADV developers have also directly reduced the rate of cropland expansion onto pasture and forest in the model. In a study released in 2013, Taheripour and Tyner reduced the

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[68] Nikos Alexandratos, "World Agriculture:Towards 2010" (Food and Agriculture Organization of the United Nations, 1995), https://www.fao.org/3/v4200e/v4200e00.htm; Nikos Alexandratos and Jelle Bruinsma, "World Agriculture towards 2030/2050: The 2012 Revision," June 2012, 154.
[69] Malins, Plevin, and Edwards, "How Robust Are Reductions in Modeled Estimates from GTAP-BIO of the Indirect Land Use Change Induced by Conventional Biofuels?"
[70] Malins, Plevin, and Edwards.
[71] Daniel P Bigelow and Allison Borchers, "Major Uses of Land in the United States, 2012" (USDA Economic Research Service, August 2017).

land conversion elasticity of pasture and forested land area to cropland by a factor of 10 in 10 of 19 regions, while increasing it by 50% in 5 regions.[72] This asymmetric treatment results in a 55% reduction in global pasture and forest conversion and is not justified based on evidence. Because cropland expansion onto forested or pasture is less likely to occur in recent GTAP updates, this increases the likelihood of agricultural land intensification and cropland pasture conversion, along with an associated reduction in ILUC emissions. Together with the nesting change in cropland pasture, these changes results in a 34% reduction in ILUC emissions, according to the 2013 study.

Cover crops

LC Associates recommend that ECY adopt an ILUC value of zero for oilseed crops such as carinata because it can be grown as a secondary or cover crop (i.e., over the winter, in addition to the regular summer crop). The reasoning for this recommendation is that if carinata is grown as a cover crop, it does not necessarily increase the demand for cropland area. This could potentially apply to other oilseed crops such as camelina and pennycress. This recommendation is partly based on the certification of camelina for the California LCFS as zero ILUC; however, this fails to note that this certification has expired and was never formally certified as a fuel pathway.[73] That feedstock certification was also limited to pathway-certified seeds verified with a chain of custody, rather than to cover crops more generally.[74] EPA in its rulemaking on camelina for the RFS, anticipates that while it is likely that camelina will be cover-cropped for economic reasons, if grown on dedicated cropland it would exceed the land-use impacts of soy (thus qualifying for a D4 RIN), though does not estimate ILUC emissions for the pathway.[75] CORSIA assigns carinata grown in the U.S. with an ILUC score of -20.4gCO2e/MJ, based on modeling that explicitly assumes that it is planted as secondary or cover crop and avoids the displacement of other crops.[76] In theory, purpose-grown cover crops also do not displace crops from other competing uses such as food, livestock feed, or the oleochemicals market.

However, cover crops are not necessarily additional and can easily displace food or feed crops grown already grown as cover crops. For example, growing a second crop over the winter is already commonplace in much of Brazil; there, the safrinha corn crop (i.e. cover crop) grown during the winter season has surpassed the production of primary corn since 2012, and, in

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[72] Farzad Taheripour and Wallace E. Tyner, “Biofuels and Land Use Change: Applying Recent Evidence to Model Estimates,” Applied Sciences 3, no. 1 (March 2013): 14–38, https://doi.org/10.3390/app3010014.
[73] CARB (n.d.) LCFS Pathway Certified Carbon Intensities. https://ww2.arb.ca.gov/resources/documents/lcfs-pathway-certified-carbon-intensities
[74] https://ww2.arb.ca.gov/sites/default/files/classic/fuels/lcfs/2a2b/apps/so-camelina-oil-rpt-110714.pdf
[75] https://www.govinfo.gov/content/pkg/FR-2013-03-05/pdf/2013-04929.pdf
[76] ICAO, “CORSIA Default Life Cycle Emissions Values for CORSIA Eligible Fuels,” March 2021, https://www.icao.int/environmental-protection/CORSIA/Documents/ICAO%20document%2006%20-%20Default%20Life%20Cycle%20Emissions%20-%20March%202021.pdf.

2021, accounted for three-quarters of Brazilian corn production.[77] Double cropping is also practiced in the U.S., although at much lower rates.[78] Thus, a low-carbon fuel policy that places high value on cover cropping incentivizes the farmer to sell the secondary (e.g. corn) crop to the biofuel market, increasing the demand for planted corn elsewhere. If farmers switch to planting an oilseed crop as the second crop instead of safrinha corn, this reduces the annual production of corn, with similar market effects. Replacing cover crops like safrinha corn that are already grown now with carinata or other biofuel feedstock will very likely cause ILUC impacts of a similar magnitude as using primary crops for biofuel production. Due to the widespread nature of multiple cropping even in the absence of biofuel use for those crops, we recommend that ECY develop a more precise definition for this feedstock category prior to incentivizing it within the CFP.

Further, planting a secondary crop on land that was previously fallow may even contribute to ILUC in regions where cover cropping practices are expanding. Under a business-as-usual, or counterfactual scenario, there is a high likelihood that farmers would have transitioned to double cropping in the absence of biofuel demand. This would result in a net deficit in crop production and associated ILUC impacts. It is hard to state with certainty that farmers that only grow in the offseason would have transitioned to double cropping without the introduction of a low-carbon fuels policy. However, oilseed cover crops grown on land that was previously used for crop production certainly have an ILUC impact that should be accounted for in emissions modeling.

Strong incentives for growing oilseed cover crops may also result in the direct clearing of land; if farmers can expect income from two crops instead of one, they would in principle be more likely to invest in clearing new cropland. Growing cover crops can also reduce primary crop yields.[79] Lastly, cover crops may increase fertilizer and water usage.

Recommendation

In its analysis, Life Cycle Associates recommends that ECY adopts ILUC values and methodology that are largely consistent with California's LCFS program. A significant exception is corn and sorghum ethanol, for which Life Cycle Associates recommends the ILUC values adopted by the state of Oregon. We raise significant concerns regarding the accuracy and methodological integrity of the CCLUB emission factor model in the discussion above and recommend that ECY uses a land conversion emission factor model more representative of real-world conditions. To maintain consistency with California, the preferred emission factor model would be AEZ-EF.

We also raise concerns regarding the accuracy and framework of the GTAP-BIO-ADV equilibrium model, adopted for every biofuel pathway. Research is currently ongoing at the EPA and National Academy of Sciences to review the state-of-the-art research on ILUC; however, at

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[77] Joana Colussi and Gary Schnitkey, "Brazil: Corn Production in Three Crops per Year," Farmdoc Daily (blog), April 12, 2021, https://farmdocdaily.illinois.edu/2021/04/brazil-corn-production-in-three-crops-per-year.html.
[78] Borchers et al., "Multi-Cropping Practices: Recent Trends in Double-Cropping."
[79] Humberto Blanco-Canqui et al., "Harvesting Cover Crops for Biofuel and Livestock Production: Another Ecosystem Service?," Agronomy Journal 112, no. 4 (2020): 2373–2400, https://doi.org/10.1002/agj2.20165.

this time, there is no clearly preferred alternative. In the interim, we recommend that ECY adopts California's ILUC values that were calculated using the GTAP-BIO-ADV model to maintain consistency with California and consult with EPA and expert reviewers to identify a more defensible LUC model for future adoption. We do not recommend WA ECY conduct new modeling using the GTAP-BIO-ADV model, but if the agency chooses to do so, we recommend that they either a) do not utilize a YDEL factor greater than 0.2, or b) utilize a YDEL factor no greater than 0.25 and exclude explicit double cropping increases in the model to avoid overestimating cropping intensity response. In the future, ECY can consult expert and state agency review and incorporate stakeholder feedback to identify more suitable ILUC models for Washington than GTAP-BIO-ADV.

For cover crops, we recommend against including an ILUC value of 0g CO_2e/MJ, particularly given the absence of any definition or verification of cover cropping. Rather than assuming that some feedstocks such as carinata are inherently cover cropped, we recommend that an ILUC estimate is developed for these crops as if they are purpose grown in the absence of verification of cover cropping. To qualify for a zero-ILUC score, we recommend the use of a separate verification scheme to ensure that they are in fact grown as cover crops and not competing with cropland.

Summary of Recommendations

Overall, this peer review finds that the bulk of the LCA estimates and methodology developed to inform the Washington draft Clean Fuel Program rule is methodologically rigorous, aligns with existing policies in other jurisdictions, and reflects best practices. We identify several small methodological discrepancies or data gaps that can be addressed to improve the accuracy of the LCA modeling for the WA CFP in the near-term. With these changes implemented, we anticipate that there is sufficient data and analysis to support the implementation of the program. However, we also provide several suggestions that can be implemented in the longer-term to improve the accuracy of the program, mitigate data gaps and provide greater certainty that the emissions reductions intended by the WA CFP are being achieved. We make the following recommendations.

In the longer-term, we recommend moving beyond the current analysis' reliance on California's previously calculated CI figures for crude oils, particularly if Washington's crude oil mix begins to diverge from what is consumed in California. We recommend additional transparency of Washington's crude oil imports and refinery activity in the future to facilitate closer analysis of field-level oil import data and life-cycle emissions accounting. With that information, a Washington-specific crude oil LCA developed using the forthcoming OPGEE 3.0 model, along with an LCA assessment of Washington's refinery emissions could enhance the accuracy of the fossil fuel baseline.

Allocate unspecified electricity based on more granular consumption data and incorporate additional electricity emission factors for waste-derived electricity. The existing work to develop a WAMX emission factor for Washington already reflects a more accurate estimate of state-specific electricity emissions than using either the California CAMX emission factor or the national-average emission factor. The impacts of data gaps on the estimated grid mix are relatively minor. However, we note that the attribution of the entire "unspecified" electricity category to natural gas may overstate emissions attributable to the electricity grid. Therefore, we recommend allocating the unspecified share of electricity to subsets of the electricity generation mix based on methodology previously used by WA Department of Commerce. Further, we recommend the inclusion of additional emission factors for landfill gas and waste-to-energy to more precisely attribute emissions from these pathways.

In the longer-term, we recommend that Washington updates its electricity CI to match ongoing changes in the electricity mix. As part of these updates, we recommend additional analysis and disclosure of electricity sources to reduce the uncertainty associated with unspecified electricity.

Include jet fuel fossil fuel baseline as a benchmark for alternative jet fuels. LC Associates estimated the life-cycle impact of fossil jet fuel to be approximately 10 gCO2e/MJ lower than that of gasoline and diesel fuel, consistent with previous estimates. Therefore, while fossil jet is not a deficit-generating fuel in the CFP, it may still be inappropriate to calculate GHG reductions from alternative aviation fuels relative to diesel or gasoline. Therefore, we recommend the inclusion of fossil jet fuel as a benchmark for assessing the GHG savings of alternative aviation fuels on an opt-in basis, similar to the inclusion of aviation fuels in the California LCFS.

Include AR 5 GWP values in WA-GREET. Since the publication of the IPCC Fourth Assessment Report (AR4) in 2007, the scientific understanding of the climate impacts of non-CO2 greenhouse gases has grown significantly, particularly their feedback effects. In order to reflect these changes and better align with forthcoming changes to greenhouse gas inventory reporting, we recommend that WA-GREET incorporate global warming potentials from the IPCC Fifth Assessment Report (AR5). This change would likely have a minimal effect on most pathways' estimates, except for those with high methane leakage or upstream avoided methane emissions.

Incorporate the full set of Indirect Land-Use Change emission factors used in the California Low-Carbon Fuel Standard. This peer review summarizes the literature on indirect land-use change and notes several weaknesses associated with the GTAP-BIO model and CCLUB land conversion emissions model, particularly with respect to underestimating the emissions impacts of cropland-pasture conversion, treatment of unmanaged forestland within the model, and assumptions of price-induced yield improvements. After more than a decade of research, ILUC emissions remain uncertain due to data limitations as well as disagreements on model choice, scenario design and risk tolerance. We find that the choice of the Oregon CFP value of 7.6 gCO_2e/MJ for corn and sorghum reflects recency and is not justified by the full body of literature on corn ILUC, particularly on soil carbon changes. Therefore, we recommend adopting the full set of existing ILUC estimates calculated previously by CARB for the California LCFS, which uses the AEZ-EF model for estimating land conversion emissions rather than CCLUB. We also recommend against including a 0 gCO_2e/MJ ILUC factor for cover crops; in order to justify this, we recommend the development of a formal definition for cover cropping and a system to ensure that these crops are being grown as cover crops without displacing existing cropland.

To develop a more robust assessment of ILUC in the WA CFP context, we recommend that in the long-term WA ECY develops an ILUC assessment of the impact of the CFP to better understand the interaction between the policy and indirect, market-mediated emissions in coordination with stakeholders, academic experts and regulators at EPA and CARB. We recommend that WA ECY consider other models beyond GTAP-BIO, and in particular, if the GTAP-BIO model is used, we recommend the use of the AEZ-EF model for estimate land conversion emissions.

Environmental outcomes of the US Renewable Fuel Standard

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The Renewable Fuel Standard (RFS) specifies the use of biofuels in the United States and thereby guides nearly half of all global biofuel production, yet outcomes of this keystone climate and environmental regulation remain unclear. Here we combine econometric analyses, land use observations, and biophysical models to estimate the realized effects of the RFS in aggregate and down to the scale of individual agricultural fields across the United States. We find that the RFS increased corn prices by 30% and the prices of other crops by 20%, which, in turn, expanded US corn cultivation by 2.8 Mha (8.7%) and total cropland by 2.1 Mha (2.4%) in the years following policy enactment (2008 to 2016). These changes increased annual nationwide fertilizer use by 3 to 8%, increased water quality degradants by 3 to 5%, and caused enough domestic land use change emissions such that the carbon intensity of corn ethanol produced under the RFS is no less than gasoline and likely at least 24% higher. These tradeoffs must be weighed alongside the benefits of biofuels as decision-makers consider the future of renewable energy policies and the potential for fuels like corn ethanol to meet climate mitigation goals.

biofuels | land use change | greenhouse gas emissions | water quality | environmental policy

Bioenergy is an essential component of most proposed pathways to reduce anthropogenic greenhouse gas (GHG) emissions and limit global warming to 1.5 or 2 °C by middle to late century (1–6). Liquid biofuels may contribute to bioenergy's share of climate mitigation by displacing petroleum-based fuels with those generated from modern-day plants (7, 8). The GHG benefits of such substitution, however, are dependent on several factors including whether biofuel production invokes additional plant growth (9–12), the extent to which combusted plants (typically crops) are replaced in the food system (13–15), and the degree to which biofuel production directly and indirectly alters patterns of land use and management (2, 16–20). Because land use changes (LUCs) and other consequences induced by biofuels have the potential to cause significant novel GHG emissions and modify other ecosystem services and disservices (21–26), accurately estimating and accounting these outcomes is critical for the formation of effective climate and environmental policy (27–29).

The United States is the world leader in biofuel production by volume and generated 47% of global output over the last decade under the purview of its Renewable Fuel Standard (RFS) (30). First enacted in 2005 and greatly expanded in 2007, the RFS requires that biofuels be blended into the transportation fuel supply at annually increasing increments. Volume targets exist for several advanced biofuel types including biomass-based diesel and those made from cellulosic feedstocks. However, the vast majority (~87%) of the mandate to date has been fulfilled by conventional renewable fuels, specifically corn grain ethanol (30, 31), such that the potential benefits of its more advanced fuel requirements have not yet materialized (32–34).

To comply with the policy's GHG reduction goals, the RFS requires conventional renewable fuels to generate life cycle GHG savings of at least 20% relative to gasoline. Upon enactment, the policy's regulatory analysis projected that life cycle emissions of corn ethanol production would just clear the 20% threshold by 2022, even when emissions from LUC were included (35). At the time, most LUC emissions were projected to occur internationally. Since the initial RFS policy-making, however, observations of widespread land conversion and resultant GHG emissions within the United States have also emerged (36–39).

Heightened demand for crops for use as biofuel feedstocks and the associated changes to landscapes may also engender broader environmental disservices upon ground and surface waters, soil resources, and other ecosystem components (40–44). The magnitudes of such effects are highly uncertain, however, as they ultimately depend upon unpredictable behaviors throughout the supply chain—from field to refinery—making it difficult to forecast impacts. As such, public policy-making and support for biofuels has needed to rely on widely varying projections of

ENVIRONMENTAL SCIENCES

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Significance

Biofuels are included in many proposed strategies to reduce anthropogenic greenhouse gas emissions and limit the magnitude of global warming. The US Renewable Fuel Standard is the world's largest existing biofuel program, yet despite its prominence, there has been limited empirical assessment of the program's environmental outcomes. Even without considering likely international land use effects, we find that the production of corn-based ethanol in the United States has failed to meet the policy's own greenhouse gas emissions targets and negatively affected water quality, the area of land used for conservation, and other ecosystem processes. Our findings suggest that profound advances in technology and policy are still needed to achieve the intended environmental benefits of biofuel production and use.

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anticipated effects—a quandary that could potentially misguide strategies for climate change mitigation and environmental protection (27, 28, 45).

The RFS legislation contains several environmental safeguards to try to prevent perverse outcomes including periodic scientific review of the conservation impacts of the program and opportunities to adjust annual fuel volumes if the program creates severe environmental harm (31). Although the most recent program review identified that biofuels may in fact be contributing to land conversion and subsequent declines in water quality, these impacts have not been causally attributed to biofuels or the RFS (32). Likewise, volume requirements for specific fuel types have not been revised based on environmental performance (31). Given the United States' leading role in biofuel production, understanding the outcomes of the RFS has direct ramifications not only for national environmental quality and global climate change but also for policy-making around the world as governments seek to modify or develop their own biofuel policies to meet climate and clean energy goals.

Here we assess the effects of the RFS on US land and water resources during the first 8 y of the policy's implementation (2008 to 2016) by integrating econometric analyses with observed changes in agricultural land use and models of biophysical impacts. We analyze how demand from the RFS affected corn, soybean, and wheat prices and how these price shocks influenced the areas planted to specific crops and cropland overall. We then assess how these changes affected key environmental indicators including nitrate leaching, phosphorus runoff, soil erosion, and GHG emissions. For all estimates, we compare outcomes under the 2007 RFS to a business-as-usual (BAU) counterfactual scenario in which ethanol production satisfies only the volume required by the initial 2005 version of the policy, equivalent to the amount needed for reformulated gasoline under the 1990 Clean Air Act. We apply our models only domestically, such that any environmental effects that occur outside the United States would be additional.

Our analyses show a modest change in the use of US agricultural land for crop production due to the RFS, which led to sizable increases in associated environmental impacts including nitrate leaching, phosphorus runoff, and soil erosion. While improvements in production efficiency have likely reduced the carbon intensity of corn ethanol since inception of the RFS, the previously underestimated emissions from US land conversion attributable to the policy are enough to fully negate or even reverse any GHG advantages of the fuel relative to gasoline. Our findings thereby underscore the importance of including such LUCs and environmental effects when projecting and evaluating the performance of renewable fuels and associated policies.

Results and Discussion

We found that the RFS stimulated 20.8 billion L (5.5 Bgal) of additional annual ethanol production, which requires nearly 1.3 billion bushels of corn after accounting for coproducts that can be fed to animals (46). This heightened demand led to persistent increases in corn prices of ~31% (95% confidence interval [CI]: 5%, 70%) compared to BAU (Fig. 1). The increased demand for corn also spilled over onto other crops, increasing soybean prices by 19% [−8%, 72%] and wheat by 20% [2%, 60%] (*SI Appendix*, Table S1). These outcomes approximate the contribution of the RFS policy specifically, although other factors including changes in fuel blending economics that favored 10% ethanol as an octane source in gasoline (E10) may also have contributed (*SI Appendix*, *Supplementary Results for Price Impacts*).

The increase in corn prices relative to other crops increased the area planted to corn on existing cropland by an average of 2.8 Mha* per year [95% CI: 2.4, 3.1], which is an 8.7% increase attributable to the RFS. This additional area resulted from producers planting corn more frequently, including a 2.1 Mha [1.8, 2.3] increase in continuous corn production (i.e., sequential year cropping) and a 1.4 Mha [0.8, 1.9] increase in the area planted in rotation with other crops (*SI Appendix*, *Supplementary Results for Crop Rotations* and Fig. S1). Collectively, corn area increased most markedly in North and South Dakota, western Minnesota, and the Mississippi Alluvial Plain—regions where the amount of corn increased 50 to 100% due to the RFS (Fig. 2*A* and *SI Appendix*, Fig. S1).

Heightened commodity prices from the RFS also increased active cropland extent. We estimate that the RFS caused conversion of an additional 1.8 Mha [95% CI: 1.5, 2.1] of natural and seminatural areas to cropland between 2008 and 2016, or 26% more than would have otherwise likely occurred (*SI Appendix*, *Supplementary Results for Cropland Area* and Table S2). Higher prices also reduced cropland abandonment; less cropland was returned to grass or natural cover, either as pasture or through enrollment into the Conservation Reserve Program (CRP), a federal set-aside that pays farmers to reestablish perennial vegetation. We estimate that the RFS decreased abandonment by 0.4 Mha [0.1, 0.6], or 6% less abandonment than expected with BAU. Together these extensive changes produced a net increase in cropland area of 2.1 Mha [1.8, 2.5] relative to BAU, with the greatest increases occurring in the western portions of existing agricultural regions (Fig. 2*B* and *SI Appendix*, Fig. S2).

The combined changes in the intensity of corn production and extent of cropland caused 7.5% more reactive nitrogen (N) from synthetic fertilizer to be applied annually to the landscape (Table 1). This contributed to a 5.3% increase in nitrate (NO_3^-) leached annually from agricultural land due to the RFS. Such nitrate losses occurred through vertical seepage below the root zone, where nutrients are no longer accessible to crops, and have been implicated in widespread groundwater contamination throughout the United States with major public health consequences (47, 48). Leaching was highest in regions with high N inputs and coarse soil texture (Fig. 2*F* and *SI Appendix*, Figs. S3 and S4), with nearly two-thirds of the overall nitrate increase stemming from changes to crop rotations.

The RFS also increased total edge-of-field phosphorus (P) runoff by 3.2% (Fig. 2*I* and *SI Appendix*, Figs. S5 and S6). This change was driven by a 3.5% increase in total P applications (Fig. 2*G*) and a 4.7% increase in soil erosion (Fig. 2*H*), which transports dissolved and sediment-bound P to downstream surface waters, where it often causes eutrophication and harmful algal blooms (41, 47, 49). Erosion losses from crop fields can also degrade soil quality over time (50, 51), contribute to enhanced GHG emissions in waterways (52), and impair water quality and aquatic habitat (53, 54) including that of threatened and endangered species (55, 56).

Collectively, increased nitrate leaching, phosphorus runoff, and soil erosion from the RFS fall within the range of outcomes projected at its outset (41, 57, 58) and substantiate longstanding concerns about the policy's environmental disservices. However, we find disproportionate effects and distinct spatial patterns from different pathways of land use response. Shifting crop rotations toward more corn increased N fertilizer applications and nitrate leaching by nearly twice that of cropland area changes, due largely to the high N requirements of corn relative to other crops. In contrast, erosion-driven P and soil losses

*See *SI Appendix* results: Our model of key growing regions accounts for 91.6% of corn acres in the United States. If one assumes a similar response in the remaining unmodeled area, then the nationwide change is 3.0 Mha or 8.9% more than the amount expected without the RFS.

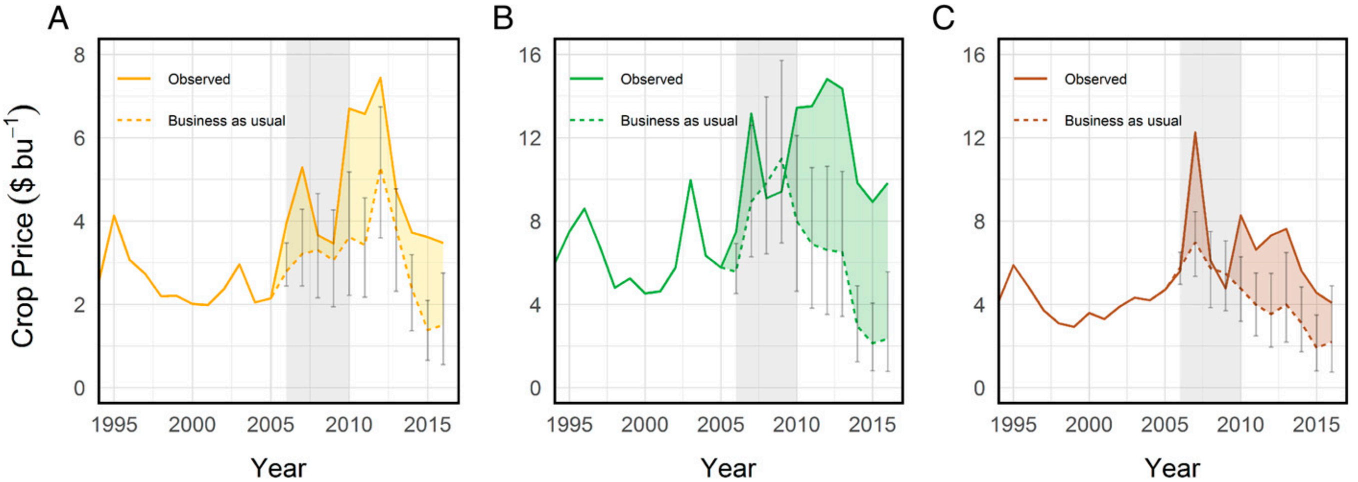

Fig. 1. Observed and BAU estimates for crop prices. (*A*) Corn. (*B*) Soybeans. (*C*) Wheat. Vertical bars represent the 95% CIs for each BAU spot price. Each year denotes a crop year; e.g., 2006 is September 2006 to August 2007 for corn and soybeans and June 2006 to May 2007 for wheat. Averages for 2006 to 2010 (highlighted in gray) were used to derive the estimates in the text, although long-run persistent impacts were consistent with these results (46).

from cropland area expansion were roughly two and three times greater, respectively, than those from increased corn planting—a difference that reflects substantially higher erodibility and P inputs of croplands relative to uncultivated land, particularly in the marginal, steeper-sloped areas that were converted (e.g., *SI Appendix*, Fig. S6*I*) (37, 59, 60).

Beyond its water quality effects, the RFS substantially increased on-site GHG emissions from cropping systems. We found that greater use of N fertilizer increased nitrous oxide (N_2O) emissions by 8.3% or 4.1 Tg CO_2e y^{-1} relative to BAU (Fig. 2*E*). Most of this (68%) can be attributed to intensified corn production on preexisting fields, where emissions increased by 5.7%, with the remainder emitted from the expanded croplands.

In addition to these annual fertilizer application emissions, degradation of ecosystem carbon (C) stocks from cropland expansion led to a substantial pulse of committed GHG emissions. These arise from clearing land for crop production and are typically realized over a period of roughly 30 y unless proactively mitigated (35, 61). We estimate emissions associated with RFS-induced conversion to cropland to be 320.4 Tg CO_2e [95% CI: 250.5, 384.3], or ∼181 Mg CO_2e ha^{-1}.

Further, reduced rates of cropland retirement—through CRP enrollment or transition to pasture—has reduced C sequestration that would have otherwise resulted from perennial grassland reestablishment and recovery. We estimate this forgone sequestration at 77.3 Tg CO_2e [95% CI: 30.8, 126.8], assuming that abandoned land would accumulate carbon for 15 y—the standard duration of a single CRP contract—after which its carbon fate becomes contingent upon subsequent management. Combined, the RFS-driven changes in cropland area between 2008 and 2016 caused a total net C flux of 397.7 Tg CO_2e [313.3, 481.7] to the atmosphere (Fig. 2*C*).

Domestic LUC emissions spurred by the RFS undermine the GHG benefits of using ethanol as transportation fuel. Assuming 30-y amortization, ecosystem C emissions from the RFS-induced LUC equate to 637 g CO_2e L^{-1} of increased annual ethanol production or an emissions intensity of 29.7 g CO_2e MJ^{-1} (*SI Appendix*, Table S3). Including on-site annual nitrous oxide emissions from increased fertilizer application further increases these emissions to 831 g CO_2e L^{-1} or 38.7 g CO_2e MJ^{-1}. These findings stand in stark contrast to the −3.8 g CO_2e MJ^{-1} of domestic LUC emissions estimated by the RFS regulatory impact analysis (RIA) and surpass the 30.3 g CO_2e MJ^{-1} estimated by the RIA for international LUC (35).

Substituting our empirically derived domestic emissions for those modeled in the RFS RIA would raise ethanol's projected life cycle GHG emissions for 2022 to 115.7 g CO_2e MJ^{-1}—a value 24% above baseline gasoline (93.1 g CO_2e MJ^{-1}). The RIA estimate, however, includes improvements in feedstock and ethanol production efficiency that were projected to occur by 2022, such that the GHG intensity of ethanol produced at earlier time periods and over the life of the RFS to date is likely much higher [*SI Appendix*, *Supplementary Results for Greenhouse Gas (GHG) Emissions from Land Use Change (LUC)*].

Incorporating the domestic LUC emissions from our analysis into other fuel program estimates similarly annuls or reverses the GHG advantages they calculate for ethanol relative to gasoline (Fig. 3 and Table 2). However, life cycle GHG emissions accounting requires consistent treatments and system boundaries across analyses (27, 64–66). As such, a full reanalysis, rather than the partial revisions we illustrate here, should be conducted to accurately assess ethanol's carbon intensity relative to other fuels, particularly given the magnitude of domestic LUC emissions identified. For instance, we likely underestimate total domestic LUC impacts since we consider only the on-site ecosystem C and nitrous oxide emissions but do not account for additional emissions from increased fertilizer production (67) or from water quality–related increases in N, P, and sedimentation, which have been shown to augment GHG emissions in downstream waterways (52, 68, 69).

Furthermore, we assess only the domestic (US) impacts of the RFS and expanded corn ethanol production. However, evidence of such effects reaffirms the likely presence of international LUC in response to the RFS (16, 19, 28, 70). As such, our results should be considered the lower bound for total GHG and other environmental impacts. We also limit our focus to select environmental outcomes but note that interconnected outcomes related to food systems (13, 14), human health (71), and the welfare of different groups of society (72) likely exist. For example, several assessments of the GHG implications of the RFS model a concomitant reduction in global food and feed consumption (13, 19).

Although we describe the incremental effects of the expanded RFS program, our findings are representative of the observed outcomes from corn ethanol development broadly, regardless of the cause. Our estimates imply that for every billion gallons per year (BGY) expansion of ethanol demand, we would expect a 5.6% increase in corn prices; 1.6 and 0.4% increases in the areas

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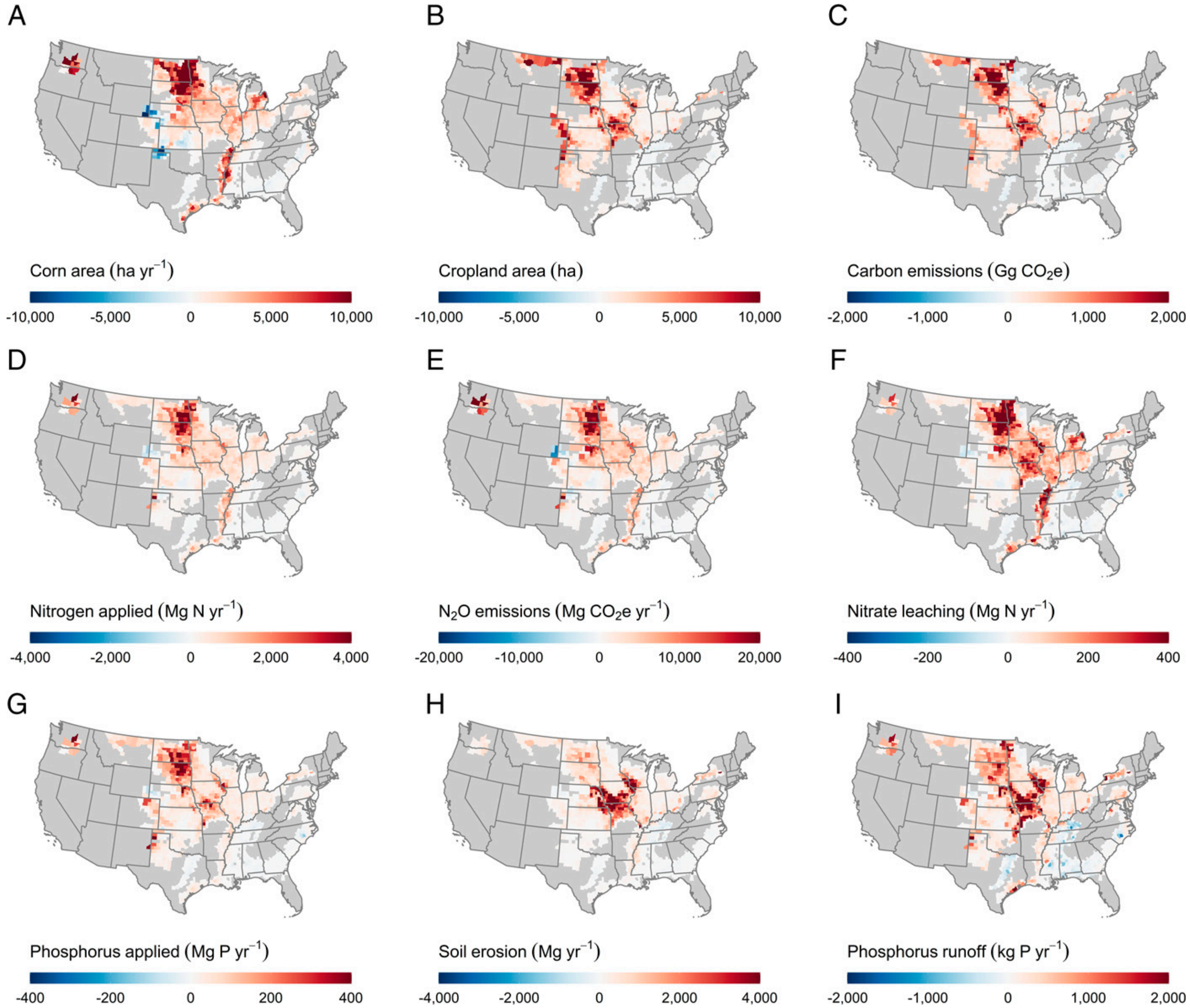

Fig. 2. Changes due to the RFS. (*A*) Corn planted area. (*B*) Cropland area. (*C*) Carbon emissions. (*D*) Nitrogen applications. (*E*) Nitrous oxide emissions. (*F*) Nitrate leaching. (*G*) Phosphorus applications. (*H*) Soil erosion. (*I*) Phosphorus runoff. Positive numbers indicate an increase due to the RFS. Field-level results were aggregated to the county level for enumeration and visualization.

of US corn and cropland, respectively; and attendant increases in GHG emissions, nutrient pollution, and soil erosion (Table 1; %Δ per BGY). Our findings are also specific to corn ethanol and do not reflect advanced renewable fuels, which have lower production volumes and are required to meet stricter GHG reduction thresholds. To date, however, most RFS biofuel production has come from conventional corn ethanol, thereby missing much of the policy's promised emissions savings and potential environmental benefits expected from more advanced feedstocks (2, 35, 73).

Despite the strong environmental tradeoffs under the RFS thus far, biofuels and bioenergy may play a key role in stabilizing atmospheric CO_2 concentrations and holding global warming below 1.5 or 2 °C, particularly with continued advancements like carbon capture and storage (2, 4, 74–76) and increased productivity from perennial feedstocks grown on marginal lands (77–80). However, our findings confirm that contemporary corn ethanol production is unlikely to contribute to climate change mitigation. Given the current US dependence on this fuel, there remains an urgent need to continue the research, development, and shift toward more-advanced renewable fuels, improved transportation efficiency, and electrification (74, 81–83).

The United States is currently at a bioenergy crossroads. The RFS specifies biofuel volumes through 2022; absent legislative action, the Environmental Protection Agency (EPA) will determine volumes for subsequent years. If conventional biofuel volumes were to increase, it is likely that further increases in crop prices, LUC, and environmental impacts would ensue. Alternatively, a decrease in mandated volumes may have less effect, given the capital investment, established markets, and economic value of producing ethanol at existing levels. More broadly, any increases in demand for corn ethanol from nonfederal jurisdictions, including US states or trade partners like Canada and China, are likely to exacerbate the domestic land use and environmental outcomes identified here.

As policy-makers worldwide deliberate the future of biofuels, it is essential that they consider the full scope of the associated tradeoffs, weighing the GHG and other environmental externalities alongside each fuel's benefits. By quantifying and attributing the outcomes of policy thus far, our findings provide

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Table 1. Net changes due to the RFS

	Land use		GHG emissions		Environmental indicators				
	Corn area (Mha y^{-1})	Cropland area (Mha)	Nitrous oxide ($TgCO_2e\ y^{-1}$)	Ecosystem carbon ($TgCO_2e$)	N applied (Gg-N y^{-1})	P applied (Gg-P y^{-1})	Nitrate leaching (Gg-N y^{-1})	P runoff (Mg-P y^{-1})	Soil erosion (Gg y^{-1})
Crop rotation Δ	2.8	—	2.8	—	480.0	21.3	87.1	203.2	222.9
95% CI lower limit	2.4	—	2.3	—	377.3	1.2	56.9	−27.7	11.6
95% CI upper limit	3.1	—	3.2	—	577.0	41.2	117.7	449.3	423.6
Cropland extent Δ	—	2.1	1.3	397.7	237.3	48.2	47.9	439.0	633.9
95% CI lower limit	—	1.8	1.0	313.3	190.5	38.4	33.5	273.6	485.9
95% CI upper limit	—	2.5	1.5	481.7	281.8	57.7	62.1	592.6	780.6
Combined total Δ	2.8	2.1	4.1	397.7	717.2	69.5	135.0	642.2	856.7
95% CI lower limit	2.4	1.8	3.5	313.3	626.7	58.9	111.6	476.9	697.6
95% CI upper limit	3.1	2.5	4.5	481.7	806.5	79.5	157.8	798.0	1,011.4
BAU baseline	31.7	88.4	48.6	—	9,545.5	1,986.4	2,535.5	19,939.3	18,038.7
%Δ from BAU	8.7%	2.4%	8.3%	—	7.5%	3.5%	5.3%	3.2%	4.7%
%Δ per BGY	1.6%	0.4%	1.5%	—	1.4%	0.6%	1.0%	0.6%	0.9%

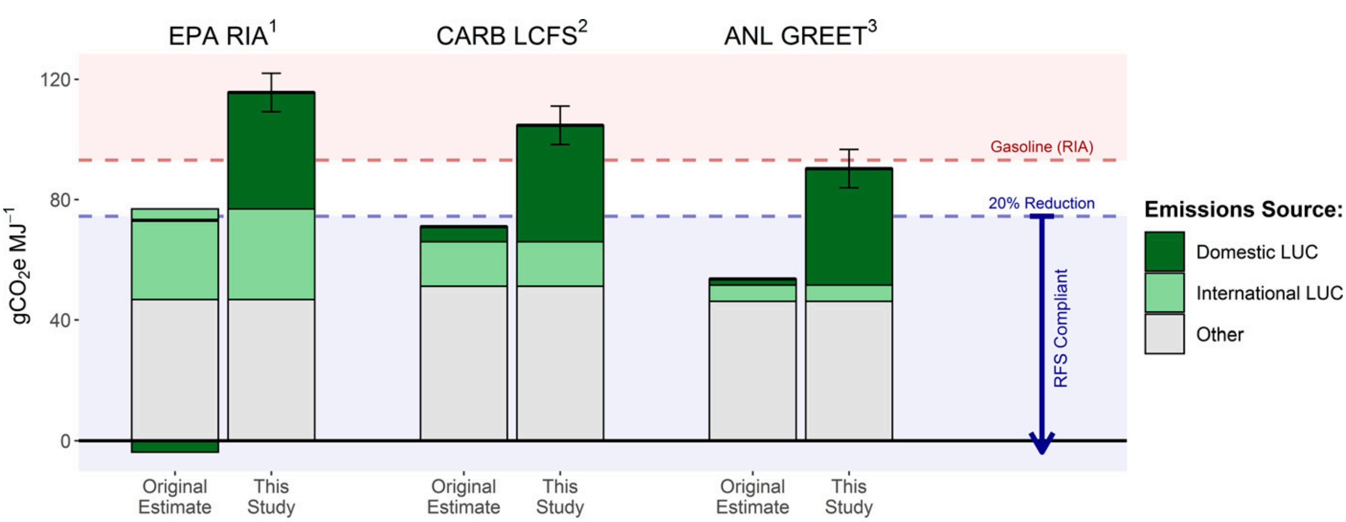
%Δ from BAU = percent change from BAU; i.e., the incremental effect of the 2007 expansion of the RFS; %Δ per BGY = percent change per BGY increase in ethanol demand.

fundamental evidence to guide this process and set realistic expectations for the contribution that current biofuel technologies can make toward climate mitigation and other environmental goals.

Materials and Methods

We estimated the domestic environmental effects of the 2007 US RFS by linking a series of empirical and explanatory models. First, we estimated the impacts of the RFS on the prices of corn, soybeans, and wheat. We then simulated, via independent models, the responses of crop rotations and total cropland area to the changes in crop prices. Last, we quantified the associated environmental outcomes by employing models specific to water quality indicators, nitrous oxide emissions, and ecosystem carbon emissions and updated existing life cycle estimates of ethanol's GHG intensity to reflect these findings.

Overall, our retrospective and purpose-built integrated assessment modeling framework has several advantages over previous projections and more generalized approaches. For example, 1) we utilize observed rather than predicted crop prices and land uses as a baseline factual scenario against which we compare our counterfactual scenario, thereby eliminating one (of the two) sets of assumptions, projections, and uncertainties required for assessment; 2) our estimates of the effects on crop prices and land use are based on empirical assessments of observed changes rather than partial or general equilibrium models that rely heavily on assumptions and prescribed parameters; 3) we use historic changes in crop prices, crop rotations, and cropland area to validate our econometric models' predictions and show strong temporal and regional fits between projected and observed changes; and 4) we utilize field-level remote sensing data to detect the location of actual LUCs—rather than rely on assumptions about the type, location, and characteristics of converted lands—and use this information to more accurately estimate the environmental impacts of conversion. We also implemented several model-specific



[1]U.S. Environmental Protection Agency (EPA) Regulatory Impact Assessment (RIA); Projection for 2022.
[2]California Air Resources Board (CARB) Low Carbon Fuel Standard (LCFS); Estimated from approved values for 2019, see SI Appendix.
[3]Argonne National Laboratory (ANL) Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) model; Default values from 2020.

Fig. 3. GHG emission intensities for corn ethanol with and without updated domestic LUC emissions. Original estimates reflect GHG intensities of corn ethanol according to the US EPA RIA [projection for 2022 (35)], California Air Resources Board (CARB)'s Low Carbon Fuel Standard (LCFS) [estimated from approved values for 2019 (62); *SI Appendix*], and Argonne National Laboratory (ANL)'s Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) model [default values for 2020 (63)]. Revised estimates (this study) replace the estimated domestic LUC emission from each source with those identified in this study. Our domestic LUC emissions estimate includes ecosystem carbon losses (including methane) from land conversion and on-site nitrous oxide emissions from additional fertilizer usage but excludes all other upstream and downstream emissions. Error bars represent 95% CIs for emissions from domestic LUC only (*SI Appendix*).

Table 2. GHG emissions intensities for LUC, total ethanol, and reference gasoline

	kg CO_2e/mmBtu	g CO_2e/MJ	% change from gasoline
LUC emissions			
This study, domestic	40.9	38.7	—
EPA RIA*, domestic	−4.0	−3.8	—
EPA RIA*, international	31.8	30.1	—
CARB LCFS†, combined	20.9	19.8	—
GREET‡, domestic	2.1	2.0	—
GREET‡, international	5.7	5.4	—
Total ethanol			
RIA*	77.2	73.2	−21.4%
RIA* + this study	122.1	115.7	24.3%
LCFS†	74.9	71.0	−23.7%
LCFS† + this study	110.4	104.7	12.5%
GREET‡	56.6	53.6	−42.4%
GREET‡ + this study	95.3	90.3	−3.0%
Other			
RIA gasoline*	98.2	93.1	0.0%

*US EPA RIA; projection for 2022 (35).
†CARB LCFS; approved values for 2019 (62).
‡ANL GREET model; default values for 2020 (63).

advances to improve the resolution, specificity, and performance of each individual component of analysis. We briefly describe each step of our analysis and its integration below and provide the full details in *SI Appendix*.

Effects on Crop Prices. We used a partially identified vector autoregression model to assess the effects of the RFS on US crop prices. Our approach closely follows that of Carter et al. (46) to account for competing shocks in demand due to changes in inventory, weather, and external markets and extends the work beyond corn to estimate the impacts of the RFS on soybean and wheat prices. We also incorporate the RFS policy as a persistent shock to agricultural markets rather than a transitory shock, whose price impacts are different (*SI Appendix, Estimating Effects on Crop Prices*).

In our analysis, we compare observed market prices to a counterfactual BAU scenario without the expanded 2007 RFS, where BAU ethanol production satisfies only the volume required by the initial 2005 RFS. This volume is roughly equivalent to the amount needed to meet oxygenate requirements for reformulated gasoline under the 1990 Clean Air Act. Our analysis therefore estimates the effects of the 2007 expansion of the RFS program above what would have otherwise likely occurred to meet demand for ethanol as an oxygenate after ethanol replaced methyl tert-butyl ether as the main oxygenate additive. As such, we assume the pre-2007 trend of increasing ethanol use would have continued without the expanded RFS, albeit at a slower rate.

Additional factors such as the Volumetric Ethanol Excise Tax Credit or improved cost competitiveness may have also contributed to ethanol's growth. Our price effects are scalable, however, such that all land use, environmental quality, and GHG emissions that we report would remain the same on a per volume of ethanol basis, independent of the magnitude of demand change (within reasonable limit) or its source. Thus, our results also reflect observed outcomes from corn ethanol development in general, irrespective of whether such changes were driven by policy, markets, or other factors.

Effects on Crop Rotations. After modeling the price impacts of the RFS, we followed the approach of Pates and Hendricks to estimate how changes in crop prices affected crop rotations and the likelihood of planting continuous corn, continuous other crops, and corn–other crop rotations (49, 84, 85). We estimated a set of Markov transition models to separately estimate the probability of planting corn conditional on the crop planted in the prior season. One model estimates the probability of planting corn given corn was the previous crop, and the other estimates the probability of planting corn given a different crop was the previous crop. We then used these transition probabilities to estimate the probability of each crop rotation. To account for price response heterogeneity, we separately estimated these models for each major land resource area (MLRA) and major soil texture group. Advantages of our approach are that it explicitly accounts for the common practice of rotating crops and spatially heterogeneous responses to price across the country, as previous work shows that using aggregate data or ignoring price response heterogeneity can significantly bias estimates (84, 85). Furthermore, our model allows us to assess the location of environmental impacts as they relate to variation in price response.

To estimate the models, we built a spatiotemporal database using field boundary data (86–88) and associated information on annual crop type (89), soil properties (90), and climate (91) as well as crop futures and local spot prices (92). We then calculated the rotation probabilities for all fields greater than 15 acres that were in regions where 1) greater than 20% of the total area was cropland, 2) more than 10% of cropland acreage was planted to corn, and 3) greater than 50% of the cropland not planted to corn was planted to a crop for which prices were available (specifically wheat, soybeans, rice, and cotton). This set of criteria ensured adequate data were available to train each model, and our final sample included 3.6 million fields that accounted for 91.6% of corn acreage in the United States. Based upon results of the price impact modeling, we used a 30% persistent increase in the price of corn and 20% increases in the prices of soybeans and wheat to estimate, for each field, the change in probability of each rotation due to the RFS. We then derived area estimates using field sizes and summed the results across all fields and rotations (*SI Appendix, Estimating Effects on Crop Rotations*).

Cropland Area Changes. To assess LUCs at the extensive margin, we estimated the probability of transitioning between cropland and pasture or transitioning between cropland and CRP as a function of cropland, pasture, and CRP returns while controlling for soil and climate characteristics. We used a correlated random effects model to reduce concerns about endogeneity because the spatial variation in returns may be correlated with any omitted variables that affect land use transitions. Thus, our model is designed to better isolate the effect of changes in cropland returns on cropland transitions than other approaches that may confound differences in cropland returns across space with other unobserved factors that affect cropland transitions. We also account for the fact that land can only enter CRP when a sign-up is offered and can only exit CRP when the contract expires.

The model uses point-level land use transition data based on observed annual land use transitions in the National Resources Inventory (NRI) from 2000 to 2012. We then used the model to predict the change in transitions between 2008 and 2016 based on changes in prices (39). During this period, we predicted changes for 8 y, with the first transitions occurring between the 2008 and 2009 growing seasons. This approach may thus underestimate the total extensive land response to the RFS, as some land likely came into production prior to the 2009 growing season and after the 2016 growing season. In order to allow for geographic variation in the extensive response of land use to crop prices, we trained independent models for each of seven different land resource regions (LRRs) corresponding to aggregated MLRAs from the Natural Resources Conservation Service (*SI Appendix, Estimating Effects on Cropland Area*).

We then mapped observed LUC at field-level resolution during our study period following the general approach of Lark et al. (93) and using updated recommended practices (94, 95) to extend the analysis to 2008 to 2016 (37). These data were used to link the estimated extent of LUC associated with the RFS in each major LRR to specific locations of observed conversion for the purpose of enumerating environmental impacts. Thus, the high-resolution field data (37) were used only to identify the possible locations and characteristics of converted land, whereas the data from the NRI were used to estimate the magnitude of conversion and how much of it could be attributed to the RFS. This hybrid approach thereby combined the high certainty and long-term temporal coverage (prior to any RFS price signals) of the NRI data with the field-level specificity of the satellite-based land conversion observed during the study period (37, 94).

Nutrient Application and Water Quality Impacts. Rates of N and P application were developed using county-level estimates of fertilizer and manure application compiled by the US Geological Survey (96, 97), county-level estimates of area planted to specific crops from the Census of Agriculture (98), and typical fertilizer application ratios for the three major crop types (corn, soybeans, and wheat) from university extension publications (99). We then used these nutrient application estimates to drive a process-based agroecosystem model to simulate fluxes of water, energy, and nutrients across our study period for each crop rotation system across the United States as well as for each patch of converted land identified by the land transition model, following the approaches of Motew et al. (100) and Donner and Kucharik (41) (*SI Appendix, Estimating Water Quality Impacts*). To determine the impacts of the RFS from crop rotation changes, we multiplied the agroecosystem model outputs for each crop rotation by the change in its probability due to the RFS as determined via the econometric model described in the section *Effects on Crop*

Rotations. To estimate the impact from cropland transitions due to the RFS, we assessed the relative differences in ecosystem outputs between cropland and noncropland for each individual transitioned parcel and multiplied each by the proportion of land transitioned within each LRR due to the RFS.

GHG Emissions. We modeled changes in N_2O emissions from fertilizer applications using the nonlinear nitrogen effect model (NL-N-RR) of Gerber et al. (101). For each change in crop rotation or cropland area due to the RFS, we used the associated change in N application to estimate the corresponding change in N_2O emissions. N_2O emission estimates were converted to CO_2e by assuming a 100-y global warming potential of 265 (102).

We estimated the ecosystem carbon emissions associated with RFS-related LUC using the methods of Spawn et al. (36). Carbon emissions from soil and biomass degradation associated with LUC were modeled for all observed conversions to cropland. In addition, a variant of the Spawn et al. model was created to assess forgone sequestration associated with reduced rates of abandonment. This model was structurally similar to that used for conversion to cropland but used a carbon response function (61) for conversion to grassland to estimate expected soil organic carbon accumulation over a 15-y period—the average length of a CRP contract. We thus assumed that any abandoned land would have been retired to the CRP and sequestering carbon for the duration of its contract. To attribute emissions to the RFS, we multiplied the combined net change in emissions from all observed LUC within a given LRR by the percentage of that region's observed LUC that could be attributed to ethanol under the RFS.

To estimate emissions per liter of increased annual ethanol demand, we followed the approach of the EPA (35) and allocated total ecosystem carbon emissions over a 30-y period. We then added these amortized ecosystem carbon emissions to the annual nitrous oxide emissions from crop rotation and cropland area changes to estimate total annual emissions. We divided total annual emissions due to the RFS by the increased annual demand in ethanol estimated in our price impacts model and subsequently converted to emissions per unit of energy equivalent using a heating value of 21.46 MJ/L (35).

Estimating Uncertainty. We quantified uncertainty at multiple points of our causal analysis framework including the price impact analyses, the crop rotation and cropland transition analyses, and the environmental impact modeling (*SI Appendix, Estimating Uncertainty*). Except for the price impacts, we propagated the uncertainty results throughout the connected components—from the land use models through to all subsequent environmental outcomes. All results are presented in the main text as 95% CIs, reported as [lower limit (0.025 quantile), upper limit (0.975 quantile)].

Data Availability. All national and regionally aggregated data are available in the main text and *SI Appendix*. All underlying field-level data aggregated to counties have been deposited in a permanent repository (https://doi.org/10.5281/zenodo.5794632). Code developed for and used in this study is available on GitHub (https://github.com/gibbs-lab-us/). All other study data are included in the article and *SI Appendix*. Previously published data were also used in this work (https://doi.org/10.5281/zenodo.3905242).

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NMED
EXHIBIT
139-C

Model Comparison Exercise Technical Document

United States Environmental Protection Agency

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Transportation and Climate Division
Office of Transportation and Air Quality
U.S. Environmental Protection Agency

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Executive Summary

A primary policy goal of the Renewable Fuel Standard (RFS) program is to reduce greenhouse gas (GHG) emissions by increasing the use of renewable fuels, such as ethanol and biodiesel. In the Energy Independence and Security Act (EISA), Congress required that biofuels used to meet the RFS obligations achieve certain lifecycle GHG reductions. To qualify as a renewable fuel under the RFS program, a fuel must, among other requirements, be produced from qualifying feedstocks and have lifecycle GHG emissions that are at least 20 percent less than the baseline petroleum-based gasoline and diesel fuels.[1] To determine whether fuels meet the lifecycle GHG emissions threshold requirement, EPA developed a methodology to evaluate the lifecycle GHG emissions of renewable fuels. EISA also provided a definition of "lifecycle greenhouse gas emissions" to guide this methodology.[2]

In the March 2010 RFS2 rule, EPA used lifecycle analysis (LCA) to estimate the GHG emissions associated with several biofuel production pathways, i.e., the emissions associated with the production and use of each biofuel, including significant indirect emissions, on a per-unit energy basis. At the time of the analysis for the 2010 RFS2 rule, there were no models available "off the shelf" that could perform the type of lifecycle analysis required by EISA. Several supply chain LCA tools existed at the time, e.g., the Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies Model (GREET). However, EPA determined in the final RFS2 rule that these tools, when used on their own, lacked the ability to consider significant indirect emissions, one of the core statutory requirements of the EISA definition of lifecycle greenhouse gas emissions. EPA thus developed a new modeling framework to perform the required analysis. The framework EPA developed and ultimately used in the 2010 RFS2 rule included multiple models and data sources, including the Forest and Agricultural Sector Optimization Model with Greenhouse Gases model (FASOM), the Food and Agricultural Policy Research Institute international model developed at the Center for Agriculture and Rural Development at Iowa State University (the FAPRI-CARD model, or, more simply, FAPRI), and the GREET model.[3]

Since the development of EPA's 2010 LCA methodology, multiple researchers and analytical teams have further studied and assessed the lifecycle GHG emissions associated with transportation fuels in general and crop-based biofuels in particular. New models have been developed to evaluate the GHG emissions associated with biofuel production and use, and more models developed for other purposes have been modified and expanded to evaluate biofuels as well. We now have over a decade of historic observations to compare with model results and parameters and to use in model calibration. There has also been rapid growth in available data on land use, farming practices, crude oil extraction and many other relevant factors. While the

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[1] See 42 USC 7545(o)(1), (2)(A)(i).

[2] EISA defines lifecycle greenhouse gas emissions as "the aggregate quantity of greenhouse gas emissions (including direct emissions and significant indirect emissions such as significant emissions from land use changes), as determined by the Administrator, related to the full fuel lifecycle, including all stages of fuel and feedstock production and distribution, from feedstock generation or extraction through the distribution and delivery and use of the finished fuel to the ultimate consumer, where the mass values for all greenhouse gases are adjusted to account for their relative global warming potential." CAA 211(o)(1)(H).

[3] EPA (2010). Renewable fuel standard program (RFS2) regulatory impact analysis. Washington, DC, US Environmental Protection Agency Office of Transportation Air Quality. EPA-420-R-10-006. Chapter 2.4.

results from our 2010 LCA methodology for the RFS program remain within the range of more recent estimates from the literature, we acknowledge that our previous framework is comparatively old, and that a better understanding of these newer models and data is needed. In consultation with our interagency partners at USDA and DOE, EPA hosted a virtual public workshop on biofuel GHG modeling on February 28 and March 1, 2022.[4] At this workshop, speakers within and outside of the federal government presented on available data, models, methods, and uncertainties related to the assessment of GHG impacts of land-based biofuels.

The workshop presentations and public input clarified that there continues to be substantial uncertainty and a wide range of estimates on the climate effects of biofuels, especially regarding biofuel-induced land use change emissions. Uncertainties in land use change emissions estimates stem from both economic modeling of market-mediated effects as well as biophysical modeling of soil carbon and other biological systems and processes. The workshop proceedings, including the workshop presentations and the comments submitted to the workshop docket, discussed a broad and complex set of topics. A general theme that emerged from this process is that, in support of a better understanding of the lifecycle GHG impacts of biofuels, it would be helpful to compare available models, identify how and why the model estimates differ, and evaluate which models and estimates align best with available science and data. Recognizing this need, we have conducted a model comparison exercise (MCE) to better understand these scientific questions.

While we are presenting the results of this MCE along with the RFS "Set" final rulemaking, the MCE does not model or otherwise inform the GHG impacts of the Set final volumes. Although this MCE produced GHG emission and carbon intensity results[5] from a range of models under different assumptions, we do not use these values in the context of RFS program implementation. For example, we do not use the MCE to determine whether or not fuel pathways meet the lifecycle GHG threshold requirements of the CAA. Rather, the MCE has three main goals:

1. Advance the science in the area of analyzing the lifecycle greenhouse gas emissions impacts from increasing use of biofuels.

2. Identify and understand differences in scope, coverage, and key assumptions in each model, and, to the extent possible, the impact that those differences have on the appropriateness of using a given model to evaluate the GHG impacts of biofuels.

3. Understand how differences between models and data sources lead to varying results.

We conducted this model comparison exercise with five models: the Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies Model (GREET), Global Biosphere Management Model (GLOBIOM), Global Change Analysis Model (GCAM), Global Trade

[4] For more information see the Federal Register Notice, "Announcing Upcoming Virtual Meeting on Biofuel Greenhouse Gas Modeling." 86 FR 73756. December 28, 2021. More information is also available on the workshop webpage: https://www.epa.gov/renewable-fuel-standard-program/workshop-biofuel-greenhouse-gas-modeling.
[5] In general, a carbon intensity, or CI, is a measure of greenhouse gas emissions per unit of fuel. Assumptions related to the estimation of emissions or changes in volumes of fuel may differ between studies which define CI with different scopes or for different purposes.

Project (GTAP) model, and Applied Dynamic Analysis of the Global Economy (ADAGE) model. To facilitate appropriate comparisons of these models, we ran common scenarios through each framework: a reference case, a corn ethanol scenario (also referred to as the "corn ethanol shock"), and a soybean oil biodiesel scenario (also referred to as the "soybean oil biodiesel shock").

Given the complex nature of these models, and the scope and scale of the analysis involved, drawing firm conclusions from a comparison of these models and their results — and presenting them for interested stakeholders — presents several challenges. We discuss these challenges in detail throughout this document. However, despite the challenges inherent in such a comparison, we have drawn several broad conclusions from this exercise, including the following:

- **Supply chain LCA[6] models, such as GREET, produce a fundamentally different analysis than economic models, such as ADAGE, GCAM, GLOBIOM, and GTAP**. Supply chain LCA models evaluate the GHG emissions emanating from a particular supply chain, whereas economic models evaluate the GHG impacts of a *change* in biofuel consumption.[7]

- **Estimates of land use change (LUC) vary significantly among the models used in this study**. Drivers of variation in these estimates include differences in assumptions related to trade, the substitutability of food and feed products, and land conversion, as well as structural differences in how models represent land categories. The variability of LUC estimates significantly influences variability in overall biofuel GHG estimates.

- **Economic modeling of the energy sector may be required to avoid overestimating the emissions reduction from fossil fuel consumption.** Economic models that include energy market impacts (ADAGE, GCAM, GTAP) estimate a global refined oil displacement that is less than the increase in biofuel consumption on an energy basis.

- **Model trade structure and assumed flexibility influence the modeled emissions results.** There is general agreement among the economic models that these trade-driven impacts will occur to some degree. However, these models show different degrees of trade responsiveness, which impacts trade flows at differing magnitudes across model results.

- Explicit modeling of the global livestock sector, and especially of the impact of biofuel feed coproducts on global feed markets, is an important capability for estimating the emissions associated with an increase in biofuel consumption.

- **The degree to which other vegetable oils replace soybean oil diverted to fuel production from other markets can impact GHG emissions associated with soybean**

[6] Many terms are used in the LCA literature to describe this type of analysis, such as attributional LCA, lifecycle inventory analysis, or process-based LCA. We use the term "supply chain LCA" as we believe it is descriptive of what this type of modeling considers.
[7] As discussed more in Section 1, different types of LCA approaches are appropriate for different applications. In this exercise, we are not evaluating which approaches could be appropriate for RFS program implementation.

oil biodiesel. Results in this exercise from economic models (ADAGE, GCAM, GLOBIOM, and GTAP) align in estimating commodity substitution as a significant part of their scenario solutions.

- **The ability to endogenously consider tradeoffs between intensification and extensification is an important capability for estimating the emissions associated with an increase in biofuel consumption.** Both intensification and extensification of corn and soybean feedstock production occur across economic model results (ADAGE, GCAM, GLOBIOM, and GTAP) in response to changing commodity prices.[8]

- **Models included in the MCE produced a wider range of LCA GHG estimates for soybean oil biodiesel than corn ethanol**. The models show much greater diversity in feedstock sourcing strategies for soybean oil biodiesel than they do for corn ethanol, and this wider range of options contributes to greater variability in the GHG results.

- Differences in model assumptions, parameters, and structure impact the results from each of the models. **Sensitivity analysis, which considers uncertainty within a given model, can help identify which parameters influence model results**. However, pinpointing the direct causes of why one estimate differs from another would require additional research.

This document describes EPA's biofuel lifecycle GHG emissions model comparison exercise in detail. In the first section, we describe our goals and scope for the exercise. Following this we describe the models included in the comparison and their key characteristics. We then describe the core scenarios evaluated for this project and the model estimates from those scenarios. After that, we describe alternative scenarios and sensitivity analyses we conducted to further improve understanding of these models. Finally, we summarize our findings and discuss areas of future research and next steps.

EPA is interested to hear from stakeholders and researchers working in this field about the results of our MCE, and we intend to engage with stakeholders to discuss this analysis. As we describe throughout the document, this MCE has helped EPA to identify important characteristics of existing models, areas for future data collection, and areas for additional research. As we engage with stakeholders, EPA will be interested to hear perspectives on the state of science and models in light of the findings of this exercise. As we engage in these conversations, we will also seek areas to collaborate with stakeholders on the priority areas for further research identified below, such as collecting new data, leveraging existing data sets, conducting economic and statistical studies, and running additional model scenarios. Ultimately, EPA hopes that the examination of models and understanding that flow from the exercise will lend itself to informing the scientific discussion on which and to what extent biofuels contribute to reduced environmental harm in comparison to consuming petroleum-based fuels.

[8] We define intensification as an increase in the amount of crop production on a given area of land, and extensification as an increase in the total area used to grow the crop of interest. Where we use the term extensification, we are including both non-cropland that was converted to cropland and shifting of cropland from one type of crop to another. However, our discussion of the results shows cropland shifting and land conversion to cropland separately.

Model Comparison Exercise Goals and Scope

1 Goals of Model Comparison

We conducted a model comparison exercise (MCE) with five models: the Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies Model (GREET), Global Biosphere Management Model (GLOBIOM), Global Change Analysis Model (GCAM), Global Trade Project (GTAP) model, and Applied Dynamic Analysis of the Global Economy (ADAGE) model. As mentioned above, this MCE had three main goals:

1) Advance the science in the area of analyzing the lifecycle greenhouse gas emissions impacts from increasing use of biofuel.

2) Identify and understand differences in scope, coverage, and key assumptions in each model, and, to the extent possible, the impact that those differences have on the appropriateness of using a given model to evaluate the GHG impacts of biofuels.

3) Understand how differences between models and data sources lead to varying results.

This effort is consistent with some of the conclusions and recommendations in the National Academies of Sciences, Engineering, and Medicine (NASEM) report titled "Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States."[9] For example, NASEM recommended that "[c]urrent and future LCFS [low carbon fuel standard] policies should strive to reduce model uncertainties and compare results across multiple economic modeling approaches and transparently communicate uncertainties," (recommendation 4-2) and "LCA studies used to inform policy should explicitly consider parameter uncertainty, scenario uncertainty, and model uncertainty" (recommendation 4-3).

LCA plays several diverse roles in the context of the RFS program. For example, LCA is used for rulemaking impact analysis as well as to determine whether an individual pathway meets the lifecycle GHG emissions reduction requirements. Different LCA tools may be appropriate for different purposes. The NASEM report concluded that, "[t]he approach to LCA needs to be guided on the basis of the question the analysis is trying to answer. Different types of LCA are better suited for answering different questions or achieving different objectives, from fine tuning a well-defined supply chain to reduce emissions, to understanding the global, economy-level effect of a technology or policy change" (conclusion 2-2).[10]

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[9] National Academies of Sciences, Engineering, and Medicine ("NAS") (2022). Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States. Washington, DC: The National Academies Press. https://doi.org/10.17226/26402.

[10] The NASEM report provided the following recommendations related to LCA approaches: "When emissions are to be assigned to products or processes based on modeling choices including functional unit, method of allocating emissions among co-products, and system boundary, ALCA [attributional lifecycle analysis] is appropriate. Modelers should provide transparency, justification, and sensitivity or robustness analysis for modeling choices" (Recommendation 2-1). "When a decision-maker wishes to understand the consequences of a proposed decision or action on net GHG emissions, CLCA [consequential lifecycle analysis] is appropriate. Modelers should provide transparency, justification, and sensitivity or robustness analysis for modeling choices for the scenarios modeled with and without the proposed decision or action" (Recommendation 2-2).

This document includes multiple sections:

- Section 2 introduces and summarizes the models considered in this exercise.
- Section 3 compares model characteristics, input parameters, and input data.
- Section 4 describes the common scenarios that were run across all the models for purposes of this analysis.
- Section 5 provides details on the reference case used.
- Section 6 compares the results of the modeling work related to corn ethanol.
- Section 7 compares the results of the modeling work related to soybean oil biodiesel.
- Section 8 describes the scenarios run as part of our alternative volume sensitivity analysis.
- Section 9 describes parameter sensitivity analyses.
- Section 10 summarizes the findings of this exercise and discusses future research.

2 Models Considered

Numerous factors influence biofuel GHG estimates, including model framework choice, data inputs and assumptions, and other methodological decisions. In this section we discuss the models considered in this MCE: GREET, GLOBIOM, GCAM, GTAP,[11] and ADAGE.[12] This selection of models provides a broad cross-section of the most common types of modeling frameworks used to assess biofuels, as discussed in this section. We chose to use these models based on discussions with our partners at USDA and DOE and our experience reviewing scientific literature on the lifecycle GHG emissions of biofuels, including for our 2022 biofuel LCA workshop discussed above. In addition, our choice to use these particular models is also informed by the statutory definition of lifecycle greenhouse gas emissions in Section 211(o)(1)(H) of the Clean Air Act, which includes significant indirect emissions, including indirect land use change emissions.[13] Furthermore, in the 2010 RFS2 rule EPA interpreted this

[11] There are multiple GTAP models. The version used for this model comparison exercise is the GTAP-BIO model. For brevity we refer to it throughout this report as “GTAP” or the “GTAP model”, except for instances where we are describing the distinctions between GTAP-BIO and other GTAP models.
[12] The model runs for this exercise were conducted by members of the modeling teams at Argonne National Laboratory, IIASA, PNNL, Purdue University, and RTI International. The final contents of this document do not necessarily represent the views of the modeling teams involved or the organizations they represent. All statements in this document are ultimately those of EPA.
[13] The full text of CAA 211(o)(1)(H) is “The term "lifecycle greenhouse gas emissions" means the aggregate quantity of greenhouse gas emissions (including direct emissions and significant indirect emissions such as significant emissions from land use changes), as determined by the Administrator, related to the full fuel lifecycle, including all stages of fuel and feedstock production and distribution, from feedstock generation or extraction through the distribution and delivery and use of the finished fuel to the ultimate consumer, where the mass values for all greenhouse gases are adjusted to account for their relative global warming potential.”

definition as including significant indirect emissions[14] occuring anywhere in the world (i.e., international impacts), as GHG emission impacts are global.[15]

In this exercise, we did not include FASOM or the FAPRI-CARD model, which we used for the 2010 RFS2 rule. Given time and resource constraints, we chose to focus on models with global scope. FASOM is not a global model, and instead covers the continental USA. The FAPRI-CARD model is no longer maintained at the same level as it was in 2010; for example, most of its projections still end in the 2022/2023 marketing year. There is another FAPRI model maintained by the University of Missouri that projects further into the future, but this model covers only the USA in detail and does not include GHG emissions. This exercise was not meant to include every possible model that could be used to estimate biofuel GHG emissions, and omission of a model from this exercise does not preclude its use in the future.

We provide a summary of each model included in this exercise, including its history, sectoral representation, spatial coverage and resolution, temporal representation, and GHG emissions representation. We then compare the characteristics of these models and describe previously published literature which may assist the reader in understanding which factors may contribute to variation in the biofuel GHG estimates these models produce. Our goal in this section is not to provide a comprehensive accounting of any one of these models. Rather, our objective is to summarize each model at a high level and highlight important similarities and differences between models that we explore further when discussing MCE modeling results in Sections 5-9.

There are four types of models commonly used for biofuel GHG analysis: supply chain LCA models, partial equilibrium (PE) models, computable general equilibrium (CGE) models and integrated assessment models (IAM). Supply chain LCA models, also known as attributional LCA (ALCA) models, such as GREET, are designed to estimate the inputs and outputs of a particular product supply chain in detail, using rule-based methods (e.g., allocation or displacement) to account for coproducts.[16] PE models, such as GLOBIOM,[17] equate supply and demand in one or more selected markets such that prices stabilize at their equilibrium level. PE models focus on representing one or a few sectors of the economy, such as the agricultural sector, but lack linkages to other sectors of the economy. In contrast, CGE models, such as GTAP and ADAGE, are comprehensive in their representation of the economy, reflecting feedback effects among all economic sectors and factors of production, such as land, capital,

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[14] When using the terms "direct" and "indirect" to refer to emissions, impacts or effects, NAS (2022) recommends carefully defining these terms, or avoiding their use altogether (Recommendation 4-1). Given that the CAA 211(o)(1)(H) definition of lifecycle emissions uses the terms direct and indirect emissions, we believe it is appropriate to use the direct/indirect terminology in this document. As a general matter, when we use the term "direct emissions" in this document we are referring to emissions from the fuel supply chain itself, whereas "indirect emissions" refers to emissions that results from market-mediated impacts induced by a change in biofuel consumption. The same distinction holds for direct/indirect impacts or effects.

[15] EPA. 2010. RFS2 Final Rule, 75 FR 14670 (March 26, 2010), https://www.gpo.gov/fdsys/pkg/FR-2010-03-26/pdf/2010-3851.pdf. See in particular Section V, pages 14764-14799.

[16] Supply chain LCA models such as GREET can also be supplemented with results from economic models to consider indirect effects such as land use changes; however, doing so "can complicate the interpretation" of the results (NAS 2022, p. 45).

[17] The FASOM and FAPRI models EPA used for the March 2010 RFS2 rule biofuel GHG analysis are also categorized as PE models.

labor and resources. IAMs, such as GCAM, integrate knowledge from several disciplines, for example, biogeochemistry, economics, engineering, and atmospheric science, to evaluate how changes in any of these areas affect the others. While it is hard to state the specific criteria for identifying an IAM, we might distinguish them from PE and CGE models by their deeper integration of human economic systems with Earth (biosphere and atmosphere) systems and GHG emissions into one modelling framework.

PE, CGE and IAM models can all be called economic models since their model solutions include achievement of a partial or general economic equilibrium. Supply chain LCA models are categorically different from the other three model types as they do not simulate economic equilibria, behavior, or prices. Instead, supply chain LCA models inventory the emissions that occur along each stage of a supply chain and assign or attribute the emissions to a functional unit, such as a volume or energy unit of fuel.[18] In contrast, the other types of models (PE, IAM, CGE) can be used for a consequential lifecycle analysis, which looks at how the emissions or impacts, including market-mediated impacts, will *change* in response to a decision or action, such as a change in the level of biofuel consumption.[19] All of these models have strengths and weaknesses, as well as uncertainties and limitations. Thus, there are often tradeoffs to consider when selecting between models for a particular analysis. For example, there may be tradeoffs between sectoral and temporal scope on the one hand, versus supply chain and technological resolution on the other. The potential tradeoffs between scope and detail most relevant to this MCE are discussed in more detail in Section 3. As discussed above, when considering these tradeoffs, the NASEM report says that analysts need to be guided on the basis of the question their analysis is trying to answer.[20]

2.1 The Greenhouse Gases, Regulated Emissions, and Energy Use in Technologies (GREET) Model

The Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) Model is a lifecycle analysis model based on supply chains of technologies and products. It provides lifecycle energy, water, GHG, and other air emissions results intended to evaluate the impacts of various vehicle and fuel combinations, as well as chemicals, products, and materials that crosscut major economic sectors. The developer is Argonne National Laboratory (ANL), and the project is sponsored by the U.S. Department of Energy (DOE). Initially made available in 1995, it was developed with the purpose of evaluating the energy and environmental (e.g., GHG emissions, criteria air pollutant emissions, and water consumption) impacts of new fuels and vehicles for use in the transportation sector.[21]

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[18] NAS (2022) lists many definitions of an attributional lifecycle analysis without prescribing one particular definition. This sentence is adapted from the first sentence under the heading "Attributional Life-Cycle Assessment on page 22 of NAS (2022).
[19] NAS (2022) lists many definitions of a consequential lifecycle analysis without prescribing one particular definition. This sentence is adapted from the first sentence under the heading "Consequential Life-Cycle Assessment on page 26 of NAS (2022).
[20] NAS (2022), conclusion 2-2.
[21] Elgowainy, A. and Wang, M. (2019) 'Overview of Life Cycle Analysis (LCA) with the GREET Model', p. 21. https://greet.es.anl.gov/files/workshop_2019_overview.

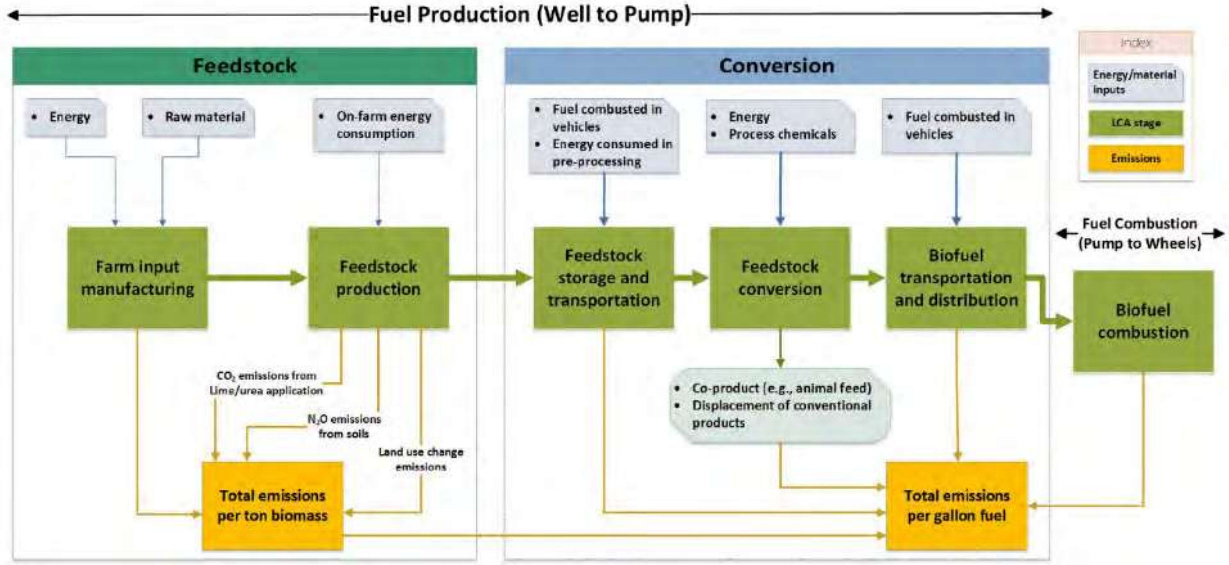
GREET includes a suite of models and tools. For the transportation sector, it includes a fuel cycle model of vehicle technologies and transportation fuels (GREET1) and a vehicle manufacturing model of vehicle technologies (GREET2). Given that our focus is on renewable fuels, we are primarily concerned with GREET1. GREET is available in two platforms, a large Excel workbook and a ".net" version. The Excel version of GREET provides transparency while the .net version offers a modular user interface with a structured database. There are several derivates of the core GREET model, such as CA-GREET developed with the California Air Resources Board (CARB) and used in support of the California Low Carbon Fuels Standard (CA-LCFS), and ICAO-GREET developed with the International Civil Aviation Organization in support of the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). New versions of GREET are normally released in October of each year, with the latest version as of the time of this writing being GREET-2022. GREET includes more than 100 fuel production pathways including fuels used in road, air, rail, and marine transportation. It also examines more than 80 on-road vehicle/fuel systems for both light and heavy-duty vehicles. The model reports lifecycle energy use, air pollutants, GHGs and water consumption. It includes detailed representations of the petroleum, electric, natural gas, hydrogen, and renewable energy sectors.

The GREET modeling framework is largely a process-based LCA approach (sometimes referred to as attributional LCA).[22] GREET can be used to estimate the carbon intensity (CI)[23] of individual supply chains and the benefits of specific supply chain adjustments, such as reducing fertilizer application rates or switching to more efficient fuel distribution modes. Fundamentally, GREET is most closely related to other supply chain LCA frameworks such as SimaPro, GaBi, and OpenLCA, though GREET differs in that it comes with predeveloped fuel pathways and pre-populated data and assumptions developed by ANL. In general, GREET evaluates production of a fuel commodity by considering the activities from the associated supply chain. In the context of GREET, the data on the activities controlled within a fuel commodity supply chain are called the "foreground" data. GREET accounts for important biofuel coproducts such as distillers grains and soybean meal through allocation or displacement rules. Figure 2.1-1 provides a schematic overview of how the biofuel lifecycle is represented in GREET. GREET can be used to estimate the CI of individual supply chains and the benefits of specific supply chain adjustments, such as reducing fertilizer application rates or switching to more efficient fuel distribution modes. The model can also consider technology improvements at the process- or site-specific level for biofuels.

[22] Wang, M. (2022). "Biofuel Life-cycle Analysis with the GREET Model." Presentation at the EPA Biofuel Modeling Workshop. Argonne National Laboratory. March 1, 2022. https://www.epa.gov/system/files/documents/2022-03/biofuel-ghg-model-workshop-biofuel-lifecycle-analysis-greet-model-2022-03-01.pdf. Slide 5.

[23] Carbon intensity is a measure of greenhouse gas emissions per unit of fuel.

Figure 2.1-1: Schematic of Biofuel Supply Chain Representation in GREET[24]



GREET primarily estimates default fuel CIs using data for average resource and energy production in the United States. In the context of GREET, these data on resource and energy production are referred to as the "background data." For example, GREET by default models electricity based on data for average U.S. electricity generation. However, GREET includes some pathways representing foreign fuel production (e.g., Brazilian sugarcane ethanol) and in some cases users can choose to model some supply chains located in particular regions of the U.S. (e.g., states or electricity grid regions). A user with enough data on their supply chain could, in certain cases, customize the background data in GREET to estimate the CI of their fuel considering regional details and particular suppliers of energy and material inputs.

GREET is not a dynamic model as it does not make projections whereby future time periods depend on the simulation of prior time periods. However, it does include projected background data, using projections from sources such as the U.S. Energy Information Administration (EIA). GREET users can select a target year, between 1990-2050, to estimate lifecycle emissions for their supply chain given background data assumptions for the selected year. Thus, it can be used to show how the estimated CI of a fuel changes over time based on changes in technological efficiency and other factors. For example, Lee et al. (2021) used data on U.S. ethanol production efficiencies and corn yields to estimate the CI of U.S. corn ethanol each year from 2005 to 2019.[25]

Although GREET does not endogenously estimate indirect emissions such as those resulting from direct and indirect land use change, GREET incorporates a static module called the Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) to account for

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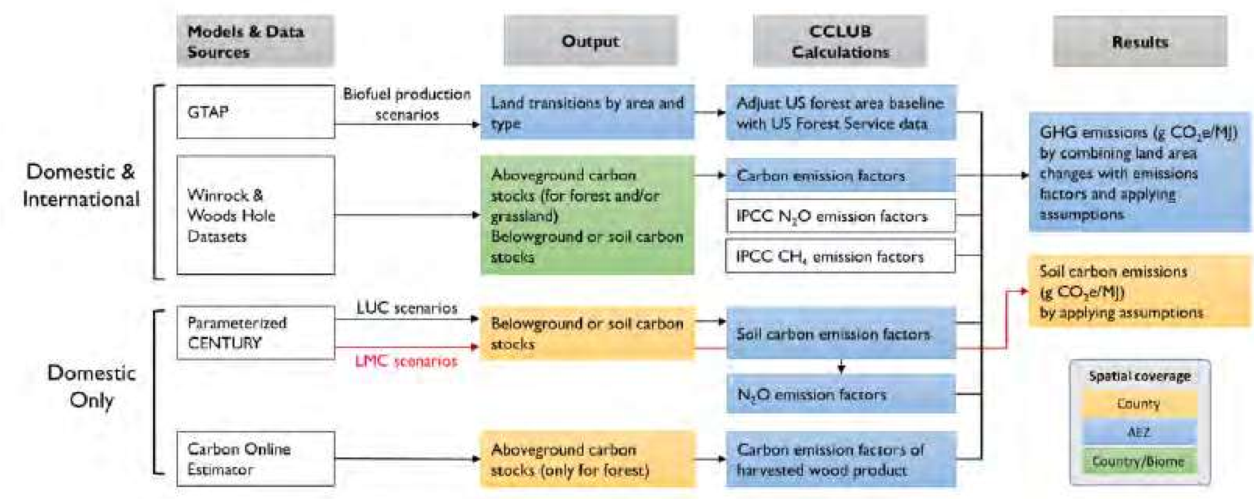
[24] Copied from Wang (2022), slide 9.
[25] Lee, U., et al. (2021). "Retrospective analysis of the US corn ethanol industry for 2005–2019: implications for greenhouse gas emission reductions." Biofuels, Bioproducts and Biorefining.

land use change emissions.[26] CCLUB relies on a set of estimated induced land use changes for various biofuel pathways obtained from GTAP studies conducted between 2011–2018 (see Table 2.1-1), combined with emissions factors estimated with a parametrized CENTURY model and derived from various data sources to estimate land use change GHG emissions per unit of biofuel production.[27] Thus, the well-to-wheel emissions for crop-based pathways are estimated as the process-based emissions plus the induced land use change estimates from CCLUB. The data sources and calculations in CCLUB are summarized in Figure 2.1-2, reproduced from the CCLUB user manual.

Figure 2.1-2: Schematic of Data Sources and Calculations in CCLUB[28]



CCLUB includes land use change area estimates from nine different GTAP scenarios: four soybean oil biodiesel shocks, two corn ethanol shocks, and one shock each for ethanol from corn stover, miscanthus and switchgrass. The corn ethanol and soybean oil biodiesel scenarios included in CCLUB are described in Table 2.1-1. The two corn ethanol scenarios are similar except that the "Corn Ethanol 2013" estimate was produced with a version of GTAP with regionally differentiated land transformation elasticities and a modified land nesting structure that makes it more costly within the model to convert forest to cropland relative to converting pasture to cropland.

[26] Kwon, Hoyoung, et al. (2021). Carbon calculator for land use change from biofuels production (CCLUB) users' manual and technical documentation, Argonne National Lab, Argonne, IL. https://greet.es.anl.gov/publication-cclub-manual-r7-2021

[27] Hoyoung Kwon and Uisung Lee (2019) 'Life Cycle Analysis (LCA) of Biofuels and Land Use Change with the GREET Model'. https://greet.es.anl.gov/files/workshop_2019_biofuel_luc.

[28] Kwon, Hoyoung, Liu, Xinyu, Dunn, Jennifer B., Mueller, Steffen, Wander, Michelle M., and Wang, Michael. (2020). Carbon Calculator for Land Use and Land Management Change from Biofuels Production (CCLUB). United States: N. p., 2020. Web. doi:10.2172/1670706. Copy of Figure 1.

Table 2.1-1: Corn Starch and Soybean Oil Based Biofuel Scenarios Available in CCLUB[29]

Case Description	Shock Size (Billion Gallons)	Source
"Corn Ethanol 2011." An increase in corn ethanol production from its 2004 level (3.41 billion gallons [BG]) to 15 BG	11.59	Taheripour et al. (2011)[30]
"Corn Ethanol 2013." An increase in corn ethanol production from its 2004 level (3.41 billion gallons [BG]) to 15 BG	11.59	Taheripour and Tyner (2013)[31]
Increase in soybean oil biodiesel production by 0.812 BG (CARB case 8)	0.812	Chen et al. (2018)[32]
Increase in soybean oil biodiesel production by 0.812 BG (CARB average proxy)	0.812	Chen et al. (2018)
Increase in soybean oil biodiesel production by 0.8 BG (GTAP 2004)	0.8	Taheripour et al. (2017)[33]
Increase in soybean oil biodiesel production by 0.5 BG (GTAP 2011)	0.5	Taheripour et al. (2017)

For each case, the estimates CCLUB uses from GTAP are the area of changes in cropland, forest, pasture in each agro-ecological zone (AEZ) and region, and cropland pasture in the U.S., Brazil, and Canada. Land use change GHG emissions are estimated based on these land conversion areas using data from a few different sources. Based upon user selections, CCLUB ultimately combines a given GTAP scenario's estimated land use change impacts with sets of user-selected emission factor data[34] to provide domestic and international land use change GHG emissions per functional unit of biofuel. By default, for corn ethanol and soybean oil biodiesel, among other crop-based fuels, GREET adds the LUC GHG estimates from CCLUB to the rest of the supply chain LCA estimates to produce a CI score for each fuel pathway.

A module called the Feedstock Carbon Intensity Calculator (FD-CIC) was more recently added to GREET.[35] FD-CIC is designed to examine CI variations of different corn, soybean, sorghum, and rice farming practices at the farm level. The FD-CIC uses county level data and allows users to input their own farm level data on energy and chemical farming inputs, tillage, cover cropping and other crop management practices. Based on these input data, the FD-CIC

[29] Adapted from Table 1 in Dunn, J. B., et al. (2017). Carbon calculator for land use change from biofuels production (CCLUB) users' manual and technical documentation, Argonne National Lab. (ANL), Argonne, IL (United States).
[30] Taheripour, F., et al. (2011). Global land use change due to the U.S. cellulosic biofuels program simulated with the GTAP model, Argonne National Laboratory: 47.
[31] Taheripour, F. and W. E. Tyner (2013). "Biofuels and land use change: Applying recent evidence to model estimates." Applied Sciences 3(1): 14-38.
[32] Chen, R., et al. (2018). "Life cycle energy and greenhouse gas emission effects of biodiesel in the United States with induced land use change impacts." Bioresource Technology 251: 249-258.
[33] Taheripour, F., et al. (2017). "The impact of considering land intensification and updated data on biofuels land use change and emissions estimates." Biotechnology for Biofuels 10(1): 191.
[34] For this model comparison exercise, we use the default emissions factor data used by GREET, which are from the parameterized CENTURY model and Winrock. See Kwon, Hoyoung, et al. (2021) for details.
[35] Liu, X., et al. (2020). "Shifting agricultural practices to produce sustainable, low carbon intensity feedstocks for biofuel production." Environmental Research Letters 15(8): 084014.

estimates the farm level emissions from energy, fertilizers, herbicide, and insecticide, as well as effects on soil organic carbon relative to the baseline assumptions in GREET. The FD-CIC may be useful to estimate the soil carbon benefits of reduced tillage and cover cropping, and to examine regional differences or farm-level differences in feedstock CI.

While GREET accounts for indirect land use change emissions, it does not consider other indirect effects associated with a change in biofuel demand, such as through market-mediated impacts on the agriculture, livestock, or energy sectors.

GREET is used by a variety of academic, commercial, and government entities. California's Low Carbon Fuel Standard (LCFS) program relies in part on a customized version of GREET called CA-GREET to provide state-specific fuel pathways and CI values.[36] Oregon uses a similar approach for their LCFS program.[37] The International Civil Aviation Organization (ICAO) uses GREET among several models to provide carbon intensities for specific aviation fuel pathways.[38] Most of these programs (with the exception of Oregon) use the non-land use change GHG estimates from GREET and add their own land use change estimates in specific market and policy contexts instead of those derived from CCLUB to calculate biofuel carbon intensities. Among other applications, EPA has used GREET since the inception of the RFS program to provide data for rulemakings and biofuel pathway support as part of our suite of tools in addition to FASOM and FAPRI.

2.2 The Global Biosphere Management Model (GLOBIOM)

The Global Biosphere Management Model (GLOBIOM) was developed and continues to be managed by the International Institute for Applied Systems Analysis (IIASA). The model was developed in the late 2000s originally to conduct impact assessments of climate change mitigation policies of biofuels and other land-based efforts.[39] It was developed on the basis of the U.S. Forest and Agricultural Sector Optimization Model (FASOM model).[40] There are several model versions of GLOBIOM available for different applications and contexts. A sample of GLOBIOM code is available to the public, and an open-source version is under development.[41]

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[36] California Air Resources Board. LCFS Life Cycle Analysis Models and Documentation. https://ww2.arb.ca.gov/resources/documents/lcfs-life-cycle-analysis-models-and-documentation.

[37] Oregon Department of Environmental Quality. Carbon Intensity Values: Oregon Clean Fuels Program. https://www.oregon.gov/deq/ghgp/cfp/Pages/Clean-Fuel-Pathways.aspx. This version is based on a previous version of Argonne GREET.

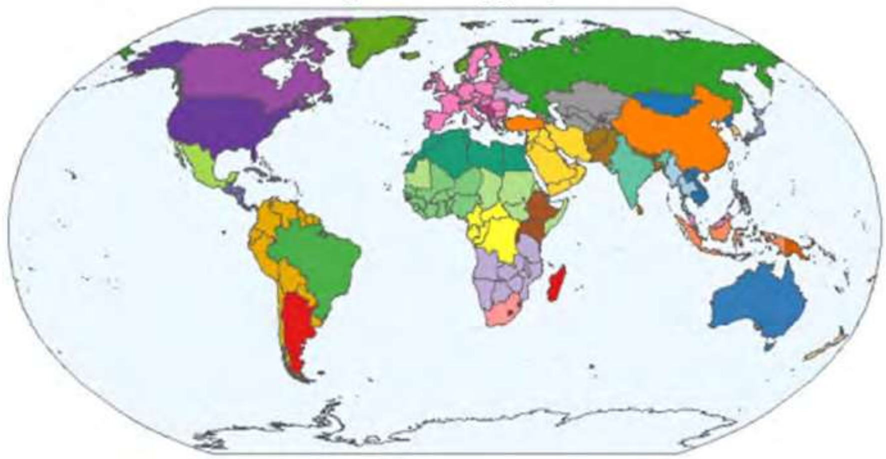
[38] ICAO. Models and Databases. https://www.icao.int/environmental-protection/pages/modelling-and-databases.aspx.

[39] International Institute for Applied Systems Analysis, "GLOBIOM," https://iiasa.ac.at/models-tools-data/globiom.

[40] Frank, Stefan, et al. "The Global Biosphere Management Model," https://www.epa.gov/system/files/documents/2022-03/biofuel-ghg-model-workshop-global-biosphere-mgmt-model-2022-03-01.pdf. See also, Valin, Hugo et al. The Land Use Change Impact of Biofuels Consumed in the EU: Quantification of Area Greenhouse Gas Impacts. August 27, 2015, pg. 128.

[41] See, GLOBIOM, "Model Code," https://iiasa.github.io/GLOBIOM/model_code.html.

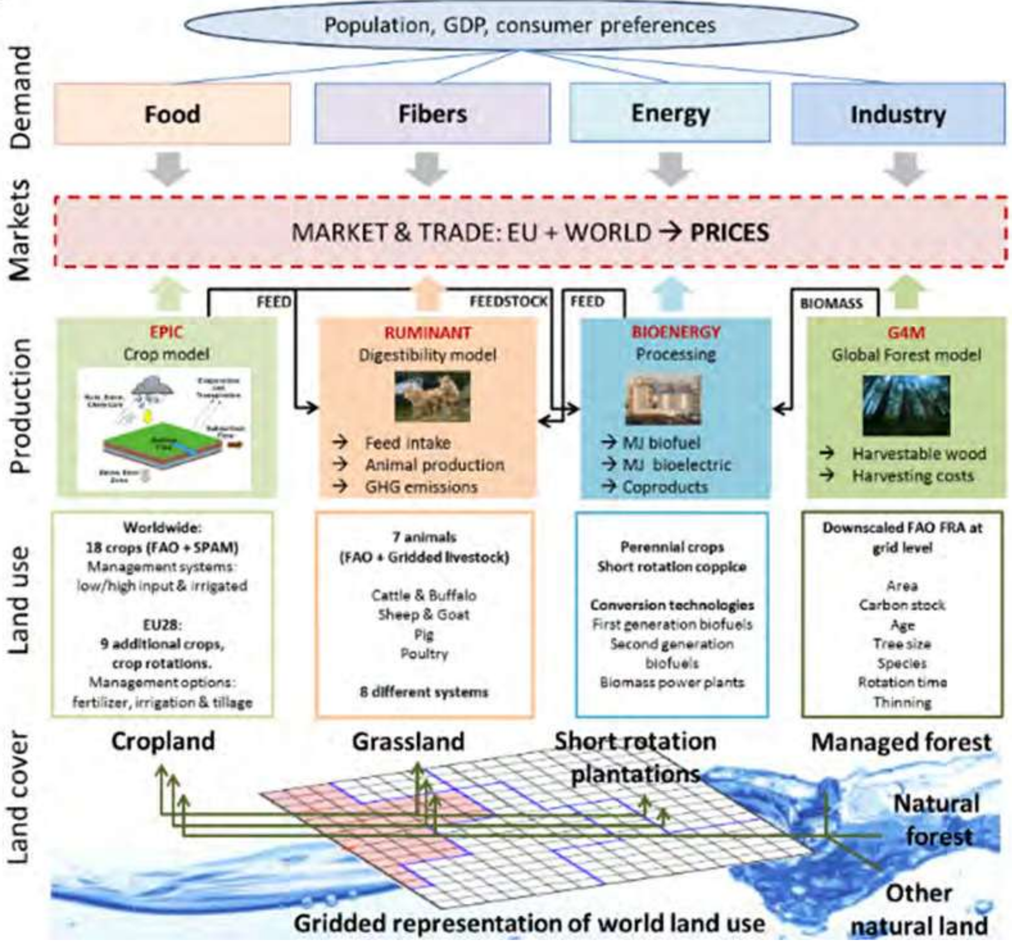
Figure 2.2-1: GLOBIOM Regional Mapping[42]



GLOBIOM is a PE model that captures the agricultural, forest, and bioenergy sectors. The model solves recursively dynamic using an economic equilibrium modeling approach with detailed grid cell land representation.[43] The model finds market equilibria that maximize the sum of producer and consumer surplus subject to resource, technological, demand and policy constraints at a country/regional level. Producer surplus is defined as the difference between market prices at a regional level and the product's supply curve at the regional level. The supply curve accounts for labor, land, capital and other purchased input. Consumer surplus is based on the level of consumption of each market and is arrived at by integrating the difference between the demand function of a good and its market price. The model uses linear programming to solve, although it also contains some non-linear functions that have been linearized using stepwise approximation.[44] GLOBIOM features global coverage with 37 regions (see Figure 2.2-1) and simulates for the years 2000-2100 using ten-year time steps. As a PE model, GLOBIOM does not have feedback from labor, capital, or other parts of the economy. However, the model can be linked to other models, such as IIASA's energy sector model MESSAGE.

[42] IIASA. (2020). "GLOBIOM regional and country level modeling." SUPREMA GLOBIOM-MAGNET Training. December 4, 2020. https://iiasa.github.io/GLOBIOM/training_material/GLOBIOM/GLOBIOM-Topic_RegionalApplications_APalazzo_Nov2020.pdf.
[43] In models with recursive dynamic solution algorithms, the model solves at each time step before moving forward to the next time step. In contrast, forward looking optimization models solve for all time periods at once.
[44] IIASA, "GLOBIOM Documentation_20180604.pdf," https://iiasa.github.io/GLOBIOM/GLOBIOM_Documentation_20180604.pdf.

Figure 2.2-2: Schematic Overview of GLOBIOM[45]



The detailed grid cell-level spatial coverage for GLOBIOM includes more than 10,000 spatial units worldwide. The model represents 18 crops globally (and nine additional crops in Europe) using FAOSTAT as the primary database for crop statistics. Area of other crops that are not represented dynamically (e.g., fruits and vegetables) are kept constant. Crop modeling includes differentiation in management systems and multi-cropping.

GLOBIOM also features highly detailed livestock representation, based on FAOSTAT data. The model includes 7 animal products, which can be produced in differentiated production systems. For ruminants there are 8 production system possibilities, including grazing systems in different climatic locations such as arid and humid, mixed crop-livestock systems, and others. Pigs and poultry are classified under either small holder or industrial systems. Based on the production system, animal species, and region, GLOBIOM differentiates diets, yields, and GHG emissions. For instance, dairy and meat herds are modeled separately, and their diets are differentiated. Poultry in industrial systems is split into laying hens and broilers, again with different dietary needs.

[45] IIASA. GLOBIOM Online Documentation. https://iiasa.github.io/GLOBIOM/introduction.html.

For ruminants, livestock production is modeled spatially in GLOBIOM's gridded cell structure. At the cell level, animal yields for bovine and small ruminants are estimated using the GLOBIOM module, RUMINANT. RUMINANT calculates a production yield that matches plausible feed rations and checks this against regional-level data of livestock production. Feed for animals is also differentiated in the RUMINANT model and can be composed of feed crops, grass, stover, and other feed. Monogastric productivities are calculated based on FAOSTAT and assumptions of potential productivities of smallholder and industrial systems. Livestock production is allowed to intensify or extensify, thereby altering the amount of feed or grass consumed.[46] Since for ruminants this is modeled spatially, any changes in grassland consumed due to changes in production systems, animal type, yield, and GHGs is captured in the spatially-relevant areas. Each final livestock product is considered a homogenous good with its own specific market (apart from bovine and small ruminant milk).

Forestry in GLOBIOM is captured through the G4M module[47] and includes detailed representation of the sector and its supply chain and a differentiation between managed and unmanaged forest areas. GLOBIOM includes bilateral trade for agricultural and wood products. These products are assumed to be homogenous and traded based on least expensive production costs though transportation costs and tariffs are also included.

The model also includes a bioenergy sector with first and second generation biofuels and biomass power plants. Perennial crops and short-rotation coppice are included as inputs to the bioenergy sector. GLOBIOM represents biofuel coproducts including distillers grains, oilseed meals, and sugar beet fibers. These coproducts can be traded either in their processed or whole forms. Coproducts that can be used for livestock feed are incorporated into the livestock RUMINANT module and can substitute other forms of feed depending on protein and metabolizable energy content.[48]

There are nine land cover types in GLOBIOM, and 6 of these are modeled dynamically: cropland, grassland, short rotation plantations, managed forests, unmanaged forests, and other natural vegetation land. The other three land cover categories are represented in the model but kept constant, they include other agricultural land, wetlands, and not relevant (ice, water bodies etc.). Greenhouse gas emission coverage includes 12 sources of emissions that cover crop cultivation, livestock, above and below-ground biomass, soil-organic carbon, and peatland. Although GLOBIOM does not track terrestrial carbon stocks dynamically, carbon fluxes from land use change are calculated with equations, following IPCC guidelines, that estimate changes over time and allocate the average annual emissions to the time period in which the land use change occurs.

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[46] Intensifying involves increasing livestock output without expanding the area of pasture land by grazing more livestock per area of land, increasing feed relative to grazing, or using feedlots. Extensifying is the opposite – it involves expanding pasture area in order to increase livestock production.

[47] International Institute for Applied Systems Analysis, "Global Forest Model (G4M)", https://iiasa.ac.at/models-and-data/global-forest-model.

[48] Valin, Hugo, et al., September 17, 2014, "Improvements to GLOBIOM for Modelling of Biofuels Indirect Land Use Change," http://www.globiom-iluc.eu/wp-content/uploads/2014/12/GLOBIOM_All_improvements_Sept14.pdf, pg. 38.

Land use in GLOBIOM allows for both intensification and extensification. When land is converted, this is endogenously determined in the model based on conversion costs, and the profitability of primary products, coproducts, and final products. Costs increase as the area converted expands. Additionally, there are biophysical land suitability and production potential restrictions. Land use change is determined at the grid cell level.[49] There is a land transition matrix that sets the options for land conversion for each cell and is based on land conversion patterns specific to that region and conversion costs depending on the type of land converted.[50] In the USA and EU regions, GLOBIOM, by default, does not allow forest conversion and restricts natural land conversion though these assumptions can be changed.

In policy settings, GLOBIOM is used for both modeling the European Union's biofuel mandates and for estimating induced land use change impacts of biofuels for the International Civil Aviation Organization's Carbon Offsetting and Reduction Scheme for Civil Aviation (CORSIA). In research contexts, the model has regularly participated in AgMIP, an agricultural model intercomparison and improvement project.[51] One result of this project was an article on the key determinants of global land use projections.[52] GCAM, discussed in Section 2.3, was also part of the AgMIP study. GLOBIOM has been used to assess other topics in the academic literature, publishing work on topics such as reducing greenhouse gas emissions from the agricultural sector, food security, and climate mitigation of livestock system transitions.

2.3 The Global Change Analysis Model (GCAM)

The Global Change Analysis Model (GCAM) is a partial equilibrium, integrated assessment modeling framework which explores human and earth dynamics. The model includes representation of energy, economy, land, water, and physical earth systems and interactions between these systems within a fully integrated computational system. The model includes all human systems and economic sectors which produce or consume energy, or which emit GHGs. GCAM operates as a recursive dynamic framework, generally in 5-year time steps. In practice, the model is often run from a base year in the recent past through the years 2050 or 2100. However, time step and scenario length are flexible input assumptions to GCAM, and the framework can support scenario analysis across a wide range of time scales. By default and for the purposes of this model comparison exercise, the model base year is currently 2015. But other historical base periods may be specified. For each modeled time period, GCAM iterates until it finds a vector of prices that clears all markets and satisfies all consistency conditions. The model

[49] GLOBIOM represents most land in the world using a 5 arcminutes by 5 arcminutes grid. At the equator, this is roughly 9km by 9km.
[50] IIASA, "Spatial Resolution and Land Use Representation," https://iiasa.github.io/GLOBIOM/documentation.html#spatial-resolution-and-land-use-representation.
[51] Several studies have estimated water use and availability impacts associated with future scenarios of increased cellulosic biofuel production. These studies often project future land use/management for different scenarios of increased production of cellulosic crops, and then estimate impacts on water use and changes in streamflow for specific watersheds. See for example: Cibin, R., Trybula, E., Chaubey, I., Brouder, S. M., & Volenec, J. J. (2016). Watershed-scale impacts of bioenergy crops on hydrology and water quality using improved SWAT model. Gcb Bioenergy, 8(4), 837-848 or Le, P. V., Kumar, P., & Drewry, D. T. (2011). Implications for the hydrologic cycle under climate change due to the expansion of bioenergy crops in the Midwestern United States. Proceedings of the National Academy of Sciences, 108(37), 15085-15090.
[52] Stehfest, E., van Zeist, WJ., Valin, H. et al. Key determinants of global land-use projections. Nat Commun 10, 2166 (2019). https://doi.org/10.1038/s41467-019-09945-w

is designed to explore different "what-if" scenarios, assessing the implications of different futures on a wide range of outcomes, such as energy supplies and demands, land allocation, or commodity prices.

The core GCAM is developed and maintained at the Joint Global Change Research Institute, a partnership between Pacific Northwest National Lab (PNNL) and the University of Maryland (UMD) in College Park, Maryland. PNNL is the primary steward of the model, though members of a larger GCAM Community also contribute to development of the framework.[53] GCAM was originally developed in the early 1980s to assess the magnitude of GHG emissions from fossil fuel CO_2 through the mid-21st Century. Over time, the model has expanded in scope to serve a wide set of scientific modeling applications. The model has now been in continuous development for over 40 years and has been applied in several studies and model inter-comparison activities, including the IPCC's Representative Concentration Pathways[54] and Shared Socioeconomic Pathways.[55] GCAM is an open-source community model that can be downloaded from a public repository.[56] The model documentation is also publicly available[57] and includes a partial list of GCAM publications.[58]

Economic systems in GCAM are divided into sectors and, within each sector, specific technologies. Figure 2.3-1 provides an overview of the sectors represented in GCAM, along with the inputs and outputs of the model. As shown in the figure, there are exogenous natural resource supply, land, economy, and demand inputs to the model. These exogenous inputs include global population and GDP. Each sector of GCAM is structured with a multi-level nesting approach that allows competition between different nodes at each level, and any number of levels. This nested competition follows a discrete logit[59] or modified logit model[60], depending on the object. The market share of each discrete technology is determined by a) a share-weight parameter that reflects the specific preferences for a particular choice, b) the cost, which includes fuel and non-fuel costs, and c) an exogenous logit exponent that determines the price responsiveness of the competition. In most cases the share-weights are derived from base-year calibration when market shares are known. Technologies that are introduced in future time periods are assigned exogenous share-weights in each model time period. The market shares are therefore influenced by a number of endogenous and exogenous parameters, including fuel and non-fuel costs, efficiency or input-output coefficients, share-weights, and logit exponents. These parameters are documented and can be consulted in online repository.[61]

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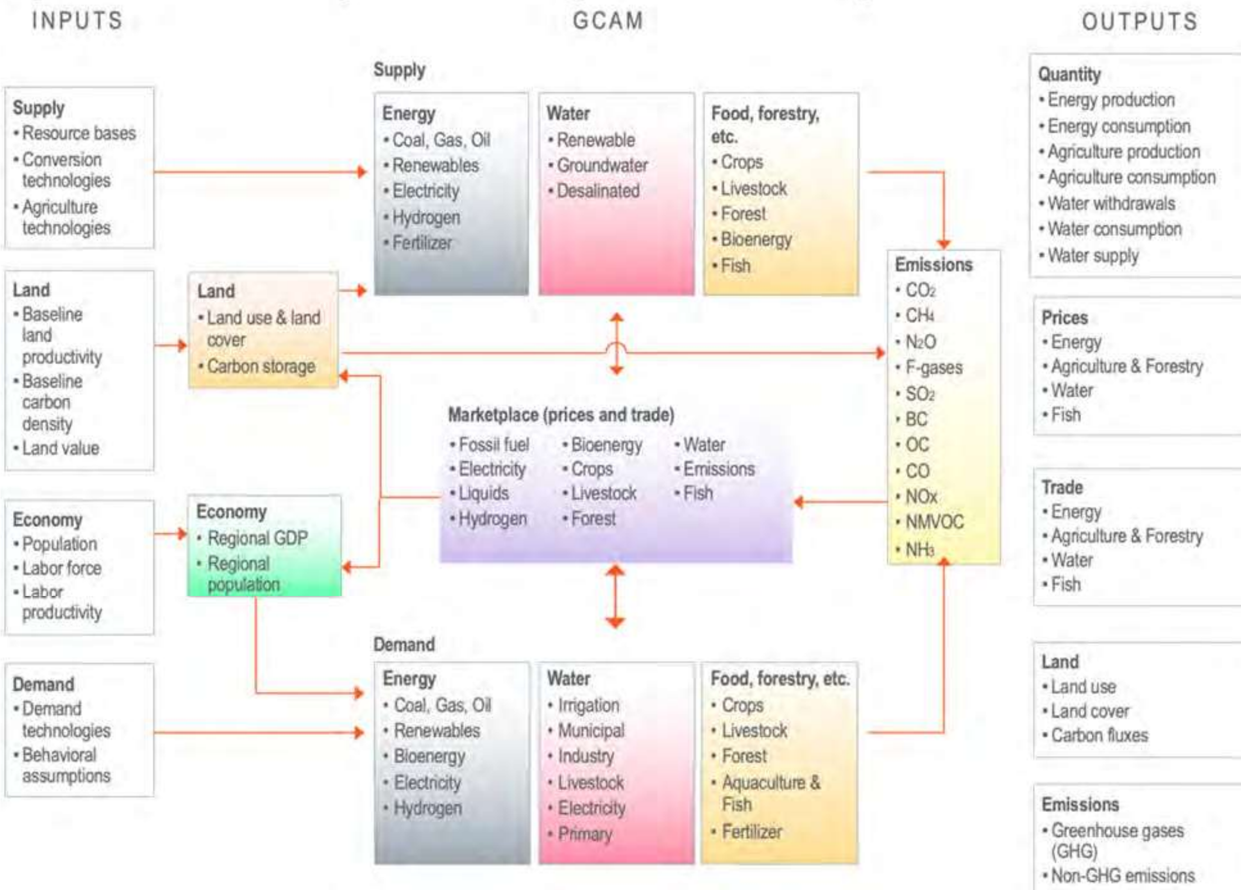
53 For more information, see https://gcims.pnnl.gov/community.
54 Thomson AM, Calvin KV, Smith SJ, Kyle GP, Volke A, Patel P, et al. RCP4. 5: a pathway for stabilization of radiative forcing by 2100. Clim Change 2011;109:77.
55 Calvin K, Bond-Lamberty B, Clarke L, Edmonds J, Eom J, Hartin C, et al. The SSP4: A world of deepening inequality. Glob Environ Change 2017;42:284–96.
56 See https://github.com/JGCRI/gcam-core.
57 See http://jgcri.github.io/gcam-doc/index.html.
58 See more specifically http://jgcri.github.io/gcam-doc/references.html.
59 McFadden D. Conditional logit analysis of qualitative choice behavior 1973.
60 Clarke JF, Edmonds JA. Modelling energy technologies in a competitive market. Energy Econ 1993;15:123–9.
61 See Calvin et al. 2019. GCAM v5.1: Representing the linkages between energy, water, land, climate, and economic systems. Geoscientific Model Development 12, 1–22. See also the online documentation (https://github.com/JGCRI/gcam-doc/blob/gh-pages/ssp.md) for the specific quantification of the inputs and parameters to the model.

International trade of commodities in GCAM is specified using one of two methods. Agricultural, livestock, and forestry primary goods are traded through regionally-differentiated markets following an Armington-style approach.[62] In the version of GCAM used for this exercise, all other commodities are traded through homogenous global markets following the Heckscher-Ohlin theorem. [63] These approaches are described in detail in GCAM's online documentation.[64]

Figure 2.3-1: GCAM diagram of model inputs, sectors, and outputs[65]



GCAM includes detailed representations of the energy sector, inclusive of liquid biofuels, and the agriculture and land sectors. The energy sector module in GCAM consists of depletable and renewable resources[66], energy transformation and distribution sectors (electricity, refining,

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[62] The Armington approach to modeling international trade is based on the premise that products traded internationally are differentiated by country of origin. This is in contrast to models that assume perfect substitution between products produced in different countries. Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. IMF Staff Papers, 1969 (001).

[63] Note that the most recent public version of GCAM trades all energy goods through the Armington-like approach, rather than through homogenous markets. This version of the model was not released in time for inclusion in this exercise.

[64] See http://jgcri.github.io/gcam-doc/details_trade.html

[65] See http://jgcri.github.io/gcam-doc/index.html.

[66] Depletable resources are based on graded supply curves for coal, oil, gas and uranium. Renewable resources include annual flows of wind, solar, geothermal, hydropower, and biomass.

gas processing, hydrogen production, and district services), and final energy demand sectors (buildings, industry, and transportation).[67] For transportation biofuels specifically (referred to in the GCAM documentation as "biomass liquids"), by default the model includes a total of 11 biofuel production technologies. These include four "first generation" technologies, representing ethanols and biodiesels produced from agricultural commodity crops, and seven "second generation" technologies representing fuels produced from a variety of feedstocks, including energy crops and residues. By default, the technology assumptions for second generation represent the inputs and outputs of cellulosic ethanol and Fischer-Tropsch fuels. However, the input assumptions for these technologies can be modified to represent other fuel production pathways. Secondary outputs such as dried distillers grains (DDG) and electricity produced from lignin can be considered, as can the potential for carbon capture and storage. Further description of these technological representations is available in the online GCAM documentation.[68]

The agriculture and land use module differentiates 384 land use regions globally, generated as the intersection of 32 socioeconomic regions with 235 water basins (see Figure 2-2). Within each land use region, up to 25 land use types compete for land share based on the relative profitability of each use, using a nested land allocator tree structure.[69] The conversion of land from one type to another is determined in part by the logit structure of the model and the land nesting structure.[70] GCAM land categories are structured in sub-nests, with easier conversion between land types within a sub-nest than across sub-nests. Land use types include exogenous land types (tundra, desert, urban), commercial and non-commercial pasture and forest lands, grasslands and shrublands, and a detailed set of agricultural crop commodities, including bioenergy crops, classified by irrigation type and fertilizer use.[71]

Within this nesting structure, the allocations of land to each land use type are calibrated in the model base year, and in the future, changes from the base-year allocations are driven by changes in the relative profitability of each land use type, including both commercial and natural lands. Profitability of lands in agricultural and forestry production changes over time as a function of future commodity prices, yields, and costs of production (including endogenous costs of fertilizer, fuel, and irrigation water). The intrinsic profitability or value of natural lands is inferred from the base year profitability of proximate land used for agriculture and forestry in each region. The logit competition for land is non-linear and exhibits diminishing marginal

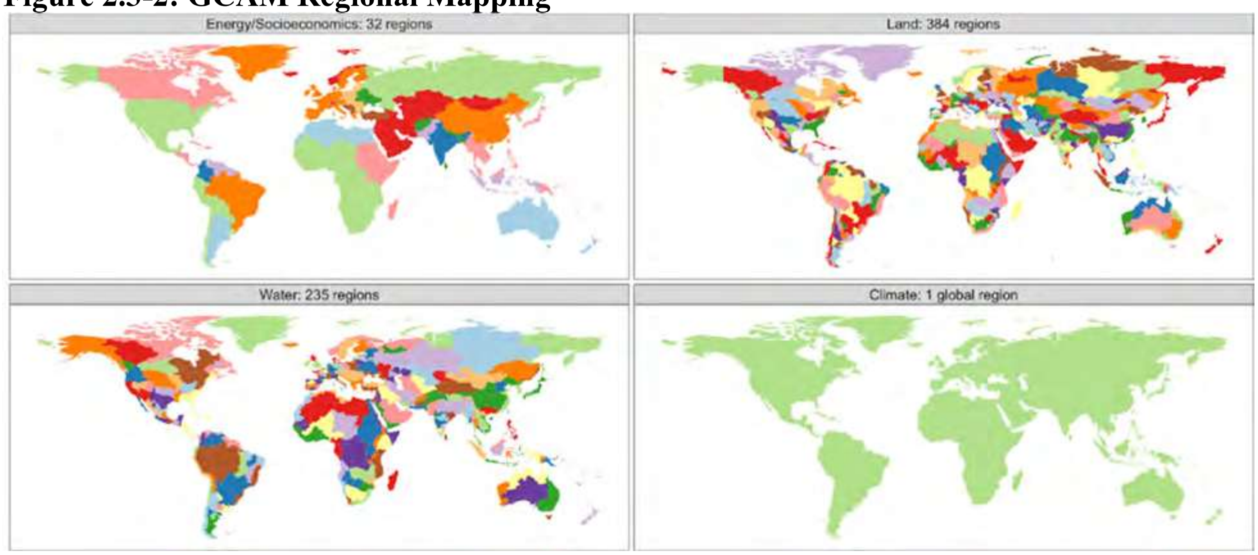
[67] More detailed information on the GCAM energy system can be found in online documentation, see http://jgcri.github.io/gcam-doc/index.html, and also in previous studies (see Clarke L, Eom J, Marten EH, Horowitz R, Kyle P, Link R, et al. Effects of long-term climate change on global building energy expenditures. Energy Econ 2018;72:667–77; Muratori M, Ledna C, McJeon H, Kyle P, Patel P, Kim SH, et al. Cost of power or power of cost: A US modeling perspective. Renew Sustain Energy Rev 2017;77:861–74.)
[68] See http://jgcri.github.io/gcam-doc/supply_energy.html.
[69] See Wise M, Calvin K, Kyle P, Luckow P, Edmonds J. Economic and physical modeling of land use in GCAM 3.0 and an application to agricultural productivity, land, and terrestrial carbon. Clim Change Econ 2014;5:1450003, and Zhao X, Calvin KV, Wise MA. The critical role of conversion cost and comparative advantage in modeling agricultural land use change. Clim Change Econ 2020;11.
[70] See http://jgcri.github.io/gcam-doc/details_land.html
[71] A complete description of the land use module can be found in the online documentation (see http://jgcri.github.io/gcam-doc/toc.html) and in Kyle GP, Luckow P, Calvin KV, Emanuel WR, Nathan M, Zhou Y. GCAM 3.0 agriculture and land use: data sources and methods. Pacific Northwest National Lab.(PNNL), Richland, WA (United States); 2011.

returns to expansion of each use as well as non-constant elasticities.[72] This nonlinear nature allows the land shares to be solved based on equal value at the margin without need the explicit constraints used in linear models.

GCAM also uses land suitability and land protection assumptions to determine what land is available for expansion. All versions of GCAM divide land into arable and non-arable categories and, by default, protect some portion of the arable land from conversion to agricultural or silvicultural use. In the version of GCAM used for this exercise, GCAM-T, other assumptions limit the suitability of arable lands for crop production based on biophysical limitations (e.g., slope, annual rainfall) and human-imposed limitations such as land protection policies. The latter are parameterized using the International Union for Conservation of Nature's (IUCN) World Database of Protected Areas.[73]

Terrestrial carbon stocks and flows are modeled for each land type in each water basin.[74] The agricultural sector of the model primarily relies on input data from the UN Food and Agriculture Organization (FAO) historical data sets, and includes all crops for which FAO reports area and production data for the model base year of 2015.[75] Major global commodity crops, such as corn, rice, soybeans and wheat are modeled individually, while all other crops are modeled as a series of thematic aggregations.

Figure 2.3-2: GCAM Regional Mapping[76]



In addition to the core GCAM described in this section, there exist several other subversions and downscaling tools which can be used to examine regions and systems at a finer grain of resolution. These include, among others, GCAM-USA[77], which models each U.S. state

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[72] See Wise et al (2020).
[73] For more information, see documentation provide at https://github.com/gcamt/gcam-core/tree/GCAM-T-2020.
[74] Input assumptions related to terrestrial carbon and land transitions are documented at http://jgcri.github.io/gcam-doc/land.html.
[75] See http://jgcri.github.io/gcam-doc/inputs_land.html for further data on land inputs to the model.
[76] See http://jgcri.github.io/gcam-doc/overview.html.
[77] See http://jgcri.github.io/gcam-doc/gcam-usa.html.

as an individual region, Tethys[78], which allows for the downscaling of modeled GCAM water impacts, and Demeter[79], which allows for the downscaling of modeled land allocation impacts. Numerous additional tools are in various stages of development at JGCRI and other research groups which participate in the GCAM Community.[80]

One of these, GCAM-T, was used in a recent study of corn ethanol impacts by Plevin et al. The results of that study are discussed in greater detail later in this chapter.[81] GCAM-T is also the version of the model used for the present model comparison exercise. This version of the model includes greater detail in several sectors relevant to the modeling of transportation energy technologies, including biofuels. The version of GCAM-T used for the Plevin et al paper, GCAM-T 2020.0, is publicly documented.[82] Additional documentation for the version of GCAM-T used for this model comparison exercise, GCAM-T 2022.0, is included as a memorandum to the docket.[83] GCAM-T 2022.0 is referred to simply as "GCAM" for the remainder of this RIA discussion and in the preamble of this final rulemaking.

In addition to biofuel modeling,[84] GCAM is used for diverse purposes across a wide range of stakeholders, including federal, state, and local U.S. government, foreign governments and international governance bodies, academia, private industry, and non-governmental organizations. As noted above, GCAM is used on an ongoing basis by the IPCC in the development of socioeconomic and climatic projections via the Representative Concentration Pathways[85] and Shared Socioeconomic Pathways.[86] Another notable recent application was the use of GCAM to produce scenario analysis for the Long-Terms Strategy of the United States, submitted to the United Nations under the Paris Agreement by the U.S. State Department and Executive Office of the President.[87] Numerous other research papers associated with GCAM are accessible via PNNL's publications page for the model.[88]

2.4 The Global Trade Analysis Project (GTAP) Model

The GTAP-BIO model is an extension of the standard Global Trade Analysis Project (GTAP) model which has been developed at the GTAP center of the Department of Agricultural Economics at Purdue University to study the economic and environmental impacts of biofuel production and policy.

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78 https://github.com/JGCRI/tethys.

79 https://github.com/JGCRI/demeter.

80 For more information, see https://gcims.pnnl.gov/community.

81 Plevin, R. J., et al. (2022). "Choices in land representation materially affect modeled biofuel carbon intensity estimates." Journal of Cleaner Production: 131477.

82 See https://github.com/gcamt/gcam-core/tree/GCAM-T-2020 and https://zenodo.org/record/4705472.

83 See "GCAM-T 2022.0 Documentation" in the docket.

84 See for example, Mignone, B. K., Huster, J. E., Torkamani, S., O'Rourke, P., & Wise, M. (2022). Changes in Global Land Use and CO_2 Emissions from US Bioethanol Production: What Drives Differences in Estimates between Corn and Cellulosic Ethanol?. Climate Change Economics, 13(04), 2250008.

85 Thomson AM, Calvin KV, Smith SJ, Kyle GP, Volke A, Patel P, et al. RCP4. 5: a pathway for stabilization of radiative forcing by 2100. Clim Change 2011;109:77.

86 Calvin K, Bond-Lamberty B, Clarke L, Edmonds J, Eom J, Hartin C, et al. The SSP4: A world of deepening inequality. Glob Environ Change 2017;42:284–96.

87 See https://unfccc.int/documents/308100

88 See https://gcims.pnnl.gov/gcims-publications

The GTAP center is the focal point of a global network of more than 27 thousand researchers, scholars, academic institutions, and policy research entities that are conducting quantitative analysis of a wide range of policy issues related to trade, energy, agriculture, and climate change. The members of this network provide and share various databases, develop modeling ideas and codes, conduct research, and disseminate their research findings. The GTAP center facilitates these activities by providing various databases and modeling tools. In particular this center assembles databases that support modeling practices around the world for various modeling approaches. The standard GTAP database is centerpiece of these activities. The most recent versions of this database include Input-output (I-O) tables for 160 regions converting the whole world economic activities; bilateral trade data at global scale; production, consumption, and trade of energy products; data on various types of GHG and non-GHG emissions generated around the world; land use and land cover data; and several other items. The GTAP database is particularly supports CGE modeling activities. However, it has been used by many other modeling practices around the world. To various extents, several of the models participated in this modeling comparison exercise rely on the GTAP database. The latest available version of this standard database represents the global economy in 2017.

In addition to providing data, the GTAP center develops standard modeling platforms as well. The standard GTAP model is the core of these platforms. This model has been originally developed in 1999 and documented in Hertel (1999).[89] This model and its extensions have been used in many research activities and thousands of publications. Corong et al. (2017) has introduced the latest version of this standard model and its capabilities and extensions, with detailed discussion on the theory and derivation of the behavioral and equations in the model.[90] The standard GTAP is a global, comparative static, multi-commodity, and multi-regional Computable General Equilibrium model that traces production, consumption, and trade of all good and service produced across the world. This model assumes perfect competition in all markets with price adjustments to ensure that all markets are simultaneously in equilibrium. Some GTAP versions deviate from the perfect competition assumption.

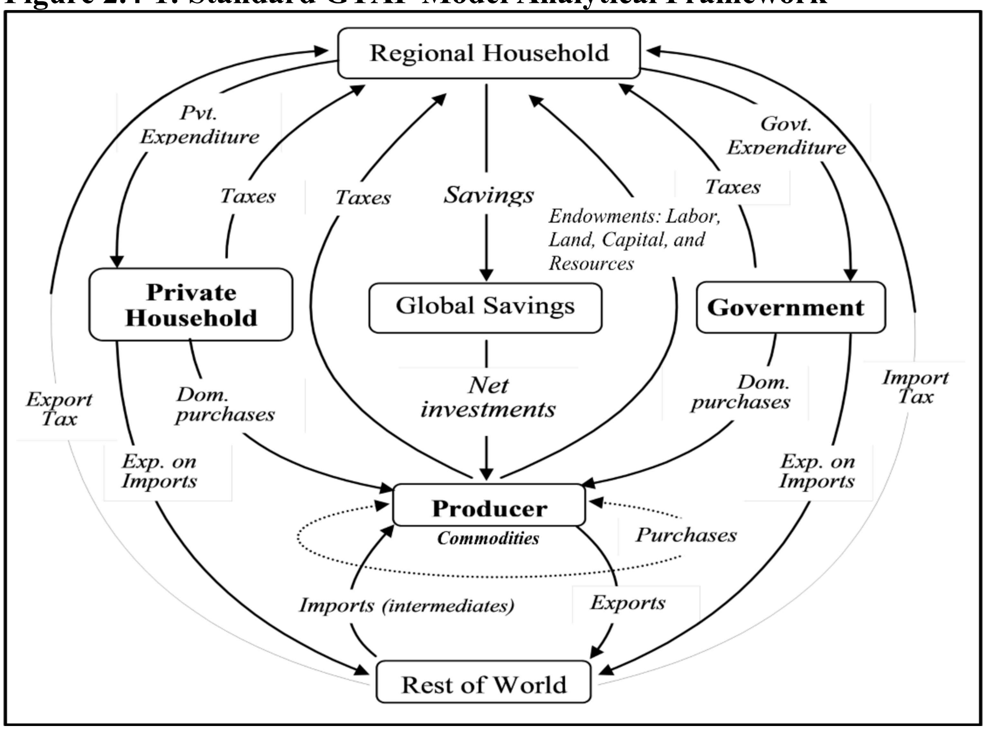
As shown in Figure 2.4-1, in each region of this model a regional household collects all the income in its region and spends it over three expenditure types: private household (representing all consumers), government, and savings, as governed by a utility function. A representative firm maximizes profits subject to a production function that combines primary factors of production including labor, land, capital, and resources and intermediate inputs to produce a final good or service. Firms pay wages/rental rates to the regional household in return for their uses of primary inputs. Firms also sell their output to other firms (as intermediate inputs), private households, government, and investment. Since this is a global model, firms also export the tradable commodities and import the intermediate inputs from other regions. These goods or services are assumed to be differentiated by region and thus the model is able to track bilateral trade flows. The model follows Armington assumptions for bilateral trade, to account for product heterogeneity among outputs produced in different regions. Taxes are paid to the

[89] Hertel, T.W., ed. 1997. Global Trade Analysis: Modeling and Applications. New York, NY: Cambridge University Press.
[90] Corong, E. L., Hertel, T. W., McDougall, R., Tsigas, M. E., & Van Der Mensbrugghe, D. (2017). The standard GTAP model, version 7. Journal of Global Economic Analysis, 2(1), 1-119.

regional household. The rest of the world receives revenues by exporting to the private household, firms, and government. These revenues are spent on export taxes and import tariffs, which eventually go to the regional household. The rest of world represents other regions of the model.

As noted above, the standard GTAP model is a comparative static model. Hence, as noted by Corong et al. (2017) "a GTAP simulation presents not changes through time, but differences between possible states of the global economy – a *base case* and a *policy case* – at a fixed point in time, or with respect to two points in time (base period vs. a future projection period)."[91] The version of GTAP used for this exercise is based on the 2014 database; thus, we can say that the biofuel simulations for this exercise with GTAP estimate changes in the 2014 economy due to a change in biofuel consumption. A typical comparative static simulation isolates the impacts of a phenomenon or changes in one or a set of variables that may affect the global economy from many other factors that vary over time.

Figure 2.4-1: Standard GTAP Model Analytical Framework[92]



Our model comparison exercise includes the GTAP-BIO model. While this comparative static model is the most widely used GTAP model for biofuel analysis, we recognize there are other GTAP models available that could potentially be used for this purpose. For example, GDyn-BIO and GTAP-DEPS are recursive-dynamic versions of GTAP that have been used to

[91] Ibid.
[92] An updated version of the depiction first developed in Brockmeier M. (2011) "A graphical exposition of the GTAP Model", GTAP Technical paper No. 08.

model U.S. corn ethanol impacts.[93] ENVISAGE is another dynamic model complemented by an emissions and climate module that links changes in temperature to impacts on economic variables such as agricultural yields.[94] While we did not have the ability to include more than one GTAP model in our current model comparison exercise, exploring and comparing the capabilities of other GTAP models for biofuel analysis is a potential area for future research. Such an exploration and comparison may consider multiple factors. For example, other GTAP models do not currently carry all the modifications incorporated in the GTAP-BIO model to show the role and importance of various factors that could affect the economic and environmental impacts of biofuel production and policy. Assessing induced land use changes due to biofuels has been the core of many of these GTAP-BIO modifications, and it has also been used to evaluate the consequences of climate change, water scarcity, and environmental policies.[95] Another factor to consider are the trade-offs between using a historical comparative static framework like GTAP-BIO, versus using a model that projects into the future. Projecting changes in the global economy over time is helpful to answer certain analytical questions, and requires making projections on many factors with associated uncertainties.

Over time, various modifications have been made in the standard GTAP databases to study the economic and environmental impacts of biofuel production and policy. The standard GTAP databases do not explicitly represent production, consumption, and trade of biofuels, their byproducts and coproducts. They also lack proper sectoral disaggregation to support biofuel studies. The GTAP-BIO databases have been generated to remove these barriers. These databases explicitly represent traditional biofuels (grain-based ethanol, ethanol produced from sugar crops and biodiesel produced from oilseeds) that are produced and consumed across the world. Some GTAP-BIO databases represent more advance biofuel technologies that produce road and aviation fuels from traditional feedstocks and lignocellulosic materials. These databases, depending on the application, provide more disaggregated crops, and further disaggregate some standard GTAP sectors to facilitate biofuel studies. For example, the substitution between biofuels and fossil fuels occurs in a newly introduced sector that blends fossil fuels and biofuels.

For analyzing land use change, the GTAP-BIO databases follow the GTAP-AEZ land databases and divide the land rents and land areas of each country into 18 Agro-Ecological

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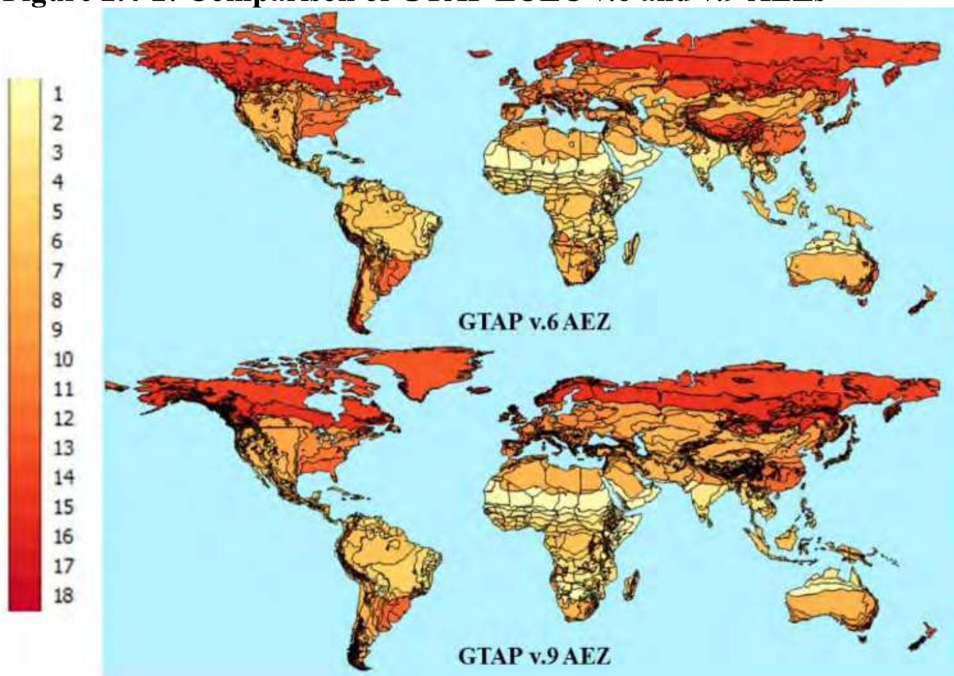
[93] Golub, A. A., et al. (2017). Global Land Use Impacts of U.S. Ethanol: Revised Analysis Using GDyn-BIO Framework. Handbook of Bioenergy Economics and Policy: Volume II: Modeling Land Use and Greenhouse Gas Implications. M. Khanna and D. Zilberman. New York, NY, Springer New York: 183-212.; Oladosu, Gbadebo, and Keith Kline. "A dynamic simulation of the ILUC effects of biofuel use in the USA." Energy policy 61 (2013): 1127-1139.

[94] Van der Mensbrugghe, Dominique. "The environmental impact and sustainability applied general equilibrium (ENVISAGE) model." The World Bank, January (2008): 334934-1193838209522.

[95] A few examples are: Taheripour F., Hertel, T. W., & Ramankutty, N. (2019). "Market-mediated responses confound policies to limit deforestation from oil palm expansion in Malaysia and Indonesia," *Proceedings of the National Academy of Sciences*, *116* (38), 19193–19199; Peña-Lévano, L. M., Taheripour, F., and Tyner, W. E. (2019). "Climate change interactions with agriculture, forestry sequestration, and food security," *Environmental and Resource Economics*, *74*, 653–675; Yao G., Hertel T., and Taheripour F. (2018). "Economic drivers of telecoupling and terrestrial carbon fluxes in the global soybean complex," *Global Environmental Change, 5: 190–200;* Liu J., Hertel T., Taheripour F., Zhu T., and Rigal C. (2014). "International trade buffers the impact of future irrigation shortfalls," *Global Environmental Change,* Vol. 29, 22-31.

Zones.[96] The AEZs represent 18 relativity homogeneous groups of lands based on length of growing days, moisture regions, and climate zones. The GTAP-BIO databases trace land cover items (forest, pasture and cropland), harvested areas, and crops produced at AEZ level. While the GTAP databases represent managed and unmanaged lands, in modeling induced land use changes due to biofuels only managed lands are represented in GTAP-BIO for various reasons.[97]

Figure 2.4-2: Comparison of GTAP LULC v.6 and v.9 AEZs[98]



The most recent version of GTAP-BIO available in time for our model comparison exercise uses GTAP-BIO database version 10, representing the global economy in 2014.[99] The geographical aggregation of this this data is presented in Figure 2.4-3. Researchers at Purdue have the ability to project a database forward in time based on macro-economic projections in

[96] Hertel et al. (2009) described the original GTAP land use data. Baldos and Corong (2020) documented the recent GTAP land use databases up to 2014. Hertel, T.W., S. Rose, and R. Tol. 2009. "Land use in computable general equilibrium models: An overview." In Economic Analysis of Land Use in Global Climate Change Policy. United Kingdom: Routledge, Routledge Explorations in Environmental Economics; Baldos U. and E. Corong (2020) Development of GTAP 10 Land Use and Land Cover Data Base for years 2004, 2007, 2011, 2014. GTAP Research Memorandum No. 36.

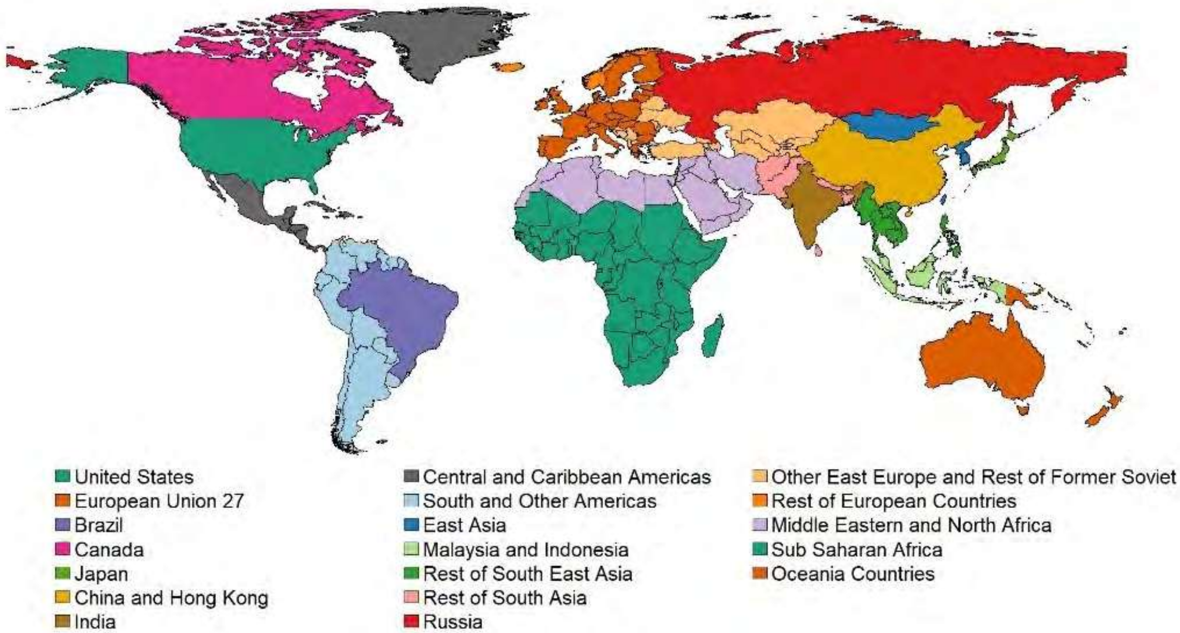
[97] Hertel, T.W., Golub, A.A., Jones, A.D., O'Hare, M., Plevin, R.J., Kammen, D.M., 2010. Effects of US maize ethanol on global land use and greenhouse gas emissions: estimating market-mediated responses. BioScience 60, 223-231. See the supporting information which says on page 27, "The current version of GTAP does not estimate conversions from unmanaged land to cropland." Also, footnote 6: "Forest land area used in this work is accessible forest land area and not managed forests. The forest accessibility is function of distance to infrastructure. Accessible forests area includes managed forests plus that part of unmanaged forests that is easily accessible."

[98] Uris, B. L. (2017) Development of GTAP 9 Land Use and Land Cover Data Base for years 2004, 2007 and 2011. GTAP Research Memorandum No. 30

[99] Aguiar, A., Chepeliev, M., Corong, E., McDougall, R., & van der Mensbrugghe, D. (2019). The GTAP Data Base: Version 10. Journal of Global Economic Analysis, 4(1), 1-27. Retrieved from https://www.jgea.org/ojs/index.php/jgea/article/view/77

order to simulate future time periods.[100] EPA and Purdue explored the possibility of creating a version of GTAP-BIO with a projected 2030 database to align better with the scenarios modeled with the dynamic models in our model comparison. Unfortunately, we were unable to complete this work in time for the model comparison exercise.

Figure 2.4-3: Economic regions represented in GTAP



GTAP-BIO has been updated multiple times to add features that are relevant for biofuel GHG modeling. Tyner et al. (2010) included marginal lands and productivity estimates for potential new cropland based on a biophysical model.[101] Taheripour et al. (2012) used a biophysical model (TEM) and estimated a set of extensification parameters which represent productivity of new cropland versus the existing land by AEZ region.[102] Taheripour and Tyner (2013) used a tuning process to differentiate land transformation elasticities by region based on FAO data.[103] Taheripour and Tyner (2013) modified the land supply tree putting cropland pasture and dedicated energy crops (e.g., switchgrass) in one nest and all other crops in another nest, "to make greater use of cropland pasture (a representative for marginal land) to produce dedicated energy crops."[104] Taheripour et al. (2016) altered the land use module of GTAP-BIO

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[100] Yao G., Hertel T., and Taheripour F. (2018). "Economic drivers of telecoupling and terrestrial carbon fluxes in the global soybean complex," *Global Environmental Change, 5: 190–200*

[101] Tyner, W. E., Taheripour, F., Zhuang, Q., Birur, D., & Baldos, U. (2010). Land use changes and consequent CO_2 emissions due to US corn ethanol production: A comprehensive analysis. *Department of Agricultural Economics, Purdue University*, 1-90.

[102] Taheripour, F., et al. (2012). "Biofuels, cropland expansion, and the extensive margin." Energy, Sustainability and Society 2(1): 25.

[103] Taheripour, F. and W. E. Tyner (2013). "Biofuels and land use change: Applying recent evidence to model estimates." Applied Sciences 3(1): 14-38.

[104] Taheripour, F. and W. E. Tyner (2013). "Induced Land Use Emissions due to First and Second Generation Biofuels and Uncertainty in Land Use Emission Factors." Economics Research International 2013: 12.

to include cropland intensification due to multiple cropping or returning idled cropland production, defined a new set of regional intensification parameters and determined, and defined regional yield responses to price based on analysis of regional changes in crop yields.[105] Taheripour et al. (2017) brought all of these modifications into one version of GTAP-BIO using the GTAP database representing 2011.[106] The version of GTAP-BIO used in this exercise includes the above developments and adds cropland pasture as a land category in all regions using the FAO land use database, whereas the previous version included cropland pasture in only the United States, Brazil and Canada.

GTAP estimates areas and types of land use change by region in response to a biofuel shock. Given that this model does not endogenously estimate land use change GHG emissions, land use change areas are translated to GHG emissions using either the AEZ-EF model[107] or the CCLUB module of GREET, which produce significantly different estimates.[108] These tools make assumptions about how land use changes will occur in the future. To calculate a land use change CI metric, the land use change emissions are annualized (e.g., over 20-30 years, depending on the policy context) and divided by the energy content of the simulated biofuel shock. For this model comparison exercise, land use change areas estimated with GTAP are converted to land use change GHG emissions with AEZ-EF, version 52, and annualized over 30 years.

In general, the GTAP-based models are able to evaluate changes in GHG emission due to changes in economic activities. While the GTAP-BIO model has been used mainly to assess induced land use change emissions, this model can also estimate changes in GHG and non-GHG emissions due to changes in economic activities. For this model comparison exercise, we are interested in broadly evaluating the capabilities of each model. Thus, we also consider GTAP estimates for all global economic sectors such as energy, livestock and forestry. These estimates include changes in CO_2 and non-CO_2 emissions due to biofuel induced changes.[109] While, this report provides these results, the results could be further studied for potential improvements in model parameters that govern changes in these emissions.

GTAP-BIO is used widely for biofuel land use change analysis. As discussed above, the GREET model incorporates land use change estimates from this model through the CCLUB module. The GTAP-BIO results are used to estimate induced land use change GHG emissions for the California, Oregon, and Washington low carbon fuel standard programs. GTAP-BIO is also one of two models, along with GLOBIOM, used to estimate induced land use change emissions for the International Civil Aviation Organization (ICAO) Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA). Furthermore, GTAP-BIO has been

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105 Taheripour, F., et al. (2016). An Exploration of Agricultural Land Use Change at Intensive and Extensive Margins. Bioenergy and Land Use Change: 19-37.

106 Taheripour, F., et al. (2017). "The impact of considering land intensification and updated data on biofuels land use change and emissions estimates." Biotechnology for Biofuels 10(1): 191.

107 Plevin, R., Gibbs, H., Duffy, J., Yui, S and Yeh, S. (2014). Agro-ecological Zone Emission Factor (AEZ-EF) Model (v52).

108 Chen, R., et al. (2018). "Life cycle energy and greenhouse gas emission effects of biodiesel in the United States with induced land use change impacts." Bioresource Technology **251**: 249-258. Figure 4.

109 Chepeliev, M. (2020). Development of the Non-CO_2 GHG Emissions Database for the GTAP Data Base Version 10A (No. 5993). Center for Global Trade Analysis, Department of Agricultural Economics, Purdue University

used to estimate biofuel induced land use change emissions for numerous journal articles (see for example the articles cited above).

2.5 The Applied Dynamic Analysis of the Global Economy (ADAGE) Model

The Applied Dynamic Analysis of the Global Economy (ADAGE) model is a multi-region, multi-sector computable general equilibrium (CGE) model developed and maintained by RTI International.[110] The original ADAGE model was a forward-looking model.[111] It was originally developed to examine impacts of climate change mitigation policies and was used, for example, to analyze economy-wide impacts of various legislative proposals, including the American Clean Energy and Security Act of 2009. More recently, the ADAGE model has been developed to have additional sectoral detail, particularly in agriculture, bioenergy, and transportation.[112] This version of the ADAGE model (hereinafter referred to as "ADAGE" or "the ADAGE model") is global, rather than national, and is recursive-dynamic, which means that decisions about production, consumption, savings, and investment are based on previous and current economic conditions.

ADAGE represents the entire economy, including private and public consumption, production, trade, and investment, and follows the classical Arrow-Debreu general equilibrium framework.[113] The model uses nested constant elasticity of substitution (CES) production functions. As illustrated in Figure 2.5-1, ADAGE includes representative households and firms, and economic flows among households, firms, and government are considered. Bilateral trade is represented using an Armington aggregation approach.[114] Dynamics in ADAGE are represented by 1) growth in the available effective labor supply from population growth and changes in labor productivity; 2) capital accumulation through savings and investment; 3) changes in stocks of natural resources; and 4) technological change from improvements in manufacturing, energy efficiency and land productivity, and advanced technologies that become cost competitive over time.

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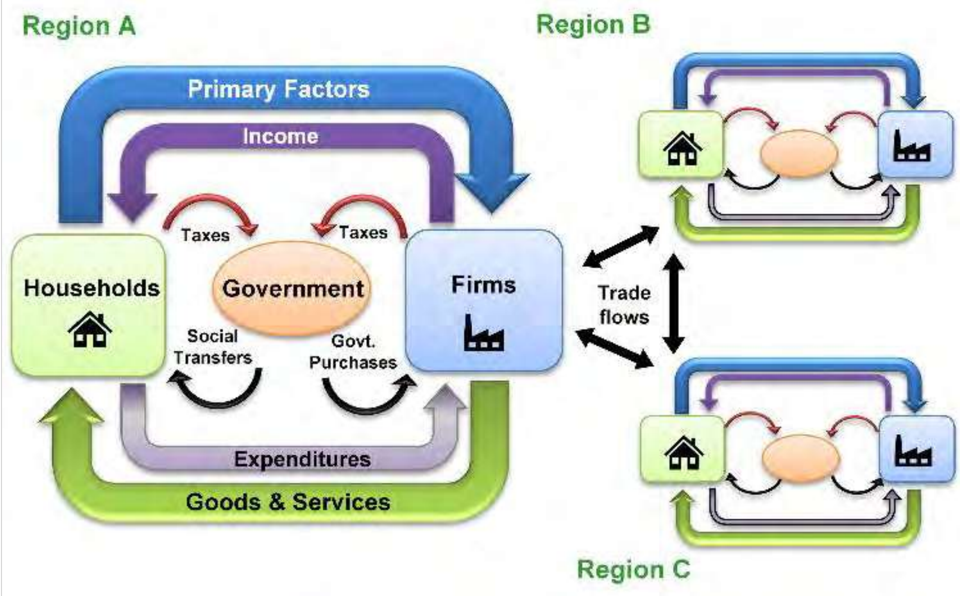
[110] The ADAGE model is available at https://github.com/RTIInternational/ADAGE.
[111] Ross, M. 2009. *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE) Model*. Working paper 09_01. Research Triangle Park, NC: RTI International.
[112] Cai Y., Beach R., Woollacott J., Daenzer K., 2023. *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE) model*. Technical Report. Available at https://github.com/RTIInternational/ADAGE.
[113] Arrow, K.J., and G. Debreu. 1954. Existence of an equilibrium for a competitive economy. Econometrica 22:265-290.
[114] Armington, P. S. (1969). A Theory of Demand for Products Distinguished by Place of Production. Staff Papers - International Monetary Fund, 16(1), 159–178.

Figure 2.5-1: Representation of Economic Flows in the ADAGE model[115]



ADAGE includes additional detail for the energy, food, agriculture, and transportation sectors. It runs in 5-year intervals from 2010 through 2050, and includes 8 global regions (Africa, Brazil, China, EU 27, United States, Rest of Asia, Rest of South America, and Rest of World; Figure 2.5-2). ADAGE is built off the GTAP v7.1 database which represents the global economy in 2004,[116] with additional data from other sources such as the International Energy Agency, U.S. Energy Information Administration, and United Nations Food and Agriculture Organization. These additional data help to extend the global economy from 2004 to 2010 through balanced growth and add more sectoral details and physical accounts. ADAGE tracks inputs and outputs in monetary units, and also tracks commodities and resources in physical units (such as energy units of fuel consumption, area of land, and mass of emissions).

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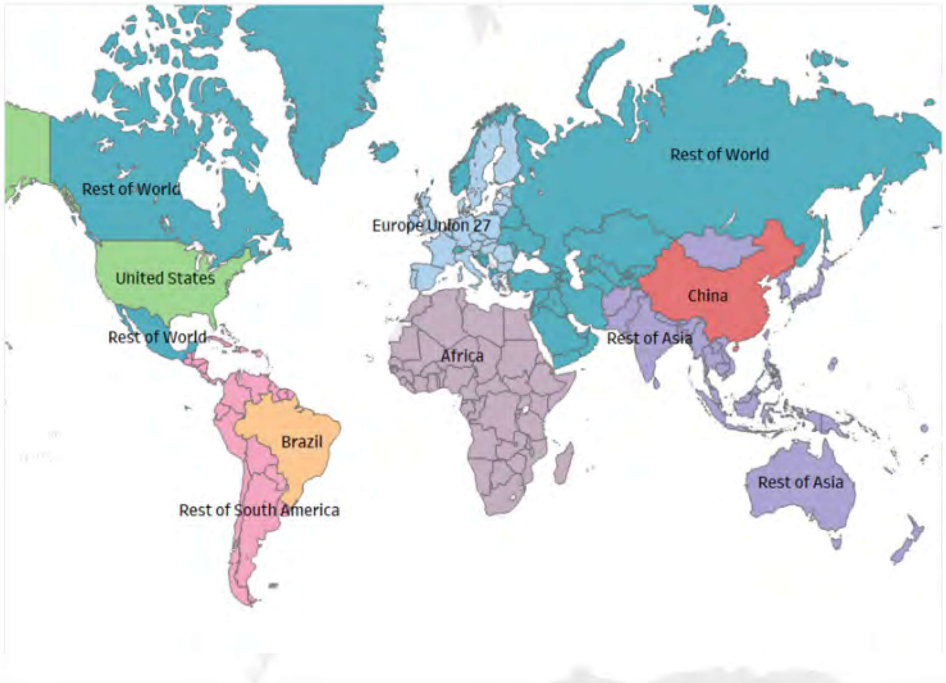
[115] Cai Y., Beach R., Woollacott J., Daenzer K., 2023. *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE) model*. Technical Report.

[116] Narayanan, G. B., and T. L. Walmsley (Eds.). 2008. Global Trade, Assistance, and Production: The GTAP 7 Data Base. West Lafayette, IN: Center for Global Trade Analysis, Purdue University. http://www.gtap.agecon.purdue.edu/databases/v7/v7_doco.asp.

Figure 2.5-2: ADAGE Regional Mapping



ADAGE models the markets for several agricultural commodities: wheat, corn, soybean, sugarcane, sugar beet, rest of cereal grains, rest of oilseeds, and rest of crops, in addition to one livestock category and one forestry category. The agricultural sector in the underlying GTAP v7.1 database is more aggregated, so creating these commodities in ADAGE required disaggregation using information on trade shares, consumption shares, cost shares, and own use shares. [117] This disaggregation was done with software called SplitCom[118] and data from the United Nations Food and Agricultural Organization FAOSTAT database and the United Nations Comtrade Database.[119,120] The "cereal grains" sector in GTAP v7.1 was split into corn and rest of cereal grains, the oil seeds sector was split into soybean and rest of oilseeds, and the combined sugarcane and sugar beet sector was split into sugarcane and sugar beet.

Agricultural sector details in ADAGE enable it to model several kinds of biofuels. ADAGE includes 8 types of first-generation biofuels (corn ethanol, wheat ethanol, sugarcane ethanol, sugar beet ethanol, soybean oil biodiesel, rape-mustard biodiesel, palm kernel biodiesel, and corn oil biodiesel) and 5 types of advanced biofuels (ethanol from switchgrass, miscanthus, agricultural residue, forest residue, and forest pulpwood). These biofuels are not included in the GTAP 7.1 database and were split from GTAP v7.1 sectors using the SplitCom software and secondary data from USDA's Economic Research Service, DOE's Energy Information

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[117] Beach, R.H., D.K. Birur, L.M. Davis, and M.T. Ross. 2011. A dynamic general equilibrium analysis of U.S. biofuels production. AAEA & NAREA Joint Annual Meeting, Pittsburgh, PA. https://ageconsearch.umn.edu/bitstream/103965/2/ADAGE-Biofuels_AAEA_Conference_Paper.pdf.
[118] Horridge, M., J. Madden, and G. Wittwer. 2005. The impact of the 2002–2003 drought on Australia. Journal of Policy Modeling 27(3):285-308.
[119] Food and Agriculture Organization of the United Nations. 2012. FAOSTAT Database. Rome, Italy: FAO. http://www.fao.org/faostat/en/#data.
[120] United Nations. 2012. UN Comtrade Database. http://comtrade.un.org.

Administration, and the United Nations Comtrade database.[121,122,123] Corn ethanol and wheat ethanol were split from the "food products sector" in GTAP v7.1, which receives inputs from corn and wheat. Sugarcane ethanol and sugar beet ethanol were split from the chemicals sector. Biodiesel from soybean, rapeseed, and palm oil were split from the vegetable oils and fats sector. Distillers grains with solubles (DGS) and corn oil biodiesel are coproducts of corn ethanol production. An oil meal coproduct was split from the vegetable oil sector in GTAP v7.1. Because ADAGE does not explicitly represent rapeseed and palm oil production, the input shares of "rest of oilseeds" is based on region-specific palm oil and rapeseed biodiesel yields (gallon of biodiesel per ton of feedstock). Advanced biofuels were not included in the 2010 base year in ADAGE but are allowed to enter the market in future years.

The energy sectors of the ADAGE model include coal, natural gas, crude oil, and refined oil, and several categories of electricity generation technologies (conventional coal, conventional natural gas, conventional oil, combined-cycle natural gas, nuclear, hydropower, geothermal, wind, solar, and biomass). The supply of fossil fuels is limited by the availability of natural resources, which is represented as a fixed factor in the model. Crude oil is used as an input for refined oil and enters the production function in a fixed proportion. Electricity generation technologies are combined into a single electricity output.

The transportation sector in ADAGE has been developed to include light duty vehicles, freight trucks, buses, marine, aviation, freight rail and passenger rail. Biofuels can be consumed in on-road transportation (light duty vehicles, buses, and trucks). Alternative fuel options (hybrid, battery electric, fuel cell, and natural gas) are available for on-road vehicles. The GTAP v7.1 database includes three types of transportation (air, water, and rest of transportation) and was disaggregated using data from several sources.[124]

ADAGE includes six land types (cropland, pasture, managed forest, natural forest, natural grassland, and other land[125]). Land use change is represented by the combination of a given land type with materials, capital, and labor to produce a new land type. The amount of conversion in a period is limited by a fixed factor that is substitutable with other inputs. Each land type has its own endowment, land rent, and usage. The conversion cost between land types is equal to the differences in land rents, involving input cost from the labor, capital, and materials inputs for conversion activity. There are also constraints on the types of land that can be converted to other types. For example, only pasture and managed forest can be converted directly to cropland, but cropland can convert to any land type.[126] A fixed factor elasticity is defined for

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[121] USDA, Economic Research Service (ERS). 2012. U.S. Bioenergy statistics. Washington, DC: U.S. Department of Agriculture. https://www.ers.usda.gov/data-products/us-bioenergy-statistics.
[122] EIA. 2012. Petroleum & other liquids. Washington, DC: U.S. Department of Energy. https://www.eia.gov/dnav/pet/pet_move_impcus_a2_nus_epooxe_im0_mbbl_a.htm.
[123] United Nations. 2012. UN Comtrade Database. http://comtrade.un.org.
[124] Data sources include GCAM 4.2, the Bureau of Economic Analysis, the Bureau of Transportation Statistics, the International Energy Agency, and the Energy Information Administration. For more details, see Cai Y., Beach R., Woollacott J., Daenzer K., 2023. *Documentation of the Applied Dynamic Analysis of the Global Economy (ADAGE) model*. Technical Report.
[125] "Other land" includes bare ground, wetlands, mangroves, salt marsh, glaciers, and lakes, and is assumed to be constant over time.
[126] Unmanaged forest can only be converted to managed forest, and grassland can only be converted to pasture. Through these conversions, unmanaged forest and grassland could be converted to cropland over two time steps.

each starting land type/ending land type pair. Elasticities are generally the same in every region. However, the elasticities governing the conversion of natural forest to managed forest and grassland to pasture vary by region. ADAGE models land in physical as well as monetary quantities. Emissions from land use change are based on the differences in carbon stocks (vegetative and soil carbon) between the land types, and emission factors (one for vegetative carbon, and one for soil carbon) that represent the fraction of the change in carbon stock that would occur over 20 years after land conversion. Land use change emissions and sequestration are all reported in the model year in which the land use change occurs. Vegetative and soil carbon stocks are based on data from GCAM 3.2, which were aggregated to ADAGE regions using weighted land area.

ADAGE includes six types of greenhouse gases: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), perfluorocarbons (PFCs), hydrofluorocarbons (HFCs), and sulfur hexafluoride (SF_6). CO_2 emissions from fossil fuel combustion are based on emissions factors ($kgCO_2$/MMBTU) for coal, gas, and oil. The emission factors are differentiated by region and based on data from EIA's International Energy Statistics. CO_2 emission factors from sources other than fossil fuel combustion and land use change are based on data from the Emissions Database for Global Atmospheric Research (EDGAR) version 4.2.[127] Non-CO_2 emission factors are based on data from EPA.[128]

CGE models often represent individual economic sectors at a higher level of commodity and technology aggregation than some PE models of those same economic sectors. However, because CGE models capture the entire economy, they can be useful for determining impacts of environmental policies across sectors and on GDP. In one study, the ADAGE model was used to analyze projected impacts of the RFS on land use, crop production, crop prices, fossil energy use, GHG emissions, and GDP.[129] ADAGE has also been used to study the impact of oil prices on biofuel expansion.[130] In model comparison studies, ADAGE was used to analyze the GHG abatement potential in Latin America,[131] and the impacts of climate policy and agriculture, forestry, and land use emissions.[132]

[127] Joint Research Centre at European Commission. 2013. Emission Database for Global Atmospheric Research. http://edgar.jrc.ec.europa.eu/overview.php?v=42FT2010.
[128] U.S. Environmental Protection Agency (EPA). 2012. Global Non-CO_2 GHG Emissions: 1990-2030. Washington, DC: EPA. https://www.epa.gov/global-mitigation-non-co2-greenhouse-gases/global-non-co2-ghg-emissions-1990-2030.
[129] Cai, Y., D.K. Birur, R.H. Beach, and L.M. Davis. (2013, August). Tradeoff of the U.S. Renewable Fuel Standard, a General Equilibrium Analysis. Presented at 2013 AAEA & CAES Joint Annual Meeting, Washington, D.C.
[130] Cai, Y., R.H. Beach, and Y. Zhang. (2014, March). Exploring the Implications of Oil Prices for Global Biofuels, Food Security, and GHG Mitigation. Presented at 2014 AAEA Annual Meeting, Minneapolis, MN.
[131] Clarke L., McFarland J., Octaviano C., van Ruijven B., Beach R., Daenzer K., Herreras Martínez S., Lucena A.F.P., Kitous A., Labriet M., Loboguerrero Rodriguez A.M., Mundra A., van der Zwaan B., 2016. Long-term abatement potential and current policy trajectories in Latin American countries. Energy Econ. 56, 513-525. http://dx.doi.org/10.1016/j.eneco.2016.01.011.
[132] Calvin K.V., Beach R., Gurgel A., Labriet M., Loboguerrero Rodriguez A.M., 2016. Agriculture, forestry, and other land-use emissions in Latin America. Energy Econ. 56, 615-624. http://dx.doi.org/10.1016/j.eneco.2015.03.020.

3 Comparison of Model Characteristics, Input Parameters, and Input Data

In this section we compare the characteristics of the five models described above in Section 2. We compare the models across several characteristics that are important for biofuel analysis. In later sections, we discuss how these model characteristics impact model results.

3.1 Model Characteristics

Table 3.1-1 summarizes some of the key characteristics of the five models featured in Section 2. Although there are many ways to compare these models, we chose six key characteristics based on their relevance to the definition of lifecycle greenhouse gas emissions in Section 211(o)(1)(H) of the Clean Air Act.[133] Specifically, we consider model sectoral coverage, temporal resolution, regional coverage, GHG emissions coverage, land representation, and trade dynamics. Differences among modeling frameworks along these coverage, resolution, and dynamics characteristics may lead to significant differences in modeled perspectives on GHG emissions outcomes. These six characteristics therefore provide a good starting point for understanding the primary differences across these frameworks. We start our discussion based on these six characteristics before touching on other key aspects of these models for biofuel GHG analysis.

While we are not ruling out consideration or future use of other models, based on the biofuel GHG modeling workshop and our review of the literature, we believe the models listed in the table are the most likely to meet our needs for evaluating lifecycle GHG emissions. In addition, the models selected provide a broad representation of the types of models that can be used for lifecycle analysis.

[133] Other important considerations are not included in this table, such as open access to the models.

Table 3.1-1 Comparison of Key Characteristics Across Models

Characteristic	ADAGE	GCAM	GLOBIOM	GREET	GTAP
Type of Model	Computable general equilibrium (CGE); consequential LCA	Integrated assessment model (IAM); consequential LCA	Partial equilibrium (PE); consequential LCA	Supply chain LCA	Computable general equilibrium (CGE); consequential LCA
Sectoral Coverage	Economy-wide with 36 sectors	Energy (conventional and renewable), industry, buildings, transportation, agriculture, forestry, water	Agriculture, forestry, and bioenergy	Fuel supply chains including energy resource and material inputs	Economy-wide aggregated into 65 sectors
Temporal Representation	Recursive dynamic (5-year time steps)	Recursive dynamic (5-year time steps)	Recursive dynamic (10-year time steps)	Static (users can select a target year from 1990-2050)	Comparative static
Regional Coverage	8 economic and spatial regions	32 economic regions; 384 land regions (water basins, intersected with economic regions)	37 economic regions; 10,000 spatial units (grid cell)	Customizable (typically U.S. average)	19 economic regions; 18 agro-ecological zones
GHG Emissions Coverage	Economy-wide GHGs including land use change	Global GHGs including land use change	Crop production, livestock, and land use change	Direct supply-chain emissions + indirect land use change from CCLUB module	Economy-wide GHGs, with land use change GHGs calculated with the AEZ-EF model
Land Representation (Arable land categories considered in biofuel land use change analysis)	Cropland, pasture, commercial forest, non-commercial forest, natural grassland, other land	Cropland, commercial pasture and forest, non-commercial pasture and forest, shrubland, grassland, "protected" non-commercial land	Cropland, other agricultural land, grassland, commercial and non-commercial forest, wetlands, other natural land	Exogenous (Land use change estimates from GTAP-BIO and CCLUB)	Cropland (including cropland-pasture and unused cropland), livestock pasture, "accessible" forestry land

As observed above, modeling inherently involves trade-offs. For example, there may be trade-offs between scope and detail, or between capabilities to understand individual supply chains versus global impacts. Among the four model types considered in this exercise, the supply chain LCA models, like GREET, have the most detailed technological representations but the most limited scope. For example, the GREET model includes detailed representations of numerous biofuel and energy production processes but does not include price-induced interactions between supply chains or economic sectors or any other features which seek to balance economic equilibria within or across sectors. PE models used for biofuel analysis tend to have a high level of detail in the agricultural sector, but limited interactions with other sectors. For example, GLOBIOM has a detailed representation of crop production, livestock, and land use, but does not include economic interactions between the agricultural and energy sectors (e.g., fuel prices are exogenous). CGE models are the broadest in economic scope, but they often represent the world using a smaller number of physical regions and fewer specific technological options within a given economic sector. IAMs focus on representing physical processes, but often lack certain sectoral details relative to PE models, and treat more economic factors (e.g., global GDP) as exogenous relative to CGE models. When considering tradeoffs between these methodological options, one must consider the goals of the analysis and whether cross-sectoral impacts are potentially influential on the overall results. In instances where such impacts are potentially influential, broader sectoral coverage is likely to be more critical. In instances where such impacts are limited, or where the goal of the analysis is to understand GHG emissions from a particular supply chain or sector, the narrower scope of a supply chain LCA or PE model may be an acceptable tradeoff. Model comparison exercises can assist with these types of assessments. We discuss below the extent to which cross-sectoral impacts appear relevant to biofuel LCA modeling.

3.1.1 Sectoral Coverage

The modeling frameworks differ substantially in the scope of economic interactions that they represent. Capturing a wide range of economic interactions is important for understanding the overall GHG impacts, including indirect impacts, of crop-based biofuel production. Based on economic theory, we expect increased consumption of crop-based biofuels to have complex ripple effects through the entire world economy. For example, as the demand for feedstocks increase, we expect the price of these commodities to increase, with consequences for agricultural markets not only in the U.S., but around the world. These interactions are complicated by the fact that the major crop-based biofuel feedstocks have coproducts (e.g., distiller grains, soybean meal) that are used as livestock feed. Given that producing biofuels requires material (e.g., fertilizer) and energy (e.g., natural gas), increased biofuel production may affect these input commodity markets as well. When biofuels displace gasoline or diesel in the U.S., this change may affect consumer fuel prices and crude oil prices, which may in turn affect other sectors of the economy.

Supply chain LCA models such as GREET do not include most of these economic interactions. However, GREET includes agricultural sector interactions to a limited extent through the exogenous addition of land use change GHG estimates. GLOBIOM models economic interactions within and between the agricultural (including crops and livestock) and forestry sectors. GLOBIOM also includes a bioenergy sector with limited economic interactions other than through its consumption of feedstocks from the agricultural and forestry sectors. GCAM models economic interactions within and among the energy, agriculture, forestry, and water systems. The energy system in GCAM is highly developed, including energy production from a broad range of technologies and resources, and energy consumption in the industrial, commercial, residential, transportation, agriculture, and forestry sectors. As CGE models, GTAP and ADAGE model interactions across the entire economy. Thus, CGE models include economic interactions that the other modeling frameworks take as exogenous or do not include. As noted above, however, this creates computational tradeoffs which often require CGE models to represent sectoral dynamics at a more highly aggregated level than other model types with narrower scope.

The three models which represent energy market interactions (ADAGE, GCAM, and GTAP) also differ in which energy commodities are represented and how demand for energy commodities is linked to other model components. ADAGE represents production and bilateral trade of crude oil, refined oil[134], natural gas, coal, electricity, biodiesel (soy, palm kernel, rape-mustard, corn oil), and ethanol (corn, wheat, sugarcane, sugar beet). ADAGE dynamically represents the energy inputs required for extracting and refining petroleum and the inputs required for production of biofuels. GCAM represents crude oil, refined oil, natural gas, coal, electricity, biodiesel (soy, palm kernel, rapeseed, other oilseed-oil), and ethanol (corn, sugar crops, energy grasses, crop residues). GCAM dynamically represents both the energy inputs required for extracting and refining petroleum and the inputs required for growing and transporting crops and producing biofuels.[135] GTAP represents coal, crude oil, refined petroleum, electricity, natural gas, corn ethanol, sugarcane ethanol, grain ethanol, soybean oil biodiesel, rapeseed oil biodiesel, palm oil biodiesel, and other biodiesel. GTAP represents production, consumption, and bilateral trade in these commodities.

3.1.2 Temporal Representation

Temporal representation, or the treatment of time dynamics, is another important characteristic that differentiates the modeling frameworks. The ability to endogenously represent temporal dynamics is an important model feature given that biofuel land use change emissions occur over time (e.g., soil carbon levels change over multiple decades following land conversion) and biofuel-induced effects are dependent on factors that change over time, such as crop yields and overall demands of the population on land to produce food, feed, and fiber. GREET is designed to simulate supply chains in a given year, and includes the flexibility for users to choose background data (e.g., grid electricity mix) for future years extending out to 2050.[136] GTAP is a comparative static model, meaning it simulates changes in the 2014 economy due to a change in biofuel production or consumption.[137] GLOBIOM, GCAM and ADAGE are recursive dynamic models in which certain production, consumption, and investment decisions are made on the basis of market conditions in each period with dependence on previous model periods through capital and/or resource stocks. Conditions from previous periods are carried forward to influence the next modeled period. This differentiates dynamic recursive frameworks computationally from comparative static frameworks.

ADAGE and GCAM use 5-year time steps, whereas GLOBIOM uses 10-year time steps. In ADAGE and GCAM, the time step represents a point in time (e.g., the 2020 time step represents the estimated state of the world in the year 2020). In GLOBIOM, the time step

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[134] In these models, refined oil is an aggregation of all refined petroleum products, including gasoline and diesel.
[135] Sampedro, J., Kyle, P., Ramig, C. W., Tanner, D., Huster, J. E., & Wise, M. A. (2021). Dynamic linking of upstream energy and freight demands for bio and fossil energy pathways in the Global Change Analysis Model. *Applied Energy*, 302, 117580. https://doi.org/10.1016/j.apenergy.2021.117580
[136] However, as discussed above, if provided with sufficient data, GREET can estimate supply chain emissions for different time periods
[137] GTAP can model different time periods if the GTAP database is first manually projected forward (or backward) based on assumptions. Due to time constraints, we were unable to perform such projections for this exercise.

represents a long-term trend of changes over the applicable 10-year period (e.g., the 2020 time step is a representative average of changes from 2011 to 2020).

3.1.3 Regional Coverage

Thorough understanding of the impacts of a change in biofuel consumption through LCA requires consideration of significant indirect emissions. Many studies have shown that biofuel consumption in the U.S. can have significant impacts in other regions of the world.[138] Consequently, models need to represent all relevant regions to consider the full indirect impacts of a change in biofuel consumption. Furthermore, regional representation is important due to geographic variations related to terrestrial carbon stocks, agricultural yields, energy resources and other factors. PE, CGE and IAM models often distinguish between economic regions and biophysical regions. These models use solution algorithms to find market clearing conditions in, and trade between, each of the economic regions. Biophysical regions are often defined based on physical geography and geology to allocate economic activities and biophysical processes to physical locations. GTAP models 19 economic regions and 18 non-contiguous AEZs (see Figures 2.4-2 and 2.4-3). GLOBIOM models 37 economic regions and uses a spatially explicit grid-cell approach to represent 10,000 spatial units worldwide. GCAM models 32 economic regions and 235 global water basins—the intersection of the economic regions and water basins produces 384 spatial subregions.[139] ADAGE models 8 economic and geographic regions. In contrast, GREET is not a geographic or regional model, but it can be customized to represent biofuel production conditions for particular regions or supply chains. Data for GREET is primarily representative of the USA. GREET also has modules that are designed to estimate soil carbon and land use change emissions at a regional level. The FD-CIC module allows users to estimate feedstock production emissions at county level, and the CCLUB module estimates indirect land use change emissions based on the geographic regions represented by GTAP.

For this exercise, based on a template we provided to the modelers, ADAGE, GCAM, and GLOBIOM reported results from eight mutually exclusive global regions: Africa, Brazil, China, EU, USA, Rest of Asia, Rest of Latin America, and Rest of World. GTAP reported results from 19 global regions. In this document, we generally present results from the USA region of each model and an aggregation of the non-USA regions of each model.

3.1.4 GHG Emissions Coverage

There are notable differences in coverage of GHG emissions sources across the models. These differences in which GHGs are included in each model lead to differences among biofuel

[138] See for example, ICAO (2021). CORSIA Eligible Fuels -- Lifecycle Assessment Methodology. CORSIA Supporting Document. Version 3: 155; Plevin, R. J., J. Jones, P. Kyle, A. W. Levy, M. J. Shell and D. J. Tanner (2022). "Choices in land representation materially affect modeled biofuel carbon intensity estimates." Journal of Cleaner Production: 131477; Taheripour, F., X. Zhao and W. E. Tyner (2017). "The impact of considering land intensification and updated data on biofuels land use change and emissions estimates." Biotechnology for Biofuels 10(1): 191.

[139] Although we did not use it for this exercise, a spatial downscaling model called Demeter is able to present GCAM land use results at higher spatial resolution (0.05° × 0.05°), but this tool is not used for this model comparison. Chen, M., Vernon, C.R., Graham, N.T. et al. Global land use for 2015–2100 at 0.05° resolution under diverse socioeconomic and climate scenarios. Sci Data 7, 320 (2020). https://doi.org/10.1038/s41597-020-00669-x.

GHG emissions estimates produced from these models. As mentioned previously, GREET estimates direct GHG emissions from a biofuel production supply chain and generally does not include indirect market-mediated emissions from other sources and sectors. The exception is indirect land use change emissions, which can be added exogenously to GREET results through the CCLUB module. GLOBIOM endogenously calculates GHG emissions from agriculture, including crop and livestock production, forestry, and land use change. GTAP reports three overall categories of GHG emissions which collectively provide an estimate of global GHG impacts: 1) fossil fuel combustion CO_2 emissions, 2) non-CO_2 emissions including changes in these emissions for energy and energy activities,[140] and 3) land use change emissions.[141] ADAGE endogenously calculates GHG emissions from the entire economy, including land use change. GCAM endogenously calculates all global GHG emissions sources, including those from the energy, agriculture, forestry and water systems, including from land use changes. Of the five highlighted models, ADAGE, GCAM, and GTAP are the only models that capture GHG emissions from market-mediated changes within the energy system.

It is important to note that although all five models seem to overlap in their coverage of GHG emissions, they estimate GHG impacts using different methods. For example, GREET and GLOBIOM both estimate GHG emissions from crop production, but they do so in fundamentally different ways. GREET estimates the GHG emissions associated with producing the crops that are directly used in the biofuel supply chain under evaluation. In contrast, GLOBIOM estimates the GHG emissions associated with the market-mediated marginal changes in crop production stemming from a biofuel shock (i.e., the difference in crop production emissions from a scenario with a given amount of biofuel relative to a scenario absent that biofuel). ADAGE, GCAM and GTAP represent a further departure from the GREET approach as they include market-mediated GHG impacts from yet more economic sectors. A notable example is the inclusion of GHG emissions from transportation fuel market effects in ADAGE, GCAM and GTAP. When these models are shocked to consume more biofuels in a particular region, they estimate the effects of the shock on transportation fuel prices and consumption, both in the region where the shock occurs and all other global regions. Instead of assuming that biofuels displace gasoline or diesel on an energy-equivalent basis, these models estimate the global market-mediated changes in gasoline and diesel consumption associated with the biofuel shock and report the resulting GHG emissions changes.

3.1.5 Land Representation

Categorization or binning of land into types is an important, but often overlooked, consideration for land use change modeling. The ways in which land is categorized and the assumptions regarding how much of it is available or unavailable for commercial use vary widely across modeling frameworks. The GREET model does not explicitly represent land. But it is able to add induced land use change emissions through the CCLUB module, which uses GTAP. The other four models estimate interactions between cropland, pasture, forestry, and, in some of these models, other land types as well. For example, GLOBIOM, ADAGE and GCAM

[140] The non-CO_2 emissions category includes "other CO_2", i.e., CO_2 emissions from activities other than fossil fuel combustion, see Chepeliev (2020). These include CH_4, N_2O, and fluorinated gases (CF_4, HFC134a, HFC23, SF_6).
[141] Land use change GHG emissions are calculated based on land category area changes from GTAP and emissions factors from the AEZ-EF model.

also model the expansion of commercial cropland, pasture and forestry activities into grassland and forests that are not otherwise used for commercial production. By default, GLOBIOM and GCAM both place various exogenous limits on conversion of certain lands, to broadly represent land protection policies and regimes (e.g., protection of ecologically sensitive lands), though these assumptions may be modified. In contrast, as discussed in Section 2.4, while the GTAP databases represent managed and unmanaged lands, the GTAP-BIO model only allows managed lands to be used for productive uses, excluding the possibility for "unmanaged" land, such as rainforests or native grasslands, to be brought into agricultural or silvicultural production. As shown in Figure 5.2-1, this assumption applies to a relatively large share of arable land and means that GTAP employs a much different representation of commercially available land than the other models. Additionally, the share of non-commercial land assumed to be protected or unavailable for commercial use is also an important assumption across models. For example, to the extent modeling assumes that policies will be implemented and enforced to protect natural forests with high carbon stocks, this will likely reduce the land use change GHG estimates by a significant amount compared to a scenario which assumes laxer enforcement of land protections.[142] Other differences in land representation, such as the representation of unused cropland and the treatment of multicropping, could also impact model results, and are discussed further in Sections 5.2 and 6.5, respectively. For land categories that are given the same name in different models (e.g., cropland, pasture), the underlying definitions and data may be different – investigating and potentially aligning these definitions and categorizations is a potential area for further research.

3.1.6 Trade

A significant source of theoretical and practical variation across the models considered in this comparison is their approach to representing commodity trade. ADAGE and GTAP represent trade bilaterally using an Armington approach (i.e., assuming imperfect substitution between the same product produced in different countries), however the degree of substitution varies across traded items. GLOBIOM models trade bilaterally based on the spatial equilibrium approach and assumes commodities to be homogenous and traded based on least expensive production costs, though transportation costs and tariffs are also included. GCAM represents trade in agricultural, livestock, forestry, and renewable fuel commodities through an Armington-like approach and trade in all other commodities, including most energy commodities, through homogenous global markets.[143] These methods have areas of overlap and similarity but lead to distinct structures of trade. These differences in structure have significance to the present model comparison exercise for multiple reasons. The ability of these models to deviate from the historical trade patterns to which they are calibrated varies. The willingness of simulated economic actors to substitute imported goods for domestically produced goods, and vice versa, also varies by model.

[142] Mignone, B. K., Huster, J. E., Torkamani, S., O'Rourke, P., & Wise, M. (2022). Changes in Global Land Use and CO_2 Emissions from US Bioethanol Production: What Drives Differences in Estimates between Corn and Cellulosic Ethanol?. Climate Change Economics, 13(04), 2250008.; Plevin, R. J., et al. (2022). "Choices in land representation materially affect modeled biofuel carbon intensity estimates." Journal of Cleaner Production: 131477. Figure S9.
[143] Note that the most recent public version of GCAM trades all energy goods through the Armington-like approach, rather than through homogenous markets. This version of the model was not released in time for inclusion in this exercise.

3.2 Input Parameters and Data

In addition to the key model characteristics discussed above, it is also important to consider differences in data and parameter inputs used within models for biofuel GHG analysis. There have been very few published efforts to compare assumptions across these models or to evaluate which parameters are highly influential on model results. However, the previous work which has been done has suggested the parameter assumptions which are among the most influential in biofuel GHG analysis are related to:

- Crop yields
- Crop intensification
- Land competition and land transitions
- Carbon stocks of different land types
- Trade
- Peatland emissions
- Substitutability in food and feed markets

In this section, we review this previously published literature related to data and parameter inputs. We explore parameter sensitivity further through modeled scenarios in Section 9.

Assumptions related to crop yields and crop intensification are important for biofuel GHG modeling. Global crop yield data is readily available from FAO; however, this data is generally available at a country level and it is also crop-specific. Many models require data inputs for subnational physical regions and must also aggregate many of the dozens of FAO-reported crops into groups for computational tractability. Modelers must determine for themselves how to downscale or aggregate data as needed. There may be differences in how the models map this historical data to the crop categories and physical regions they represent. Assumptions about how crop yields may change in the future are also influential and inherently uncertain. Perhaps even more important for biofuel modeling are assumptions about how crop yields may change in response to price changes. Plevin et al. (2015) performed a sensitivity analysis of biophysical and economic inputs to the GTAP+AEZ-EF modeling framework, and found the elasticity of crop yield with respect to price (YDEL) to be "by far" the most influential parameter in terms of its effect on the estimated ILUC emissions associated with corn ethanol, sugarcane ethanol and soybean oil biodiesel.[144] In the GTAP model used in this model comparison, the YDEL parameter may have less influence on the results, as it now accounts for the ability of increased harvest frequency and use of "unused cropland" to increase crop production without extensification..[145] However, a sensitivity analysis with GCAM did not identify crop yield assumptions to be among the most influential parameters determining corn ethanol land use change GHG emissions.[146] This suggests that input parameters that are highly

[144] Plevin, R. J., et al. (2015). "Carbon Accounting and Economic Model Uncertainty of Emissions from Biofuels-Induced Land Use Change." Environmental Science & Technology 49(5): 2656-2664.
[145] Taheripour, F., et al. (2017). "The impact of considering land intensification and updated data on biofuels land use change and emissions estimates." Biotechnology for Biofuels 10(1): 191
[146] Plevin, R. J., et al. (2022). "Choices in land representation materially affect modeled biofuel carbon intensity estimates." Journal of Cleaner Production: 131477. Figure 7.

influential in one model might not highly influential in another model due to structural differences between frameworks.

The parameters which control land competition and land transitions within models are also important. These parameters control the amount of substitution between land types that occurs based on changes in commodity prices and land rental rates. A sensitivity analysis of GCAM found the parameter controlling ease of transition between cropland, forest, and grassland to be an influential parameter. A sensitivity analysis of GTAP also found that the assumed elasticity of transformation between managed forest, cropland, and pasture is influential for corn ethanol LUC GHG estimates.[147]

Sensitivity analysis using GCAM found other assumptions to be influential when estimating corn ethanol land use change GHG emissions, including the soil carbon density of cropland, ease of transition between crop types, the soil carbon density of grassland, and the soil carbon density of other arable land.[148] Other influential assumptions identified through sensitivity analysis with GTAP include the relative productivity of newly converted cropland, trade elasticities (i.e., ease of substitution among products imported from other countries) and emissions from conversion of cropland pasture.[149]

Sensitivity analyses have shown that other influential assumptions within GTAP include, but are not limited to, tropical peat soil oxidation and the share of palm oil expansion on peatland for vegetable oil based biofuel modeling, and the share of vegetable oil biofuel feedstock that is supplied through expanded vegetable oil production versus reduced demand and substitutions with other products.[150]

Another influential assumption in biofuel GHG modeling is the choice of data sets for soil carbon and biomass carbon stocks, and how these data are mapped to land categories and regions to determine the GHG emissions from converting an acre of land from one use to another. The soil and biomass carbon data sources used in each model are discussed in the model descriptions above. Soil carbon data and analysis are active areas of research, and higher resolution datasets have recently been produced using statistical methods and remote sensing data.[151] For example, the SoilGrids250m version 2.0 dataset provides soil carbon estimates for the globe with quantified spatial uncertainty,[152] and Spawn et al. (2020) developed global maps

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[147] Plevin, R. J., et al. (2015). "Carbon Accounting and Economic Model Uncertainty of Emissions from Biofuels-Induced Land Use Change." Environmental Science & Technology 49(5): 2656-2664. Table S9 in the Supplemental Information.
[148] Plevin, R. J., et al. (2022). "Choices in land representation materially affect modeled biofuel carbon intensity estimates." Journal of Cleaner Production: 131477. Figure 7.
[149] Plevin, R. J., et al. (2015). "Carbon Accounting and Economic Model Uncertainty of Emissions from Biofuels-Induced Land Use Change." Environmental Science & Technology 49(5): 2656-2664. Table S9 in the Supplemental Information.
[150] ICAO (2021). CORSIA Eligible Fuels -- Lifecycle Assessment Methodology. CORSIA Supporting Document. Version 3: 155. Section 6.2
[151] Spawn-Lee, Seth. (2022). "Carbon: Where is it and how can we know?" Presentation for EPA Biofuel GHG Modeling Workshop. February 28, 2022. EPA-HQ-OAR-2021-0921-0022
[152] Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D.: SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240, 2021.

of above and below ground biomass carbon density in the year 2010.[153] With few exceptions,[154] these newer data sets have not yet been incorporated into published estimates of biofuel land use change.

Model Comparison Core Scenarios

4 Description of Core Modeled Scenarios

To compare the five models described above, we ran two scenarios through each framework: 1) a reference case, 2) a corn ethanol scenario (also referred to as the "corn ethanol shock"), and 3) a soybean oil biodiesel scenario (also referred to as the "soybean oil biodiesel shock"). All of these scenarios are hypothetical and designed solely for the purpose of evaluating and comparing the models. The modeled scenarios do not represent our forecast of what is likely to occur in the future, nor should they be interpreted as reflecting EPA's expectations about future biofuel policy decisions.

For the three dynamic models (ADAGE, GLOBIOM, and GCAM), we defined a hypothetical reference case for modeling purposes with U.S. biofuel consumption volumes for each modeled fuel set to constant values from 2020-2050, based on the 2016-2019 average from EPA-Moderated Transaction System (EMTS) data (Table 4-1). We used the EMTS sum of biodiesel and renewable diesel for the biodiesel baseline. For GTAP, the reference case is the global economy as represented in the 2014 GTAP database.

The core GREET model, excluding the ILUC module, does not include an explicit reference case for corn ethanol or soybean oil biodiesel. As discussed above, GREET does not model GHG impacts resulting from a change in biofuel production relative to a reference case. Instead, it estimates the GHG emissions associated with, or attributable to, each biofuel supply chain. Although it does not include scenarios, GREET considers background and foreground data. The foreground data represents the processes in the supply chain evaluated (e.g., corn farming, ethanol production). The background data represents processes that are outside of the supply chain, but that provide energy and material inputs to the supply chain (e.g., electricity grid, natural gas supply chain, fertilizer supply chain). While GREET is a static time step model, it provides default assumptions and estimates for individual years out to 2050. For the purposes of this model comparison, we use GREET with the analysis year set to 2030.[155]

[153] Spawn, S. A., et al. (2020). "Harmonized global maps of above and belowground biomass carbon density in the year 2010." Scientific Data 7(1): 112.
[154] Lark, T. J., et al. (2022). "Environmental outcomes of the US Renewable Fuel Standard." Proceedings of the National Academy of Sciences 119(9): e2101084119.
[155] Argonne National Lab updates GREET on an annual basis with modifications that impact results across many of the pathways. Results in this section are from GREET-2022.

Table 4-1: U.S. annual biofuel consumption volumes in the model reference case, for 2020-2050[156]

	Billion Gallons	Quad BTU
Ethanol from Corn	14.82	1.126
Biodiesel from Soybean Oil	1.19	0.14
Biodiesel from Canola/Rapeseed Oil	0.26	0.03
Biodiesel from Palm Oil	0.09	0.01
Ethanol from Sugarcane	0.1	0.007

In addition to the reference case, we ran a corn ethanol scenario and a soybean oil biodiesel scenario. The corn ethanol scenario is a consumption shock with an additional one billion gallons (0.076 QBTU) of U.S. corn ethanol consumption in each year, with all other U.S. biofuel consumption volumes set by assumption at the reference case levels. The soybean oil biodiesel scenario is a consumption shock with an additional one billion gallons (0.118 QBTU) of U.S. soybean oil biodiesel consumption in each year, with all other U.S. biofuel consumption volumes set by assumption at the reference case levels. We selected the one billion gallon shock size as a simple and reasonably sized shock that is large enough for the purposes of testing these models. For the large economic models considered in our model comparison, it is necessary to specify a change that is large enough to produce a tangible change in the model. We also did not want to specify a shock that would be unreasonably large given current biofuel production levels. As discussed above, these scenarios are hypothetical and designed solely for research purposes.

For the dynamic models (ADAGE, GCAM, GLOBIOM), the shocks increase linearly from 2020 to 2030, such that that there is a 0.5 BG shock in 2025, and the full 1 BG shock is reached in 2030. In these models, volumes are held at the 2030 value for 2030 to 2050 (Table 4-2). The results from this exercise may be sensitive to the shape of the implemented shock of time. We designed the scenarios with this ramp up to 2030 for a few reasons. First, these models are primarily designed for evaluating future scenarios. While it is possible to set up these models for retrospective analysis to simulate historical years ("hindcasting"), we did not have the time or resources to complete such an analysis as part of this model comparison exercise. Second, we designed the scenario with a linear ramp up to 2030 as that is the first future time period represented in GLOBIOM.

For GTAP, these U.S. biofuel consumption volumes were added to the 2014 base year. Because GTAP is a comparative static model, there is no ramp up period for the biofuel consumption shocks in the modeled results for this framework.

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[156] To convert between gallons and Quad BTU, we used a lower heating value for ethanol of 0.076 Quad BTU/Billion gallon, and a lower heating value for biodiesel of 0.118 Quad BTU/Billion gallon. For GTAP, the reference case is 2014, which includes the following U.S. biofuel volumes: 14.29 billion gallons (1.09 Quad BTU) of corn ethanol, 0.20 billion gallons (0.01 Quad BTU) of other ethanol, 0.68 billion gallons (0.08 Quad BTU) of soybean oil biodiesel, and 0.61 billion gallons (0.07 Quad BTU) of other biodiesel.

Table 4-2: U.S. corn ethanol and soybean oil biodiesel consumption volumes, in Quad BTU, for ADAGE, GCAM, and GLOBIOM

	2020	2025	2030	2035	2040	2045	2050
Reference Case							
Ethanol from Corn	1.126	1.126	1.126	1.126	1.126	1.126	1.126
Biodiesel from Soybean Oil	0.140	0.140	0.140	0.140	0.140	0.140	0.140
1 BG Soybean Oil Biodiesel Case							
Ethanol from Corn	1.126	1.126	1.126	1.126	1.126	1.126	1.126
Biodiesel from Soybean Oil	0.140	0.199	0.258	0.258	0.258	0.258	0.258
1 BG Corn Ethanol Case							
Ethanol from Corn	1.126	1.164	1.202	1.202	1.202	1.202	1.202
Biodiesel from Soybean Oil	0.140	0.140	0.140	0.140	0.140	0.140	0.140

For these scenarios, we aligned the conversion factors for vegetable oil to biodiesel and corn to ethanol across ADAGE, GCAM, and GLOBIOM (Table 4-3). These factors were aligned to represent a standard dry mill process for production of corn ethanol, assuming natural gas use to dry 100 percent of the DDG coproduct produced, and a transesterification process for production of soybean oil biodiesel. The 2015 conversion factors are based on data received from petitions under the RFS. For corn ethanol, the yield increase over time assumes that the corn ethanol yield will approach the theoretical maximum efficiency of corn conversion to ethanol by 2050, based on the assumed quantity of convertible material in a given quantity of corn. Compared to our assumed 2020 yield, this is approximately a 10 percent increase in ethanol yield per unit of corn feedstock. For soybean oil biodiesel, the yield increase over time assumes that current state-of-the-art technology will become the nationwide industry average by 2050. Compared to our assumed 2020 yield, this is approximately a 5 percent increase in biodiesel yield per unit of soybean oil feedstock. By default, the GTAP model uses conversion assumptions based on historical data from 2014. While it is possible to adjust the conversion yield in GTAP, we did not do so for his exercise in order to maintain the consistency of the 2014 database. In GTAP, the conversion factor for corn to ethanol is 2.8 gal/bushel, and the conversion factor of soybean oil to biodiesel is 0.132 gal/lb oil. For the corn ethanol shock, GTAP models a natural gas-fired dry mill corn ethanol process with dry DGS coproduct and no corn oil coproduct. For the biodiesel shock, GTAP models a standard natural gas-fired transesterification biodiesel production process. The GREET analysis relies on the assumptions in GREET for 2030, which are a conversion factor for corn to ethanol of 2.92 gal/bushel, and a conversion factor for soybean oil to biodiesel of 0.136 gal/lb oil. For 2030, GREET assumes by default that 99.6 percent of the energy use in dry mill ethanol production will be from natural gas, with the remainder from coal.

Table 4-3: Conversion factors for vegetable oil to biodiesel and corn to ethanol, for ADAGE, GCAM, and GLOBIOM

	Corn conversion to ethanol *gal/bushel*	Soybean oil conversion to biodiesel *gal/lb oil*
2015	2.75	0.130
2020	2.78	0.132
2025	2.80	0.133
2030	2.85	0.134
2035	2.91	0.135
2040	2.96	0.135
2045	3.02	0.136
2050	3.06	0.136

Corn ethanol production creates DDG and corn oil coproducts. Table 4-4 shows the assumptions in the models related to these coproducts. We did not align these assumptions across the models. However, ADAGE, GCAM, and GLOBIOM already had similar DDG and corn oil production assumptions. In GREET, less DDG and more corn oil is produced than in the other models. In GTAP, more DDG is produced, and corn oil is not represented. ADAGE, GCAM, and GLOBIOM all produce less DDG coproduct over time as corn ethanol production becomes more efficient (i.e., more gallons per bushel) and a greater share of the initial feedstock mass is converted to fuel. Soybean oil biodiesel production creates a glycerin coproduct. ADAGE, GCAM, GLOBIOM and GTAP do not explicitly model this coproduct, while GREET does explicitly model the glycerin coproduct.[157]

Table 4-4: Coproduct assumptions for corn ethanol

	DDG (lb/gal ethanol)	Corn oil (lb/gal ethanol)
ADAGE (2020)	5.9	0.2
ADAGE (2050)	5.1	0.2
GCAM (2020)	5.9	0.2
GCAM (2050)	5.1	0.2
GLOBIOM (2020)	5.9	0.2
GLOBIOM (2050)	5.1	0.2
GREET (2030)	4.2	0.4
GTAP (2014)	6.1	--

Note: Model year shown in parentheses.

A key assumption in soybean oil biodiesel production is the shares of soybean oil and soybean meal produced per unit of soybeans crushed. Table 4-5 shows the soybean crush yield share assumptions for each model. ADAGE, GCAM, and GLOBIOM all assume that 0.19 tons of soybean oil are produced per ton of soybean crushed. These values are not assumed to change over time in these models, and the assumptions are uniform across model regions. GREET and

[157] In GREET, roughly 0.1 lb of glycerin is produced per pound of soy oil input.

GTAP assume higher oil yields and lower meal yields relative to ADAGE, GCAM, and GLOBIOM. In GTAP the amount of soybean oil produced from crushing varies by region.

Table 4-5: Production assumptions for soybean oil biodiesel

	Soybean oil (tons oil/tons soybean)	Soybean meal (tons oil/tons soybean)
ADAGE (2020)	0.19	0.8
ADAGE (2050)	0.19	0.8
GCAM (2020)	0.19	0.8
GCAM (2050)	0.19	0.8
GLOBIOM (2020)	0.19	0.8
GLOBIOM (2050)	0.19	0.8
GREET (2030)	0.22	0.78
GTAP (2014)[158]	0.2	0.8

Note: Model year shown in parentheses.

5 Comparison of Reference Case Estimates

In this section we compare the estimates and assumptions from the reference case. We look, in turn, at the following elements from the reference case:

- Crop production
- Land use impacts
- Crop yields
- Energy consumption
- GHG emissions

The majority of these comparisons include ADAGE, GCAM, GLOBIOM, and GTAP. The comparison of energy consumption does not include GLOBIOM as this model does not endogenously consider energy markets. Only the comparisons of crop yield and GHG emissions includes GREET. GREET is a supply chain LCA model that does not represent changes in agricultural and economic markets between reference and modeled scenarios, as the other models in this comparison exercise are designed to estimate.

5.1 Crop Production

ADAGE, GCAM, GLOBIOM, and GTAP each include different crops, which we aggregated into common categories for reporting purposes to better enable comparison across the models. Table 5.1-1 shows the crops included in each model, and how they are reported here. Of the models, GLOBIOM includes the most disaggregated set of modeled crop categories. In

[158] Values are approximate for the USA region. GTAP crushing rates are based on the mean data provided by the World Oil data set. This data set shows the crushing rate for soybeans varies across countries, and is generally 18-20 percent, with some rare cases of 17 percent (in Bangladesh and Thailand) and 21 percent (in Japan). The World Oil data shows a crushing rate of 19.75 percent for the U.S. in 2014, which is implemented in the GTAP database construction.

ADAGE, palm fruit and rapeseed are not explicitly represented, but are included under "rest of oilseeds."

Table 5.1-1: Crops represented in ADAGE, GCAM, GLOBIOM, and GTAP

Model Comparison Category	ADAGE	GCAM	GLOBIOM	GTAP
Corn	Corn	Corn	Corn	Corn
Soybean	Soybean	Soybean	Soybean	Soybean
Wheat	Wheat	Wheat	Wheat, Durum wheat*, Soft wheat*	Wheat
Rice	Not explicitly represented; aggregated with "other grains"	Rice	Rice	Paddy rice
Sugar crops	Sugarcane, Sugar beet	Sugar crops	Sugar cane, Sugar beet*	Sugar crops
Palm fruit	Not explicitly represented; aggregated with "rest of oilseeds"	Oil palm and coconuts	Palm fruit	Palm fruit
Rapeseed	Not explicitly represented; aggregated with "rest of oilseeds"	Rapeseed	Rapeseed	Rapeseed
Other oil crops	Rest of oilseeds	Oil crops	Groundnut, Sunflower	Other oil seeds
Other grains	Rest of cereal grains	Other grain	Barley, Millet, Sorghum	Other grain
Energy crops	None[159]	Herbaceous biomass crop; woody biomass crop		
Other crops	Rest of crops	Root/tuber; Fiber crop; Fodder herb, Fodder grass, Miscellaneous crops	Cassava, Chickpeas, Dry beans, Potatoes, Sweet potatoes, Cotton, Peas*, Rye*, Oat*, Flax*	Other crops

*EU region only

[159] ADAGE has the ability to model switchgrass and miscanthus, but production of those crops were not included in these scenarios.

Figure 5.1-1 shows the reference case crop production in 2014 (GTAP) and 2020 and 2050 (ADAGE, GCAM, and GLOBIOM). Total crop production in 2020 in the USA region is highest in the ADAGE results and lowest in the GLOBIOM results. In the non-USA regions, GCAM results have the highest 2020 crop production, and GLOBIOM results have the lowest production. In 2050, the total production is again the highest in ADAGE results in the USA region, and the highest in GCAM results in the non-USA region. The total crop production in the USA region has a similar percent increase between 2020 and 2050 in the ADAGE and GCAM results (30 percent and 27 percent, respectively). However, the ADAGE and GCAM results differ in the growth rate of the production of individual crops. GLOBIOM results have a lower percent increase in crop production (13 percent). In the non-USA regions, GCAM and GLOBIOM results have a similar percent increase in total crop production (47 percent and 50 percent, respectively), whereas ADAGE results have a lower percent increase in total crop production (21 percent).

Figure 5.1-1: Crop production (million metric tons) in the reference case[160,161]

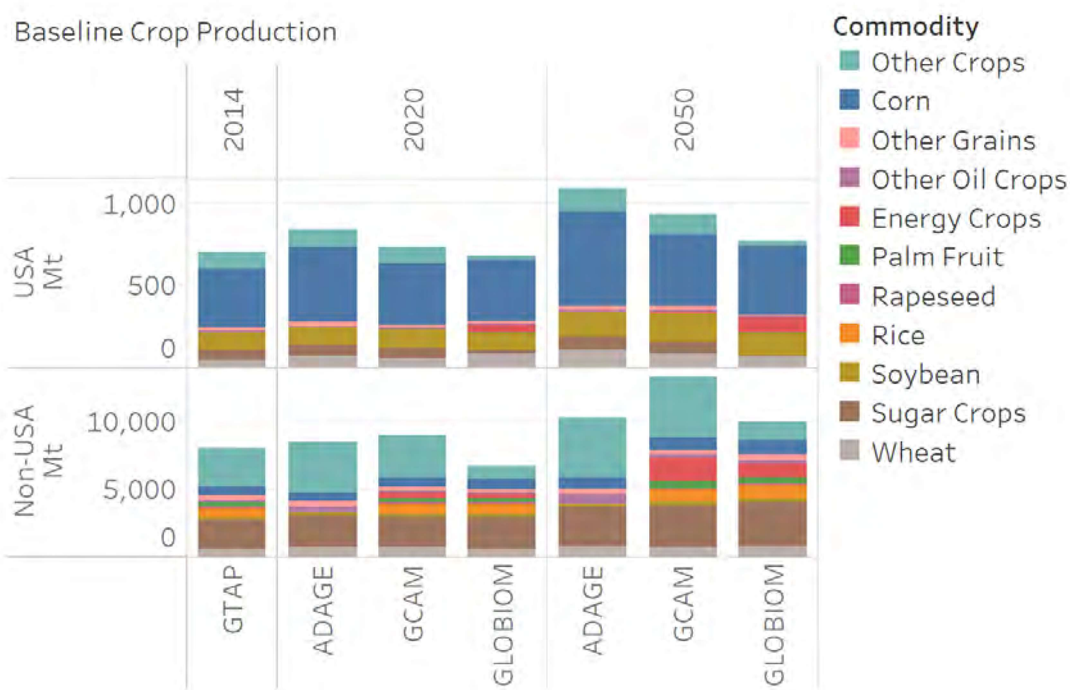

Table 5.1-2 compares these modeled values with crop production data from FAOSTAT. GTAP's crop production, which is calibrated to 2014 data, aligns closely with the FAOSTAT 2014 production data for corn and soybeans. 2020 crop production in ADAGE, GCAM and GLOBIOM differs from the 2020 FAO values, for a few reasons. First, these models project 2020 production from a 2010, 2015, and 2000 model base year respectively. Long run economic modeling projections do not, as a general methodological practice, attempt to build in exogenous representation of short term historical economic shocks in modeled periods (i.e., times steps after

[160] Note that the USA and non-USA regions are shown on different scales to better show differences across the models.
[161] Reference case production values in the "Other Crops" category are mostly incomparable between models because the models differ in which crops are represented in this category (see Table 5.1-1).

the model base year), and these models should be expected to endogenously predict such shocks. This alone leads to some variation in modeled estimates from the historical record for years like 2020, where a significant economic shock occurred in the form of the COVID-19 pandemic. Second, as described in Section 3.1.2, the 2020 time step in ADAGE and GCAM represents a slightly different time period than the 2020 time step in GLOBIOM. The ADAGE, GCAM, and GLOBIOM crop production in 2020 generally falls within the range of production over the years 2015-2021, with a few exceptions. The ADAGE corn production results are higher than the FAO range in the USA region, but lower than the FAO range in the non-USA regions. ADAGE and GCAM soybean production results are both lower than the FAO range in the non-USA regions.

Table 5.1-2: Corn and soybean production (million metric tons) from reference case and FAOSTAT data[162]

Data source	Corn, USA Region	Soybean, USA Region	Corn, Non-USA Region	Soybean, Non-USA Region
GTAP, 2014	361	107	678	199
FAOSTAT, 2014	361	107	680	199
ADAGE, 2020	462	114	622	199
GCAM, 2020	376	111	733	204
GLOBIOM, 2020	368	99	742	219
FAOSTAT, 2020	358	115	805	240
FAOSTAT, 2015-2021 range	345-412	97-121	708-826	216-251

5.2 Land Use

ADAGE, GCAM, GLOBIOM, and GTAP each include different land types, and different assumptions about the reference area of each land type over time. For this exercise, for reporting purposes we mapped land types to common categories across the models, as shown in Table 5.2-1. Areas of land types in the "other non-arable land" category are held constant over time and cannot convert to other land types.

[162] FAOSTAT data from: https://www.fao.org/faostat/en/#data. Non-USA values were calculated by subtracting the United States production from the World production. FAOSTAT 2015-2021 range shows the highest and lowest production from the years 2015 to 2021. These do not necessarily correspond to the 2015 and the 2021 values.

Table 5.2-1: Land representation in ADAGE, GCAM, GLOBIOM, and GTAP

Model Comparison Category	ADAGE	GCAM[163]	GLOBIOM	GTAP
Cropland	Cropland	Cropland	Cropland, short rotation plantation	Cropland*
Forest (managed)	Managed forest	Commercial forest	Managed forest	Forest[164]
Forest (unmanaged)	Natural forest	Forest	Unmanaged forest	
Grassland	Natural grassland	Grassland	Grassland	
Other arable land	Not included	Other arable land	Other agricultural land, other natural land	Cropland pasture*, "unused land"*
Other non-arable land	Other land: includes bare ground, wetlands, mangroves, salt marsh, glaciers, lakes	Tundra, Rock/ice/desert, Urban	Wetlands, "not relevant" (e.g. ice, water bodies)	
Pasture (managed)	Pasture	Intensively-grazed pasture	Pasture	Pasture[165]
Pasture (unmanaged)	Not included	Other pasture		
Shrubland	Not included	Shrubland		

* GTAP results report an aggregated "Cropland" category which is meant to represent fallow cropland in addition to actively cultivated cropland. For the scenario difference values, we are able to disaggregate those fallow land categories – "cropland pasture" and "unused land" – and assign them to the "Other arable land" model comparison category. For this model comparison exercise, GTAP assumes no change in U.S. Conservation Reserve Program area due to the biofuel shocks.

Reference case land use for arable land is shown in Figure 5.2-1 for 2014 (GTAP) and 2020 and 2050 (ADAGE, GLOBIOM, and GCAM).[166] The GTAP reference case land areas differ most from the other models because GTAP does not include unmanaged land such as unmanaged forest, grassland or shrubland.

[163] In the version of GCAM used in this exercise, land types are further split by mineral soil and peat soil.
[164] In the GTAP database the managed forest area is the sum of managed/commercial forest and "accessible" forest, with accessibility determined based on an analysis of distance from roads.
[165] In the GTAP database pasture area includes areas of grassland.
[166] Land cover and land use changes in the model reference cases are based on the agricultural demand, differences in land rent among land types, ease of substitution among land, and relative changes in land productivity.

Figure 5.2-1: Arable land use (million metric hectares) in the reference case[167,168]

For cropland, GLOBIOM shows lower area than other models in the non-USA regions. For forest, ADAGE and GLOBIOM have similar area in the non-USA regions, and GCAM has lower area. Because GTAP only represents managed forest, the total forest area is smaller than the other models. But the managed forest area is larger than the other models. Grassland is highest in ADAGE, followed by GCAM then GLOBIOM. For pasture, only GCAM differentiates between managed and unmanaged pasture. GCAM has very little managed pasture in the non-USA regions, but similar total pasture as GTAP. GTAP shows the largest area of managed pasture, as it represents pasture and grassland jointly. ADAGE and GLOBIOM have lower total pasture.

ADAGE, GCAM, and GLOBIOM all project an increase in cropland area and a decrease in grassland area over time, both in the USA region and the non-USA regions. Each of these models also shows a decrease in non-USA total forest area over time, with an increase in managed forest and a decrease in unmanaged forest. In the USA region, GCAM and GLOBIOM both show an increase in total forest area over time, with an increase in managed forest and a decrease in unmanaged forest. In ADAGE, the USA region has a small decrease in managed forest and increase in unmanaged forest, with an overall decrease in total forest area. For pasture, ADAGE, GCAM, and GLOBIOM show different trends. In the non-USA regions, total pasture decreases over time in ADAGE and GCAM, but increases in GLOBIOM. In the USA region, total pasture increases over time in ADAGE, and decreases in GCAM and GLOBIOM. In GCAM, managed pasture area increases over time, and unmanaged pasture area decreases over time, in both the USA region and non-USA regions.

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[167] Note that the USA region and the non-USA region have different scales.
[168] Cropland area in GTAP represents the sum of land cultivated for row crops, cropland pasture, and other unused land that GTAP classifies as cropland. This differs from the "Cropland" category of land presented in Figure 6.6-2 and Figure 7.6-2 which illustrate changes in cropland compared to the reference case. In those figures, cropland pasture and other unused cropland are assigned to the "Other Arable Land" category.

The GLOBIOM and GCAM reference case results include reductions in "other arable" land over time from 2020 to 2050. For GCAM, the other arable land category includes fallow, unused, and unharvested cropland and also serves to represent differences in land area estimates between FAO and other data sources. None of the models explicitly represent Conservation Reserve Program (CRP) land in the USA as a unique land category. For agricultural land areas, GLOBIOM and GCAM rely on FAO data, which does not explicitly list CRP. CRP may be implicitly represented in the "other arable" category of GCAM and GLOBIOM, but without explicitly accounting for the particular incentives offered to farmers by the program. ADAGE does not include CRP and does not explicitly account for conservation management decisions. The GTAP database includes data on CRP area, but the GTAP model included in our comparison exercise assumes no change in CRP area due to the biofuel shocks, and this is the standard assumption used in the GTAP model. Given that other studies focusing on the U.S. suggest that biofuel consumption may have a significant effect on CRP area,[169] this may be an area for future research and model development.

5.3 Crop Yield

ADAGE, GCAM, and GLOBIOM use different exogenous assumptions about crop yield growth over time. In GLOBIOM, exogenous yield improvements represent technological change and multi-cropping. Crop yield growth is based on an extrapolation of historic yield trends from FAO data. Exogenous assumptions on multi-cropping are based on a literature review and apply to areas such as Brazil. In GCAM, exogenous yield growth is based on FAO data. In ADAGE, land productivity by land type is from the linked EPPA-TEM model, and a 1 percent annual growth in crop yield is assumed.

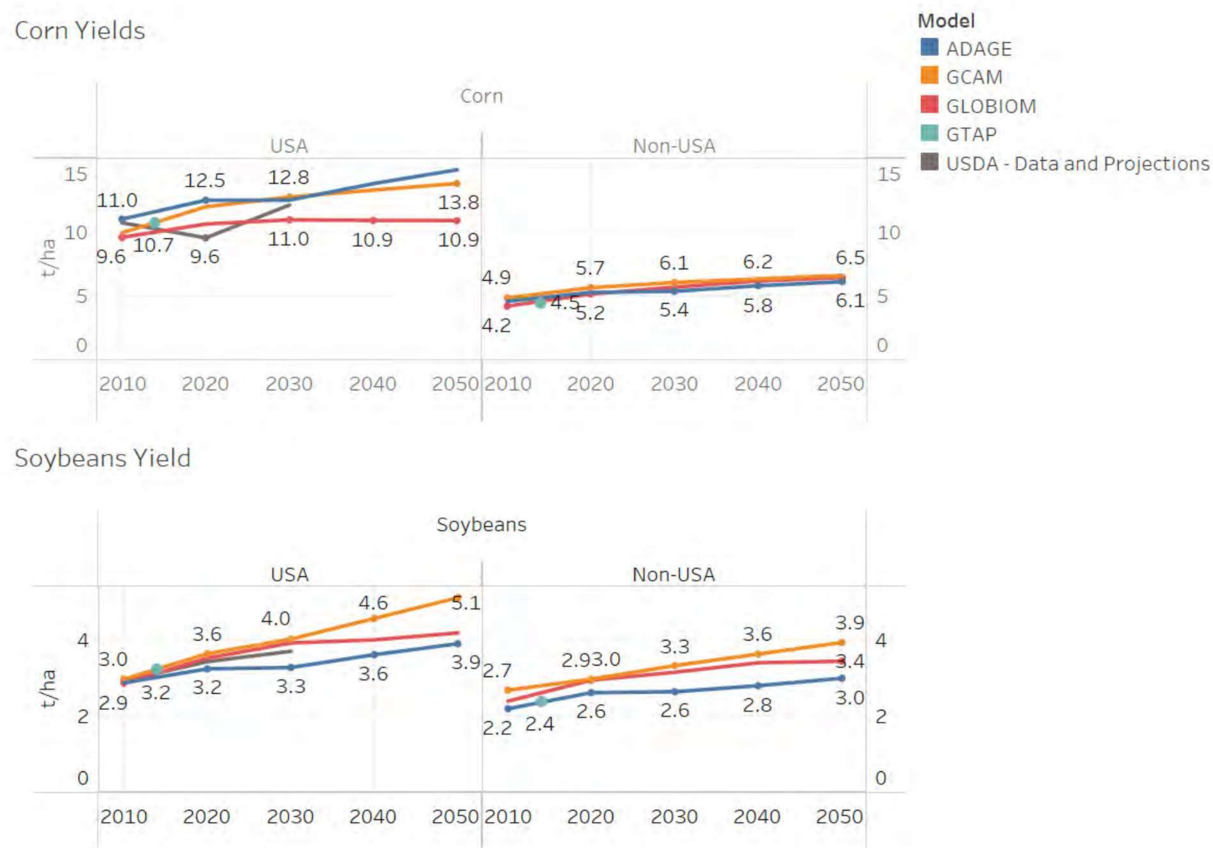
These models also have the ability to change crop yields endogenously, based on changes in prices or other factors, as does the GTAP model. In ADAGE and GTAP, a nested CES (constant elasticity of substitution) function governs the endogenous yield changes. Materials (e.g., fertilizer) or energy (e.g., for farm equipment) can be substituted for land to increase the yield. Additional capital or labor can also be invested to increase yields. GTAP imposes a restriction on substitution among labor, land, and a mix of capital-energy in crop sectors to reach a target for price-induced yield response. GCAM has four different technology options (rainfed vs. irrigated; low-yield vs. high-yield), each with different yields. A logit function determines the share of production in each of these technology options based on profit rates, and the prices of fertilizer and irrigation water also affect the competition of these technologies. Yields within any land use region, crop type, and irrigation level can increase or decrease by up to 20 percent based on the profitability. GLOBIOM also has four management options with different intensity levels (subsistence, low input, high input, irrigated high input). Crop production is represented at the grid level, and GLOBIOM can reallocate production from one cell to another based on the productivity and profitability.

Reference case corn and soy annual yields for these models are shown in Figure 5.3-1. This figure also shows the 2014 yields in GTAP, and data and yield projections from USDA.

[169] See for example, Chen, X., & Khanna, M. (2018). Effect of corn ethanol production on Conservation Reserve Program acres in the US. *Applied Energy*, 225, 124-134.

Models show a range in the crop yield and the yield growth rate. For corn, ADAGE and GCAM have the highest yields in the USA region. For soybeans, GCAM has the highest yield and ADAGE has the lowest yield in the USA region. USDA data and projections are generally within the range of the modeled yields. In the USA region, the 2030 corn yield in GREET is 12.5 t/ha, and the soybean yield is 3.7 t/ha. The non-USA region yield is weighted by crop production for each individual region outside of the USA region. The corn and soybean yield in the non-USA region is similar across models, although there is more variation in the soybean yields over time.

Figure 5.3-1: Corn and soybean yields (tons per hectare) in the reference case[170]



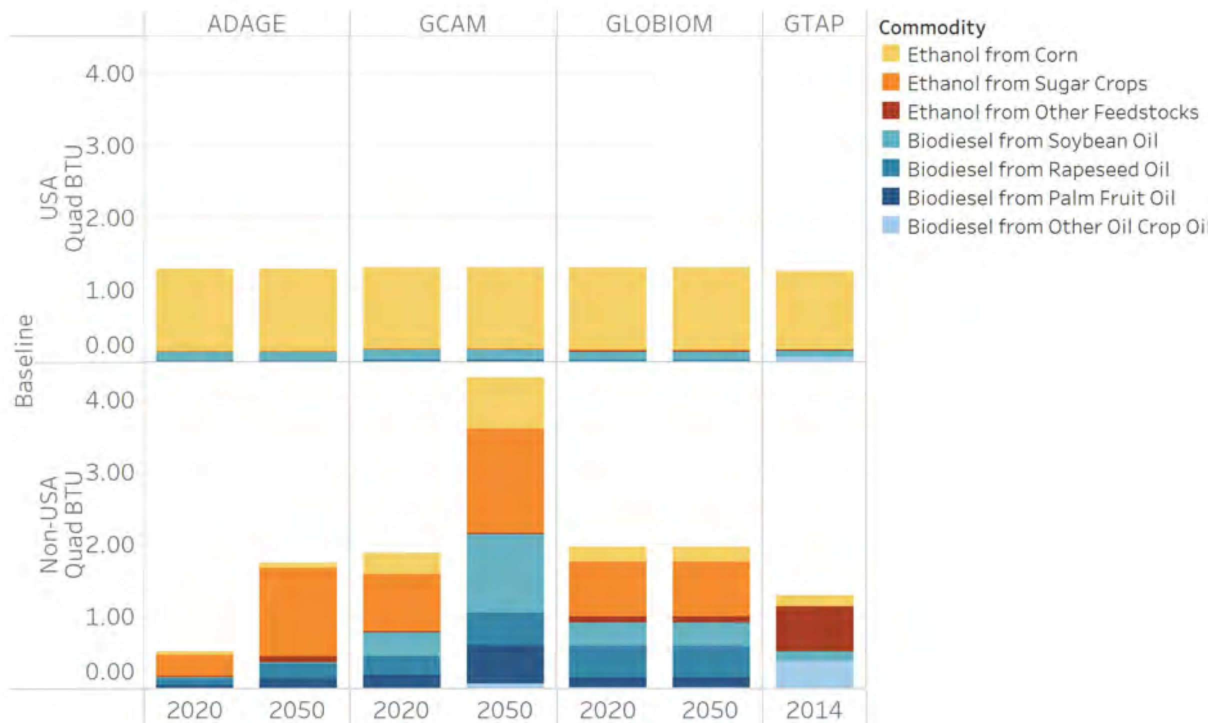
5.4 Energy Consumption

Each model was given specifications for biofuel consumption in the USA region to stay constant at specific levels in the reference case.[171] However, constraints were not placed on biofuel consumption in non-USA regions. Figure 5.4-1 shows the biofuel consumption in ADAGE, GCAM, GLOBIOM, and GTAP. The models show very different reference case amounts of biofuel consumption in the non-USA regions in 2020, and different projections over

[170] Yields reported from ADAGE, GLOBIOM, GTAP, and in the USDA data and projections are calculated as crop production per harvested area (i.e., production per harvest). Yields reported from GCAM are calculated as crop production per cultivated area (i.e., production from all harvests per cultivated area, where cultivated area is equal to harvested area divided by harvest frequency).
[171] ADAGE does not include rapeseed oil consumption in the USA region, so that consumption volume is set at zero instead of the specified amount.

time through 2050. Since GLOBIOM does not endogenously represent energy markets, levels of consumption of biofuels are set exogenously for all regions. For this exercise, consumption levels of biofuels in the non-USA regions are held constant throughout the period of analysis. GCAM shows similar total biofuel consumption in the non-USA region as GLOBIOM in 2020, but the consumption more than doubles by 2050. ADAGE has much lower total biofuel consumption in non-USA regions in 2020 than the other models, with almost no consumption of soybean oil biodiesel.[172] Biofuel consumption increases over time, with most of the increase in ethanol from sugar crops. In GTAP, the 2014 non-USA biofuel consumption is higher than the 2020 consumption in ADAGE and lower than the 2020 consumption in GCAM and GLOBIOM. There are also differences in the fuel categories, with most of the ethanol in GTAP coming from an aggregated "other feedstocks" category rather than sugar crops, and most of the biodiesel coming from "other oil crop oil."

Figure 5.4-1: Biofuel consumption (Quad BTU) in the reference case

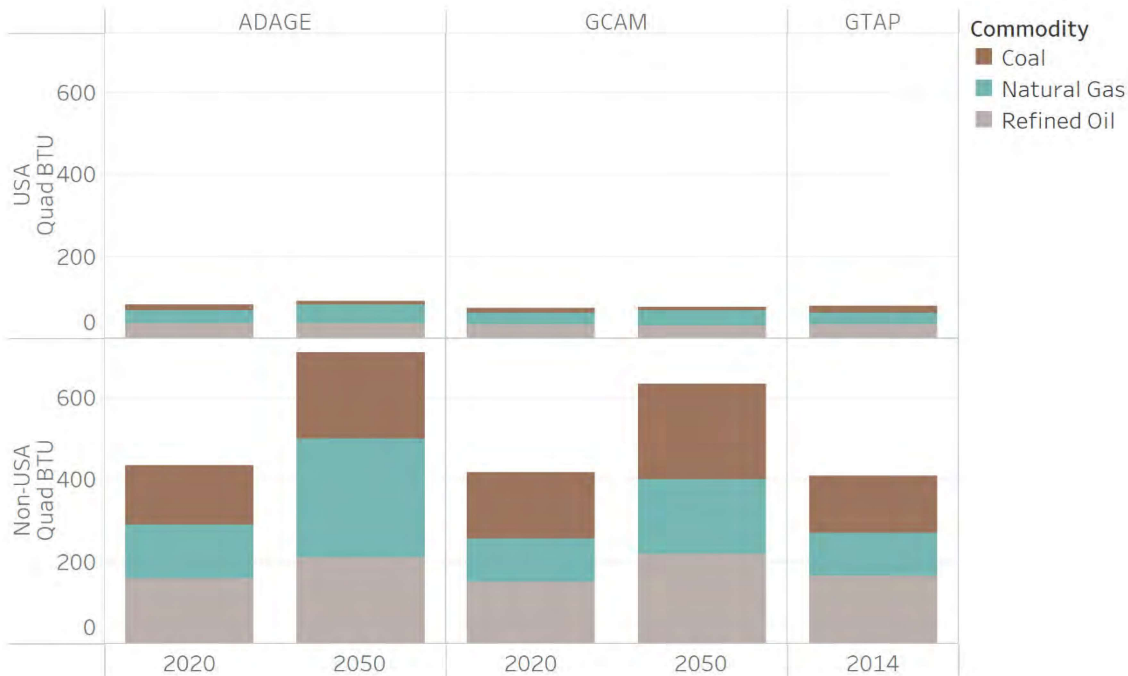


ADAGE, GCAM, and GTAP show similar fossil fuel consumption in the reference case (Figure 5.4-2).[173] Consumption of natural gas, coal, and refined oil is slightly higher in the USA region in 2020 in ADAGE than GCAM. In GTAP, the 2014 coal consumption in the USA is higher than the 2020 consumption in ADAGE and GCAM, but the 2014 natural gas and refined oil consumption is lower than the 2020 consumption in ADAGE and GCAM. In both ADAGE

[172] ADAGE includes conventional vehicles and alternative fuel vehicles in its transportation sector. In this reference run, ADAGE projects biofuel consumption in non-USA regions based on the relative competitiveness of conventional and alternative fuel vehicles in the model over time. As electric vehicles become more competitive, less biofuel is consumed. In the assumptions used by ADAGE in this run, soybean oil biodiesel is more costly to produce than other biofuels in non-USA regions, so it is not consumed in these regions in the reference.
[173] GLOBIOM does not model fossil energy consumption.

and GCAM, natural gas consumption in the USA region increases over time, and coal consumption decreases. In GCAM, refined oil consumption in the USA region decreases between 2020 and 2050, whereas in ADAGE refined oil consumption increases. In the non-USA regions in 2020, ADAGE has higher refined oil and natural gas consumption, but lower coal consumption than GCAM. Both models show increases in consumption of these fossil fuels over time in the non-USA regions, with ADAGE showing a larger increase. GTAP's 2014 non-USA coal consumption is higher than the ADAGE and GCAM 2020 consumption, whereas the refined oil consumption is lower. Natural gas consumption in 2014 in the non-USA region of GTAP is slightly higher than GCAM's 2020 consumption. The differences between GTAP and other models may reflect the difference in time periods represented. Differences across the models in the reference case fossil fuel and biofuel consumption over time could impact the results of the amount and type of fuel displaced in the biofuel volume shocks. Exploring the impact of these differences could be an area for future research.

Figure 5.4-2: Fossil fuel consumption (Quad BTU) in the reference case



5.5 GHG Emissions

The models in this exercise include emissions from different sectors, with ADAGE and GCAM including emissions from the entire global economy, GTAP including emissions from land use change, the energy sector, and emissions from other sectors and activities, and GLOBIOM including emissions from crop production, livestock, and land use change (Table 3-1). GREET reports emissions associated with the supply chain of biofuel production. GREET's CCLUB module is able to add indirect land use change emissions as well. Each model also reports different greenhouse gases (Table 5.5-1).

Table 5.5-1: Greenhouse gases represented in each model

ADAGE	GCAM	GLOBIOM	GREET[174]	GTAP
CO_2, CH_4, HFC, N_2O, PFC, SF_6	CO_2, CH_4, HFC125, HFC134a, HFC152a, HFC227ea, HFC23, HFC236fa, HFC32, HFC365mfc, N_2O, PFC, SF_6	CO_2, CH_4, N_2O	CO_2, CH_4, N_2O	CO_2, CH_4, N_2O, Fluorinated gases (CF_4, HFC134a, HFC23, SF_6)

Total GHG emissions in 2020 in the reference case are around 57 gigatons CO_2 equivalents ($GtCO_2eq$) in ADAGE and 59 $GtCO_2eq$ in GCAM. For comparison, the IPCC Sixth Assessment Report estimates that global GHG emissions were 59±6.6 $GtCO_2eq$ in 2019.[175] In both ADAGE and GCAM, CO_2 is the largest contributor to the emissions, with methane the second largest contributor. The GCAM reference case has higher non-CO_2 emissions in 2020 than ADAGE and GLOBIOM.

Figure 5.5-1 groups reference case emissions into a several broad categories. "Energy from Fossil Fuels" includes all GHG emissions from fossil fuel combustion. Consequently, fossil fuel emissions are not included in other categories. For example, emissions from diesel used to drive tractors for crop production are included under "Energy from Fossil Fuels" rather than "Crop Production." "Other (Industrial & Waste)" includes non-fossil fuel emissions from the industrial and waste management sectors, such as CO_2 from cement manufacturing and CH_4 from landfills. "Livestock Production" includes emissions such as CH_4 from enteric fermentation and N_2O and CH_4 from manure. "LUC" includes emissions from biomass and soil carbon associated with land use change. "Crop Production" includes emissions from crop inputs such as N_2O from fertilizer use and from crop production processes such as CH_4 from rice production.

As shown in Figure 5.5-1, most emissions from ADAGE and GCAM come from CO_2 from the energy from fossil fuels category. “Other (Industrial & Waste)” emissions are similar in ADAGE and GCAM in 2020, but higher in GCAM than ADAGE by 2050. Emissions in this category come from a mix of greenhouse gases. Emissions in this sector are not reported in GLOBIOM. Emissions from livestock production are similar in ADAGE and GLOBIOM, and higher in GCAM, and come primarily from methane. Land use change emissions are significantly lower in ADAGE and GLOBIOM than GCAM. Crop production emissions are similar in ADAGE and GCAM in 2020, but are 50 percent lower in GLOBIOM. Crop production emissions increase over time in GCAM and GLOBIOM, but decrease over time in ADAGE. GTAP reports land use change emissions by comparing land use areas between two scenarios, but it does not track terrestrial carbon stocks or report total land use change emissions

[174] GREET includes the ability to represent GWPs of short-lived climate forcers (volatile organic compounds, carbon monoxide, NOx, and black carbon) but does not include them in results by default.
[175] IPCC, 2023: Summary for Policymakers. In: Synthesis Report of the IPCC Sixth Assessment Report (AR6). Available at: https://www.ipcc.ch/report/ar6/syr/downloads/report/IPCC_AR6_SYR_SPM.pdf

in each scenario. GTAP does also report several other categories of emissions, including emissions from use of fossil fuels and total non-CO_2 emissions from sources other than land use change. GREET is a supply chain LCA model that is designed to represent the emissions emanating from the fuel supply chain rather than estimate the global economic impacts of a change in biofuel consumption. GTAP and GREET are not included in Figure 5.5-1 because they do not represent scenario-based emissions over time.

Figure 5.5-1: Global greenhouse gas emissions in ADAGE, GCAM, and GLOBIOM in the reference case[176]

[176] Note that the rows of this figure use different scales. GTAP is not included in this figure because it does not represent emissions over time, and due to time constraints, we do not have GTAP LUC emissions in the reference case, or GHG emissions by gas for the source categories used in this figure. For comparison, for GTAP, in the reference case (2014), fossil fuel combustion and industrial CO_2 emissions = 30,048 Mt, and other GHGs emissions from all covered sources = 16,616 Mt CO_2e, of which N_2O = 2,891 Mt CO_2e, CH_4 = 8742 Mt CO_2e, fluorinated gases = 986 Mt CO_2e, and other CO_2 = 3996 Mt CO_2e. GREET is not included in this figure because it does not include an explicit reference case, and therefore does not provide reference case emissions.

5.6 Summary of Reference Case Estimates

The previous sections illustrate differences in the reference case in ADAGE, GCAM, GLOBIOM, GTAP and GREET. Notable differences are observed across the models in crop production, land use areas, biofuel and fossil fuel consumption in non-USA regions, and overall emissions. These include differences in the reference case for 2020, as the models are initialized with older data and define the 2020 time period in different ways.

Some of these differences could impact the results of the corn ethanol and soybean oil biodiesel shocks from these models. For example, differences in the reference case crop yields among models would cause differences in the amount of land needed to produce additional crops. Differences in reference case biofuel and fossil fuel consumption among models could affect energy sector responses the biofuel shocks. Potential future research could focus on how the reference case influences the results of the biofuel shocks.

6 Comparison of Corn Ethanol Estimates

In this section, we present the results of the corn ethanol shock. The results in this section show the difference between the corn ethanol shock and the reference case. We consider the following elements in turn:

- Sources of corn ethanol to meet the shock
- Energy market impacts from the shock
- Crop production and consumption
- Trade impacts
- Yield changes
- Land use impacts
- Emissions: the modeled results of energy consumption, crop production, and land use change described above come together in the modeled greenhouse gas emissions.

The majority of these comparisons include ADAGE, GCAM, GLOBIOM, and GTAP. Only the comparison of GHG emissions includes GREET. GREET is a supply chain LCA model that does not represent changes in agricultural and economic markets between reference and modeled scenarios, as the other models in this comparison exercise are designed to estimate.

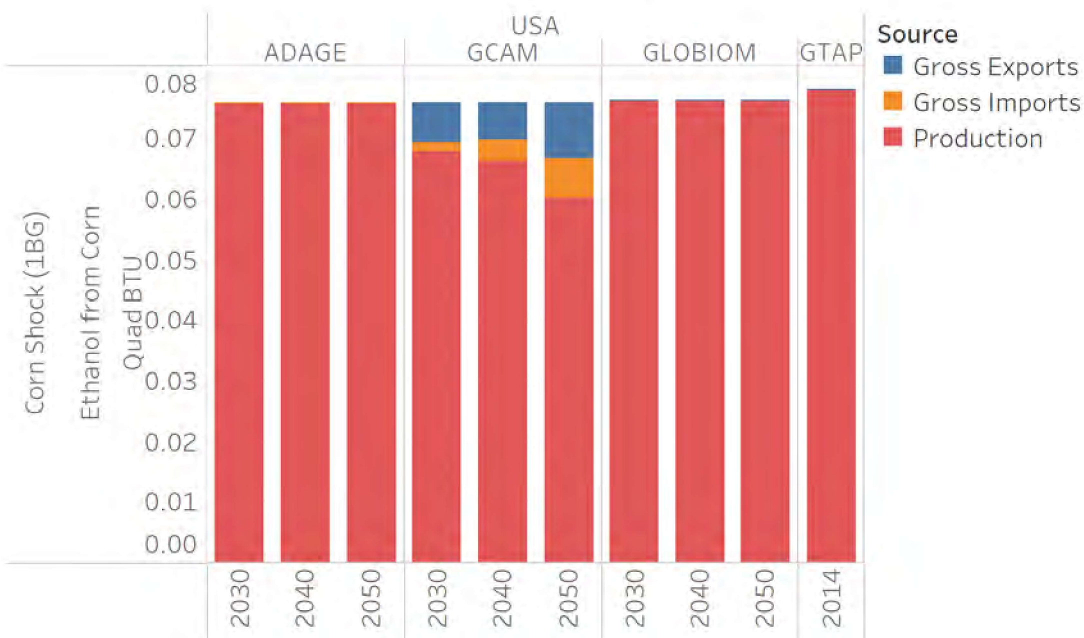
6.1 Sourcing Overview

The models included in this analysis have many options available for meeting the corn ethanol consumption shock. For example, the USA region could produce additional corn ethanol, import more corn ethanol, or export less corn ethanol. Additional imported corn ethanol supplies could come from reduced consumption of corn ethanol in non-USA regions, or increased production of corn ethanol. Increased domestic corn ethanol production could come from diversion of corn from other uses, or increased production of corn, through yield increases or increases in the area of corn cropland. This section will give an overview of the extent to which the models rely on each of the available options for meeting the corn ethanol consumption shock.

In the corn ethanol shock, most of the additional corn ethanol consumed in the USA region comes from increased corn ethanol production in the USA region (Figure 6.1-1). In ADAGE, GLOBIOM, and GTAP, the shock is met entirely by increased corn ethanol production, with no change in gross imports or exports of corn ethanol in the USA region. In GLOBIOM, because there is no energy sector, there cannot be a change in corn ethanol exports or imports, so the shock must be met by corn ethanol production in the USA region.

In GCAM, up to 20 percent of the shock is met by changes in gross imports and exports of corn ethanol, with the change in exports contributing to a larger percentage of the shock over time. This change in exports is consistent with a reduction in the consumption of corn ethanol in non-USA regions (blue bars, Figure 6.1-2).[177] These GCAM results illustrate the potential impact of dynamic energy sector modeling. Because some of the corn ethanol shock in GCAM is met through changes in the energy sector in the non-USA regions, less new corn ethanol needs to be produced, which reduces the impact on corn production and end uses.

Figure 6.1-1: Sources of additional corn ethanol consumed in the corn ethanol shock relative to the reference case[178]



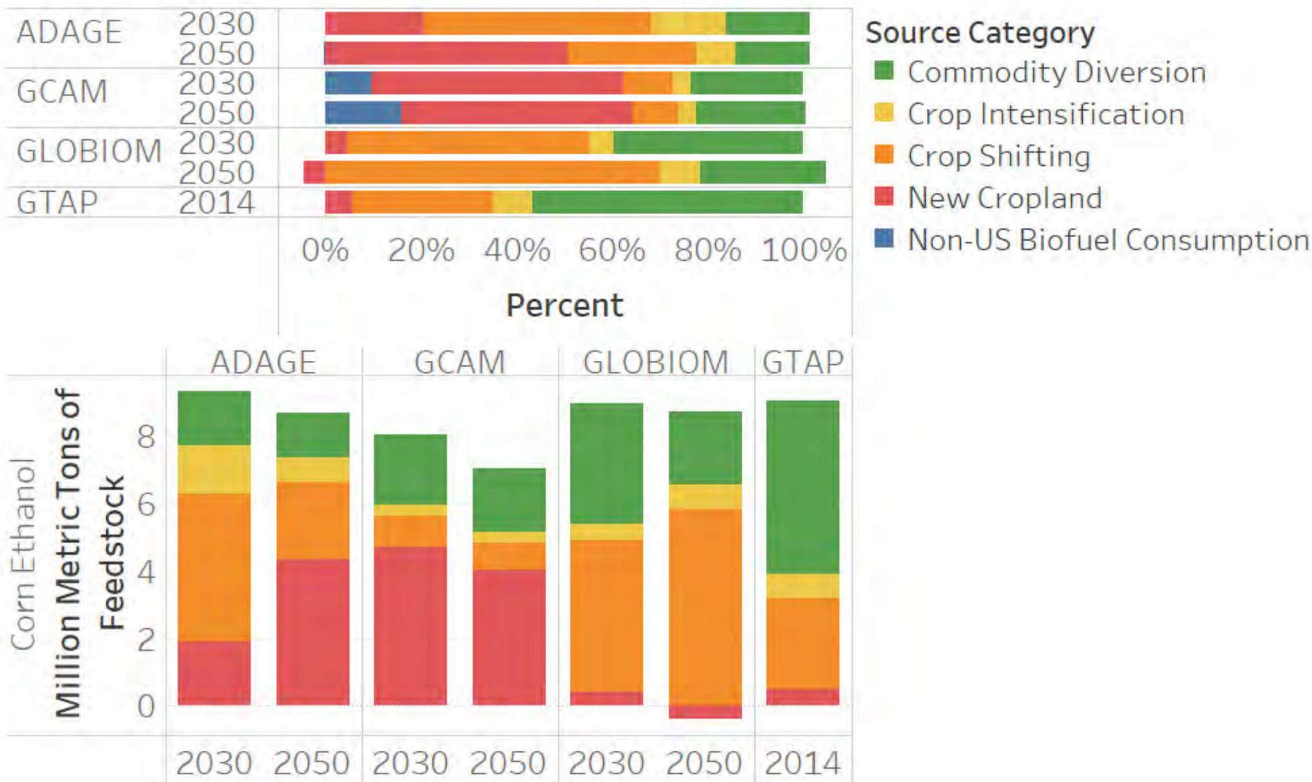
ADAGE, GCAM, GLOBIOM, and GTAP meet the corn ethanol shock through different amounts of corn diversion from other uses, crop intensification, crop shifting to corn, and new cropland (Figure 6.1-2). Based on the assumed conversion factor of corn to corn ethanol (Section 4), if all of the shock were met by new corn ethanol production, ADAGE, GCAM, and GLOBIOM would need 8.9 million metric tons of additional corn for ethanol in 2030 and 8.3 million metric tons of additional corn for ethanol in 2050. GTAP would need 9.1 million metric

[177] As shown in Figure 6.2-1, sugarcane ethanol is substituting for corn ethanol in non-USA regions of GCAM.
[178] Red shows the contribution increased corn ethanol production in the USA region; orange shows the contribution from increased corn ethanol gross imports to the USA region; blue shows the contribution from reduced corn ethanol gross exports from the USA region.

tons of additional corn for ethanol in 2014. The bottom panel of Figure 6.1-2 shows the sourcing of corn for corn ethanol in units of million metric tons. In these results, GCAM needs less corn feedstock than ADAGE, GLOBIOM, and GTAP because some of the shock is met by a decrease in corn ethanol consumption in the non-USA region.

In these results, commodity diversion (reduced crop use for other purposes) accounts for 15-17 percent of the shock in ADAGE, 23-24 percent of the shock in GCAM, 26-40 percent of the shock in GLOBIOM, and 57 percent of the shock in GTAP. These results are described more in Section 6.3. Of the additional corn production, ADAGE, GCAM, GLOBIOM, and GTAP each use a different mix of crop intensification (increased corn yields), shifting of cropland from other crops to corn ("crop shifting" in Figure 6.1-2), and shifting land from other land types to cropland ("new cropland" in Figure 6.1-2). In the GCAM results, most of the new corn comes from new cropland. In the GLOBIOM and GTAP results, most of the new corn comes from shifting of cropland from other crops to corn. In the ADAGE results, there is a transition over time from more cropland shifting in 2030 to more new cropland in 2050. For GTAP, the primary strategy for meeting the corn ethanol shock is commodity diversion, highlighted by a 1 percent reduction in USA region feed consumption (DDG feed increases, corn feed decreases). However, this reduction in total feed use has a much smaller impact (0.002 percent reduction) on USA region meat and dairy production. Corn production and land use results are described in more detail in Sections 6.3 and 6.6.

Figure 6.1-2: Top panel: Percentage of the corn ethanol shock that is met by different categories in 2030 and 2050. Bottom panel: Million metric tons of additional corn production (red, orange, and yellow) and corn diverted to corn ethanol production from other uses (green)[179]



6.2 Energy Market Impacts

Corn ethanol has the potential to reduce GHGs and mitigate climate change if its use reduces consumption of sufficient quantities of other fuels derived from fossil sources (e.g., petroleum, natural gas). Thus, the effect of increased corn ethanol consumption on other energy markets is a critical component of the overall assessment of GHG impacts of corn ethanol use.

While the market impacts of increasing the use of one category of fuel are complex and interrelated, we can consider several broad mechanisms that affect the use of other sources of energy. First, increasing the use of a liquid biofuel can directly replace the use of petroleum-derived fuels, thereby decreasing the amount of petroleum-derived fuel consumed. Secondly, an increase in the production of additional biofuel requires additional energy inputs; increased corn ethanol production, for example, would result in increased demand for natural gas and any other

[179] A negative percent contribution means that there was decrease in corn production or an increase in non-fuel uses of corn. New cropland in GLOBIOM has a negative percent contribution in 2050 because the amount of corn cropland in non-USA regions is lower in the corn ethanol shock than in the reference case. In 2050, non-USA regions in GLOBIOM produce less corn and more of other types of crops to make up for lost production in the USA region. There are also shifts in the feed market from corn to DDG. These types of dynamics are discussed more in Sections 6.3.

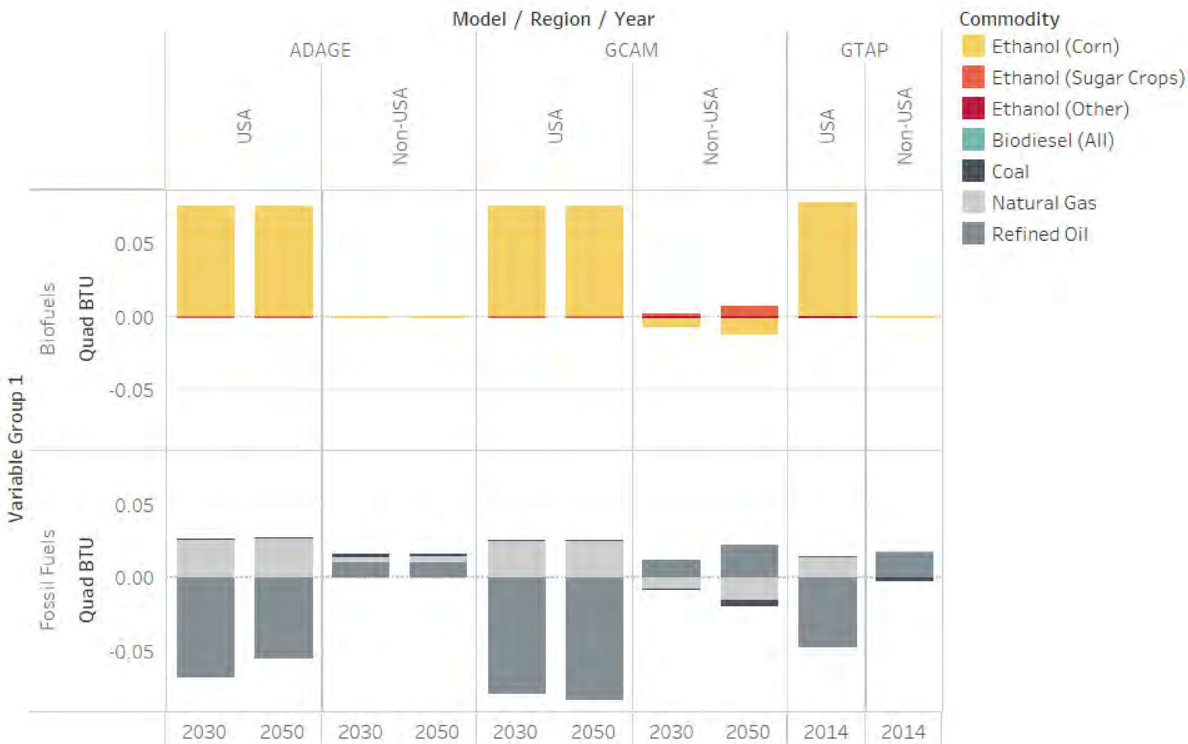
energy inputs required to grow, transport, and process additional feedstock. Correspondingly, a reduction in the extraction and refining of petroleum would result in decreased demand for the energy sources required in those processes. Finally, all of the above effects on demand for energy sources will affect fuel prices, which, in turn, affect supply and demand for those fuels. We refer to these adjustments in supply and demand to price as market-mediated effects.

Towards the end of this section, we present modeling results describing changes in liquid fuel consumption relative to the size of the cumulative corn ethanol shock.[180] These metrics indicate whether one BTU of increased corn ethanol consumption in the USA region displaces more or less than one BTU of refined oil[181] or biofuel consumption, when averaged across all years represented in the scenarios, and including the indirect effects discussed above. These effects vary depending on whether they are considered within the USA region or non-USA regions. As an illustration of the regional differentiation, we consider the expected effect of an increase in corn ethanol consumption in the USA region on consumption of refined oil in the non-USA regions. The primary theoretical mechanism for this effect is as follows: 1) biofuel consumption increases in the USA region, displacing some quantity of refined oil consumption in the USA region; 2) this reduces global demand for petroleum which puts downward pressure on the price of crude and refined oil in non-USA regions; 3) the effect on crude and refined oil prices leads to increasing demand for refined oil outside of the USA. The degree to which these effects are reflected in the model results is presented in Figure 6.2-3 and the accompanying discussion at the end of this section.

As discussed in Section 3, the models considered in this section differ in their representations of energy markets. GREET is largely an attributional framework which includes detailed accounting of the energy inputs for production of feedstocks, biofuels, and fossil fuels but does not include a representation of markets for energy goods, the displacement effect of an increase of biofuel use, nor of any other market mediated effects. GLOBIOM does not represent energy commodities or markets, so it cannot be used to estimate the effects of a biofuel shock on these markets. ADAGE, GCAM, and GTAP each represent a selection of energy commodities, end use sectors, and market interactions.

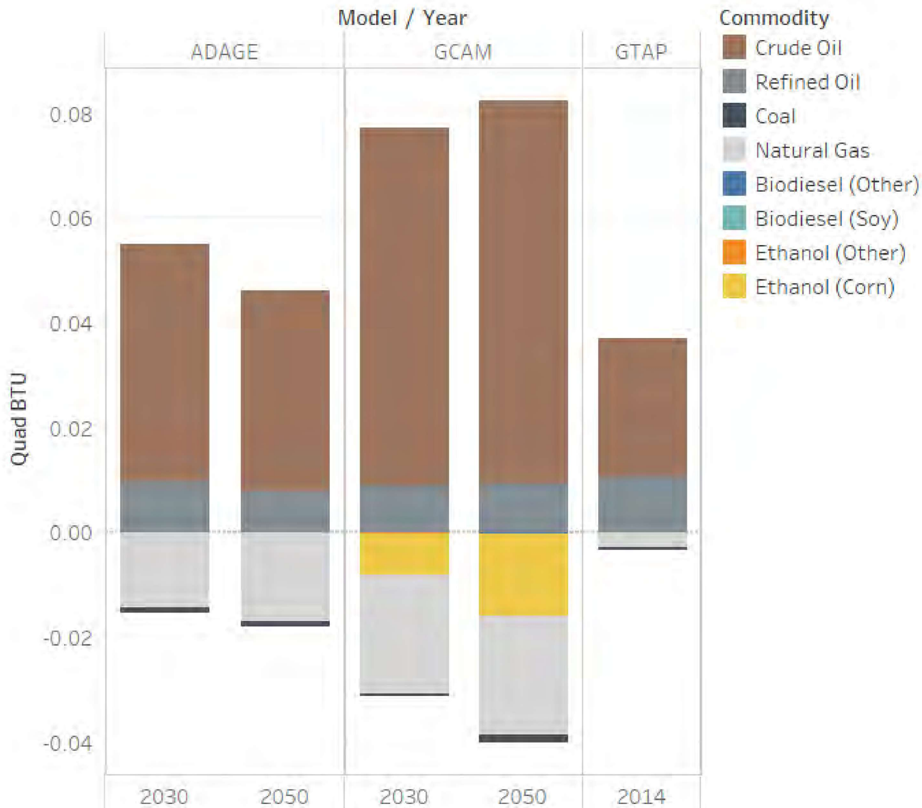
[180] I.e., the cumulative changes in energy consumption expressed as a percentage of the cumulative change in US corn ethanol consumption over the duration of the modeled period.
[181] In these models, refined oil is an aggregation of all refined petroleum products, including gasoline and diesel.

Figure 6.2-1: Difference in consumption of energy commodities (quadrillion BTUs) in the corn ethanol shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM) and 2014 (GTAP)



ADAGE, GCAM, and GTAP results show differing estimated net impacts on biofuel consumption and fossil fuel consumption under a one billion-gallon corn ethanol shock scenario (Figure 6.2-1). As illustrated in Figure 6.1-1, a portion of the corn ethanol shock in GCAM is met through decreased U.S. net exports of corn ethanol, the majority of which (95 percent in 2030) is a reduction in gross exports, as opposed to increased gross imports. This results in a decrease in corn ethanol consumption in the non-USA regions (roughly ten percent when compared to the total energy content of the corn ethanol shock in 2030) and an increase in consumption of ethanol produced from sugar crops in non-USA regions (two percent of the shock in 2030). While ADAGE and GTAP do represent trade in biofuel commodities (see Figure 6.2-2 below), the corn ethanol shock has little effect on trade of ethanol, and, consequently, little effect on consumption of biofuels in non-USA regions, in the results from these models.

Figure 6.2-2: Difference in U.S. net exports of energy commodities (quadrillion BTUs) in the corn ethanol shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM) and 2014 (GTAP)



Results in all three models show increased consumption and decreased U.S. net exports of natural gas, largely due to increased production of corn ethanol and drying of DDGs, though the size of these impacts is notably smaller in GTAP results compared to in ADAGE and GCAM. Impacts on natural gas use in the non-USA regions differ. GCAM results show consistent and decreasing consumption of natural gas, corresponding with decreased demand for natural gas used in ethanol production in non-USA regions and with other market mediated effects. The lack of significant impacts on non-USA ethanol consumption in ADAGE and GTAP results in a smaller effect on non-USA natural gas consumption in results from those models.

ADAGE, GCAM, and GTAP each model an aggregated refined oil commodity which represents a range of petroleum products including gasoline, distillate fuel, and other industrial chemicals and products. The primary displacement effect of increased corn ethanol consumption is seen in the consumption of this modeled refined oil commodity. Within the USA region, ADAGE, GCAM, and GTAP results show differing reductions in refined oil use; 0.068 and 0.079 quads in ADAGE and GCAM respectively in 2030, and 0.048 quads in GTAP in 2014. The decrease in refined oil use in both ADAGE and GCAM is predominantly in the transportation end use sector – this is the primary displacement effect – with some relatively minor market mediated effects in other end use sectors. Results available from the GTAP model did not disaggregate refined oil use by end use.

The decrease in demand for crude and refined oil in the USA region observed in these model results corresponds with a decrease in the price of these commodities. However, the impact of the modeled shock on estimated prices of crude oil and refined oil is very small in absolute terms because the one billion gallon shock represents only around one tenth of one percent of global liquid fuel consumption. The result is a decrease in the estimated prices of crude and refined oil by between one and three hundredths of one percent in the USA and non-USA regions in ADAGE and GCAM results. Since crude and refined oil are globally traded, the modeled price changes within and outside of the USA region are similar in direction and magnitude. Outside of the USA region, all three model results show increased refined oil consumption, largely driven by the downward price pressure on oil discussed above, though the magnitude varies among models and model years.

Displacement and other net market impacts on refined oil consumption are often presented in metrics normalized to the biofuel shock volume. This representation facilitates comparisons of the effect across different studies and shock volumes. This indirect fuel use effect is sometimes described in the literature as "oil rebound," though the scope of what is included within the definition of "rebound" varies.

In the case of this model comparison exercise, we find it illustrative to consider the ratio of cumulative net impacts on refined oil and other biofuels to the cumulative impacts on consumption of corn ethanol in the USA region. These metrics indicate whether one BTU of corn ethanol displaces more or less than one BTU of refined oil or other biofuel consumption, when averaged across all years represented in the scenarios, and including the indirect effects discussed above.

Figure 6.2-3: Difference in liquid fuel consumption relative to the volume of the corn ethanol shock[182]

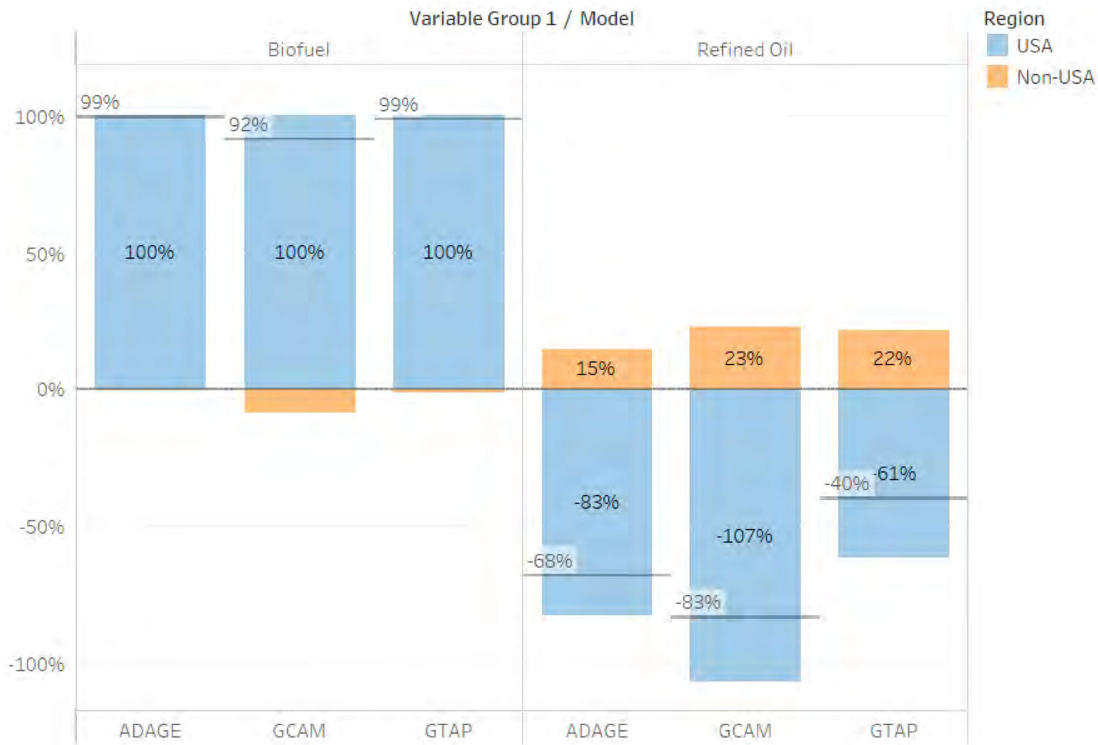


Figure 6.2-3 illustrates these cumulative relative effects within the USA region and non-USA regions for both biofuels and refined oil. The left pane depicts the effect of the corn ethanol shock on total biofuel consumption within the USA region (blue) and non-USA region (orange). As discussed in Section 4, in the corn ethanol shock scenario, U.S. consumption of corn ethanol is increased by one billion gallons, while U.S. consumption of all other biofuels is held constant at reference case levels. Thus the cumulative difference in biofuel consumption in the USA region between the corn ethanol scenario and the reference case is equivalent to the cumulative size of the corn ethanol shock, which is the denominator of all of these relative metrics. Therefore, by definition, the blue bar in the left pane is 100 percent, and represents the full cumulative corn ethanol shock. Note that the scenarios in this model comparison exercise did not place any additional constraints on consumption of biofuels in non-USA regions, so the cumulative difference in consumption of biofuels in non-USA regions, depicted in orange on the left pane of Figure 6.2-3, represents net impacts of the shock on consumption across all represented biofuels. As discussed above, in the GCAM results for the corn ethanol scenario, some of the required corn ethanol shock volume is met through adjustments in net trade of corn ethanol. In the ADAGE and GTAP results for this scenario, the shock is met almost entirely through increased corn ethanol production in the USA region. The cumulative effect of this

[182] Values in the figure represent the difference between the shock and reference case of the given fuel category (refined oil vs. liquid biofuels) and given region (USA region vs non-USA regions) divided by the difference in consumption of liquid biofuels in the USA region (i.e., the shock volume). For ADAGE and GCAM, this is calculated using cumulative volume differences between 2020 and 2050. For GTAP, which only estimates differences in a single time step, the calculation uses only the volume differences in 2014.

difference is seen in the orange bars; in GCAM, cumulative non-USA consumption of biofuels decreases by eight percent of the cumulative USA corn ethanol shock volume, whereas ADAGE and GTAP only show a one percent decrease in non-USA biofuel consumption. Thus, on net, the shock scenario in GCAM increases global biofuel consumption by 92 percent of the total specified cumulative shock, whereas the shock scenario in ADAGE and GTAP increases global biofuel consumption by 99 percent of the total specified cumulative shock.

The righthand pane in Figure 6.2-3 illustrates the cumulative effects on refined oil consumption within and outside the USA region. Under the corn ethanol shock scenario, that additional volume is required to be consumed within the USA region, so the primary displacement of refined oil used for transportation is within the USA region. If one BTU of ethanol use displaced exactly one BTU of refined oil use in a given set of model results, and all of the other indirect effects within the USA region discussed above were negligible, the blue bars in this pane would show 100 percent. Thus, the size of the bar relative to 100 percent shows whether the cumulative net impacts within the USA region are more or less than perfect energy equivalent displacement.

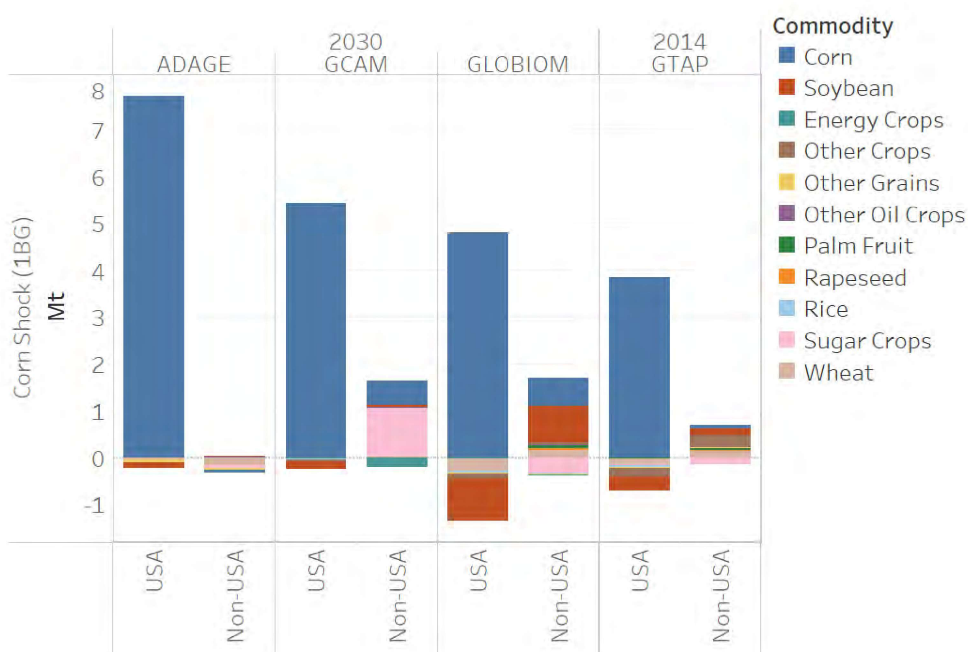
As seen in the figure, there is greater than perfect displacement of refined oil in the USA region in the GCAM results (107 percent). This displacement exceeds 100 percent primarily because GCAM projects that the corn ethanol shock will increase the average price of fuel in the USA region's gasoline pool. This causes a small decrease in USA region demand for gasoline in addition to the energy equivalent displacement. In contrast, the ADAGE and GTAP results show less than perfect displacement of refined oil in the USA region (83 percent and 61 percent, respectively). In ADAGE, this difference is largely due to smaller reductions in refined oil consumption in 2040 and 2050.

The effect on cumulative net non-USA oil consumption – a commonly used definition of "oil rebound" in the literature – shows how global oil consumption changes as a result of the shock. GCAM and GTAP results show larger increases in non-USA refined oil consumption (23 percent and 22 percent of the cumulative shock, respectively) than ADAGE (15 percent). The global net effect of the shock on refined oil consumption is that, on average, 100 BTUs of corn ethanol required to be consumed in the USA displaces 68 BTUs of global refined oil consumption in ADAGE, 83 BTUs of global refined oil consumption in GCAM, and 40 BTUs of global refined oil consumption in GTAP. That the estimated net effect of a U.S. biofuel shock on global oil consumption amounts to less than one-for-one displacement makes intuitive sense; oil and refined oil products are globally traded commodities. Any reduction in consumption of refined oil in the USA makes available some additional supply to the rest of the world, which would be expected to reduce the price of crude and refined oil globally and result in adjustments to consumption patterns in all regions. We note, however, that the range of reductions in refined oil use varies widely across the three models with energy sector representation, directly resulting in the wide range of energy sector emissions savings estimated by these models. These emissions results are presented in Section 6.7 below. Future research could better define and understand the parameters and assumptions that lead to this range in reduction of refined oil consumption.

6.3 Crop Production and Consumption

As shown in Section 6.1, ADAGE, GCAM, GLOBIOM, and GTAP results estimate about 40-85 percent of the corn ethanol shock would be sourced from new corn production. Estimated new corn production comes primarily from the USA region in these ADAGE, GCAM, GLOBIOM, and GTAP results, with some new corn also produced in the non-USA regions in the GCAM and GLOBIOM results (Figure 6.3-1). All four models estimate some reduction in production of other crops in the USA region, though the magnitude varies.[183] Soybean production accounts for a large percentage of this decrease in all four models, but the displacement of other crops is more variable across the results. GLOBIOM estimates the largest decrease in non-corn USA crop production and GTAP the second largest, with GCAM and ADAGE showing similar, more modest decreases.

Figure 6.3-1: Difference in commodity production (million metric tons) in the corn ethanol shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)



Results from three of the four models – GCAM, GLOBIOM, and GTAP – also estimate a net increase in crop production in the non-USA region. These increases are multi-faceted, but generally the crops with greater non-USA production are those for which U.S. net exports are decreasing in the results for each respective model, i.e., some combination of corn, soybeans, and/or wheat. One notable outlier to this general trend is the increase in sugar crop production in GCAM. As shown in Section 6.2 and Figure 6.3-2, this additional sugar crop production is used for fuel production in the non-USA regions of GCAM, which contributes to an increase in the

[183] We also looked at forest product production for the models that are able to report it (ADAGE, GCAM, GLOBIOM), and the change relative to the reference case is negligible.

consumption of sugar crop ethanol. Conversely, in the ADAGE results, we observe a small net decrease in crop production in the non-USA regions.

Globally, crop production increases in all four sets of model results. Most of the net increase globally is from new corn production to produce additional corn ethanol. One exception is the aforementioned increase in sugar crop production in GCAM; this is also occuring indirectly to allow for greater consumption of corn ethanol in the USA region. We observe substantial variation across the models regarding the magnitude of increased crop production, and the share occurring within the USA region versus the non-USA regions. This is an area of uncertainty across the models.

As explained in Section 6.1, in the ADAGE, GCAM, GLOBIOM, and GTAP results, some of the corn ethanol shock is met by diversion of corn to fuel production from other end uses. All four of these models show a reduction in the amount of corn used for feed, but there is variation across the model results in how much the corn feed consumption is reduced (Figure 6.3-2). Part of the feed market impact may be attributable to the increase in corn prices which follows from increased demand for corn in the shock case (changes in prices in the corn ethanol shock case are discussed further below in Section 6.5). But it is also in part attributable to greater production of corn DDG in the shock case.

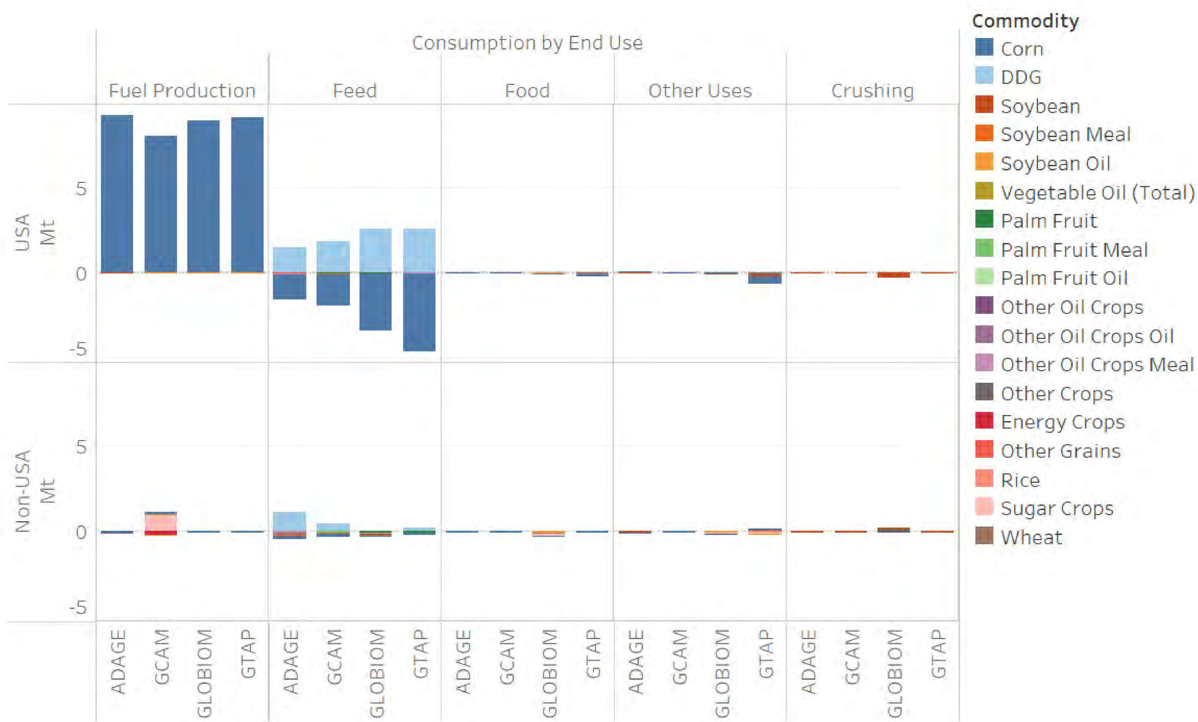
DDG is a coproduct of corn ethanol production used almost exclusively for animal feed. In these model results, the additional DDG produced from the additional corn ethanol production is used for feed to replace the corn (that is, the DDG "backfills" for the corn diverted from feed use to fuel use). Historically, USA-produced corn DDG is both consumed domestically and exported. The degree to which future additional DDG production might be consumed domestically versus exported is therefore a key uncertainty in forward-looking scenario analysis for corn ethanol consumption. In the GLOBIOM results shown in Figure 6.3-2 below, the DDG is consumed entirely within the USA region in 2030, displacing mostly corn in the feed market. In ADAGE, GCAM, and GTAP, some of the additional DDG is consumed domestically and some is exported for consumption in the non-USA regions (see also Figure 6.4-1). ADAGE shows the largest share of exported DDG. Within the USA region, mostly corn is displaced in the feed market. In non-USA regions, larger proportions of other crops are displaced, commensurate with the dominant feed products in the affected regions. The results across all four models agree however that, on a global basis, corn is the primary feed commodity displaced by additional DDG. There is also good agreement across these four sets of results about the magnitude of increased DDG production and consumption in response to the corn ethanol shock.

We observe from these results that there is more consistency among the models we considered about the global magnitude of DDG consumption in response to a corn ethanol shock than there is about where in the world that additional DDG consumption will occur. From this we can conclude that exogenous assumptions about the location of DDG consumption carry uncertainty. A possible area for further sensitivity analysis is to explore the potential impacts on estimated GHG emissions should additional DDG be consumed primarily in the USA versus primarily outside the USA.

The ADAGE, GLOBIOM, and GTAP results estimate more additional corn for fuel production than do the GCAM results. This is because, as discussed above, GCAM is meeting some of the shock by reducing corn ethanol consumption in non-USA regions and reducing the U.S. net exports of corn ethanol. To make up for the loss of corn ethanol in the GCAM results, non-USA regions produce and consume some additional sugar crop-based ethanol. The question of whether non-USA biofuel production and consumption would be measurably affected by additional demand for corn ethanol in the USA therefore remains an uncertainty. However, it is clear that such potential impacts on the energy sector may meaningfully affect the results; these impacts cannot confidently be assumed to be zero.

The scenario results from ADAGE, GCAM, GLOBIOM, and GTAP consistently show only minimal changes in the consumption of commodities for food, crushing, and other uses. These results also consistently show only minimal changes in the consumption of commodities and coproducts other than corn, DDG, and sugar crops.

Figure 6.3-2: Difference in consumption by end use (million metric tons) in the corn ethanol shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[184]



6.4 Trade of Agricultural Commodities

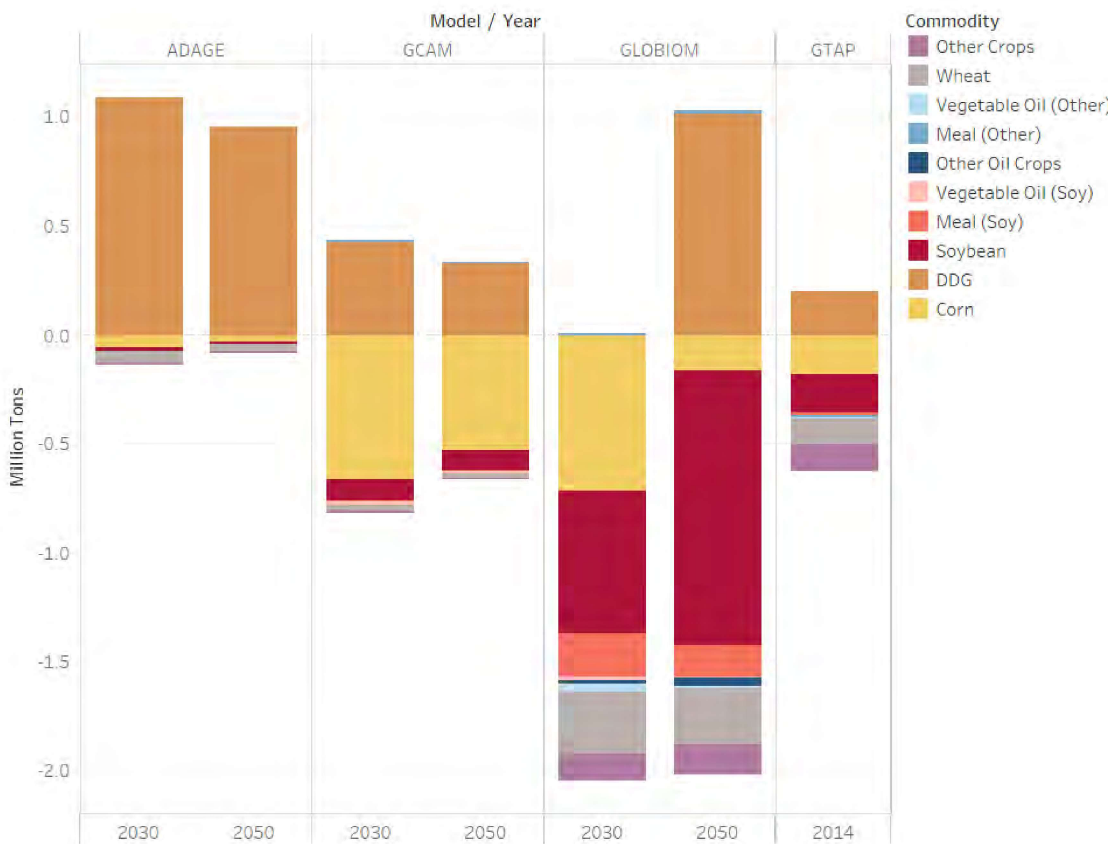
As discussed in Section 3.1.6, the structural representations of trade vary across the four economic models considered in this exercise (ADAGE, GCAM, GLOBIOM, GTAP). Because trade is more elastic by default in some model trade structures than others, one would expect the

[184] Results are shown in million metric tons of each feedstock.

impact of the corn ethanol shock on U.S. corn and other agricultural commodity exports to vary by model. One would also expect the shares of domestic versus international consumption of the DDG coproduct to vary by model, as imported DDG from the U.S. would be valued differently based on how simulated economic actors are calibrated to value imported versus domestically produced feed products.

Consistent with this expectation, we do observe ADAGE, GCAM, GLOBIOM, and GTAP differ in their agricultural commodity trade responses to the corn ethanol shock. This is illustrated by differences between the shock scenario and reference case in U.S. net exports of crops and secondary agricultural commodities (see Figure 6.4-1). Results from all four models show relatively minor changes in gross imports relative to gross exports, so the data displayed in Figure 6.4-1 are roughly equivalent to differences in gross exports from the USA region. In general, these reductions appear largely commensurate with the declines in crop production from the USA region discussed in Section 6.3 above.

Figure 6.4-1: Difference in U.S. net exports of crops and secondary agricultural products (million metric tons) in the corn ethanol shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM, GLOBIOM) and 2014 (GTAP)



As discussed in Section 6.1, most of the corn ethanol shock in the ADAGE results is met through additional corn production in the USA region, rather than imported corn. This results in additional DDG production, roughly 41 percent of which is exported to the non-USA region. There is very little change in trade of corn in the ADAGE results. In the GCAM results, the USA region reduces gross exports of corn to supply a portion of the additional demanded ethanol feedstock. Of the additional DDG production in the USA region, roughly 18 percent is exported. In these GCAM results, there are also decreases in U.S. net exports of other crops, most notably soy and wheat. This is due to competition for land leading to some crop switching from other crops to corn production in the USA region, resulting in less of these crops being available for export. The GTAP results show a similar pattern as the GCAM results, i.e., net exports of DDG increase while net exports of other commodities decrease relative to the reference case. Relative to the GCAM results, the GTAP results include a smaller increase in DDG net exports, a smaller decrease in corn net exports, but a larger decrease in net exports of other commodities such as soybeans. As discussed in Section 6.1, in these GLOBIOM results most of the additional corn used for ethanol feedstock in the corn ethanol shock scenario is produced in the USA region by switching cropland from other crops to corn production. This results in greater reductions in the production of other crops compared to what we observe in the ADAGE and GCAM results, most notably in production of soy, wheat, and other crops. This results in larger decreases in exports of those crops from the USA region in the GLOBIOM results. In these results, GLOBIOM chooses to consume most of the additional DDG production domestically in 2030 and 2050, which creates greater flexibility to divert corn used to meet the ethanol shock from the feed market. In 2050, however, GLOBIOM estimates additional crop switching from soy to corn, increasing the amount of corn which is used for animal feed and freeing up some DDG for export in that model period.

6.5 Crop Yield

As discussed in Section 5.3 above, the four economic models included in this comparison exercise all have the ability to increase crop yields in response to changes in crop price. The theoretical basis for yields responding to price is similar across models; to the extent producers see long-term revenue per ton of crop increasing, they may choose to invest in more expensive but higher yielding agricultural technologies (i.e., invest more revenue in capital and material inputs to production) and/or increase their personnel (i.e., invest more revenue in labor inputs to production).

As discussed in Section 5.3 above, the endogenous mechanisms within each model which simulate these decisions vary in structure. GCAM and GLOBIOM each represent four distinct crop management options for each crop, though the characteristics of the four options in each model are not fully aligned with one another. In ADAGE and GTAP, inputs of labor, capital, and materials may be increased to generate higher yields through nested CES production functions. The main similarity across these four models when it comes to changes in crop yield is that an increase in crop price is the mechanism by which higher crop yields are induced. However, these differences in endogenous yield response mechanisms indicate that each model would be expected to simulate somewhat different patterns and magnitudes of crop yield response to a given change in price.

Reference case yield trends are also an important factor in understanding differences across models. As shown in Figure 5.3-1, reference case corn crop yield trends across the four economic models are fairly similar in the historical periods of 2010 and 2015, though not identical. However, for the three dynamic models, ADAGE, GCAM, and GLOBIOM, the trends in reference case corn yields diverge over time. Yields are calibrated to improve over time in all three models however, reflecting a shared assumption that agricultural technologies will continue to improve into the future. In reviewing the change in corn yields in our shock scenario relative to the reference case shown by these dynamic models, the reader should keep in mind that yields are improving over time in both the USA and non-USA regions in both scenarios, as they do in the reference case.

As shown in Figure 6.1-2, crop intensification contributes to the sourcing of corn for the ethanol shock to varying degrees across the models. In the biofuel volume shock scenarios modeled for this exercise, we observe that the contributions from intensification are a minority of the feedstock sourcing solution, accounting 15 percent or less of the additional feedstock required. Intensification is a part of each model solution to at least some degree however, and we can make some useful observations about how this effect is similar and different across the models considered.

Before discussing the modeled crop yield results from this exercise, it is important first to understand what is meant in this case by the term intensification. Increasing crop yield per harvested unit of land is only one method of intensifying crop production. In regions of the world where climatic conditions allow for it, multi-cropping (i.e., planting more than one crop per year) is another option. GLOBIOM and GTAP consider this option explicitly to some extent by distinguishing between the physical area on which crops are planted and the number of harvests achieved annually on that area. In ADAGE and GCAM, no such distinction is made, and multi-cropping is represented implicitly, embedded in the average yield for a given crop in a given growing region. GTAP does not report total areas of multi-cropping in a given scenario, but it does calculate and report changes between scenarios in harvested cropland area, unused cropland and multi-cropping area. Thus, increasing the ratio of harvested to planted cropland area is a distinct intensification strategy for GTAP.

Another intensification option is to shift production from less productive land or growing regions to more productive land or regions. More productive land is assumed in these models to garner a higher rental rate (i.e., the land is more expensive to purchase or use) because of the higher revenues it can generate. As crop prices rise however, crop producers can potentially afford more of this more expensive land. This intensification option is represented in all four models to varying degrees, as the spatial detail of growing regions and land cover varies across models.

When models report average yield for a given crop across a broad geopolitical region, that output value mixes together some, but not necessarily all, of these effects. Depending on how the reported yield value is calculated, different information about intensification may be embedded. For the purposes of this section, yield output is calculated as regional production of a crop divided by reported regional cropland use for that crop (these outputs are discussed in greater detail in Section 6.6 below). Therefore, the reader should keep in mind that what is discussed in this section as modeled crop yield output represents intensification more broadly and is not only an improvement in the yield of a crop on specific acres of land through greater investment in crop production inputs on that land.

As shown in Figure 6.5-1 below, average USA region corn yields increase in all four models in response to the corn ethanol shock. One can compare these results with the reference case yields presented in Figure 5.3-1 and observe that these improvements are minor, less than a 1 percent improvement in USA region average yield in all cases. While improvements may be larger in particular growing regions, the average yield across the USA region is instructive in understanding why intensification plays only a minor role in the sourcing of corn for the ethanol shock. As a collective, these four models estimate the corn ethanol shock modeled for this comparison would induce relatively minor improvements in corn yield. This small observed change in USA region corn yields is reasonable in light of the crop price changes. Figure 6.5-2 below shows that the change in corn price is also small, less than 0.5 percent in 2030. As discussed above, crop price is the primary driver of increased crop yields and intensification in general, and a small price change would be expected to induce a small yield response as well.

Looking at the non-USA results, there is even less effect on corn yield. This is not an unexpected result. Figure 6.3-1 above shows the increase in corn production in response to the shock is concentrated in the USA region. Figure 6.5-2 shows there is virtually zero change in corn prices in the non-USA regions in response to the shock as well. This lack of perturbation of the non-USA corn systems would not be expected to induce much change in corn yields.

Figure 6.5-1: Difference in corn yield in the corn ethanol shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM, GTAP)

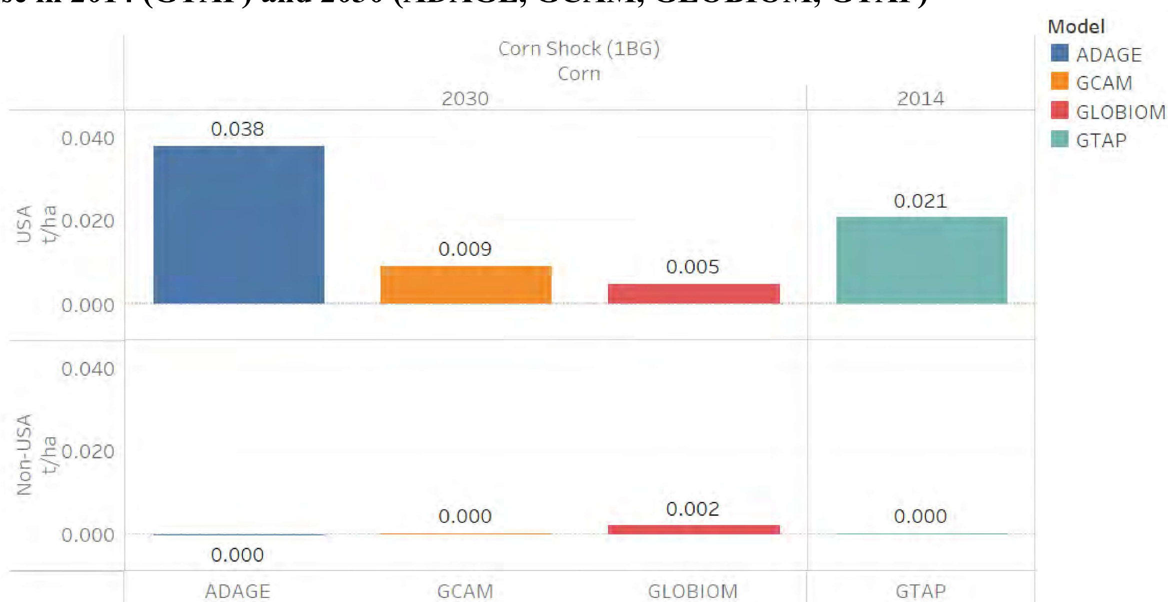
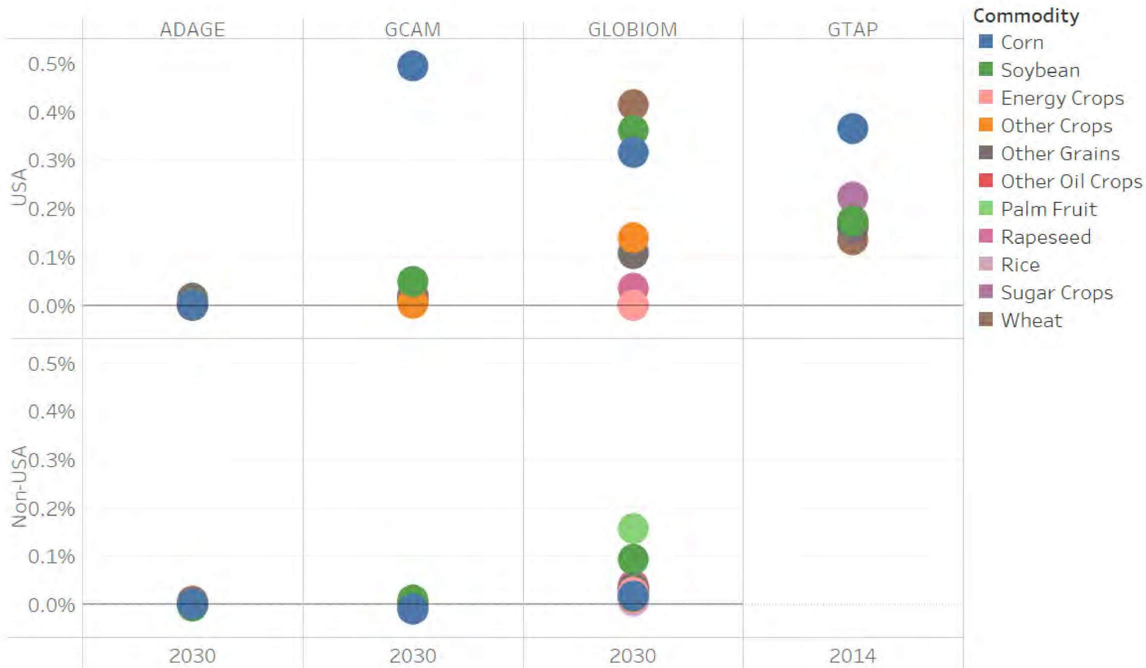


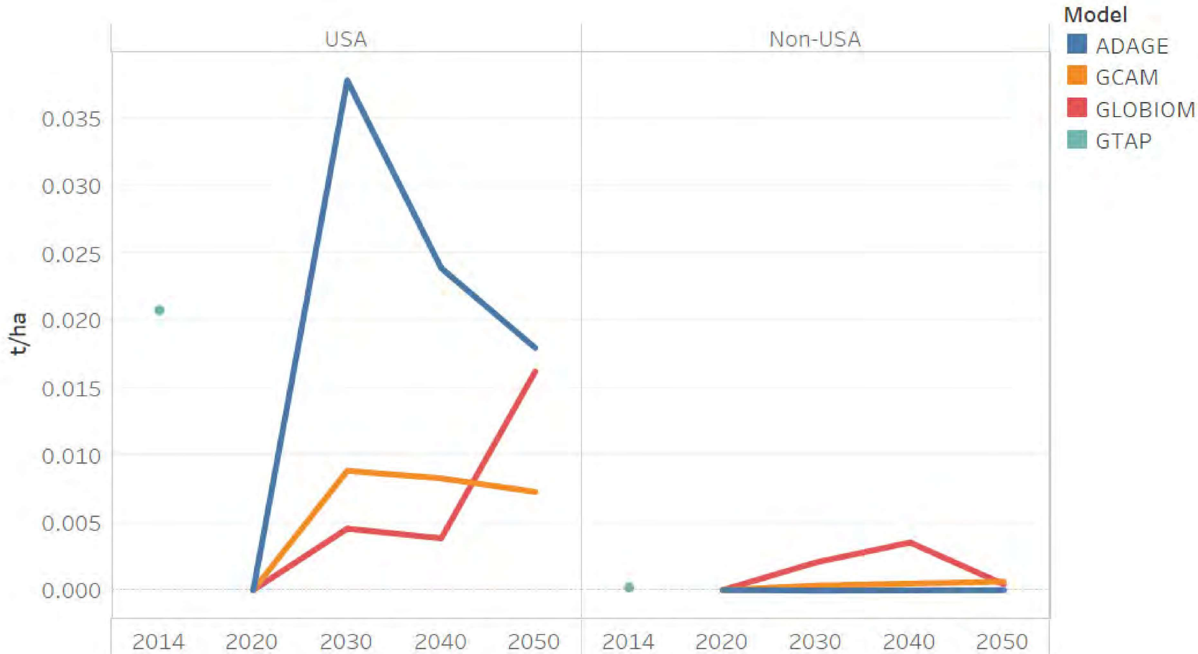
Figure 6.5-2: Percent difference in commodity prices in the corn ethanol shock relative to the reference case[185]



In the dynamic models, it is also instructive to consider the trend in yield change over time, relative to the reference case. As shown in Figure 6.5-3 below, the pattern of this change over time varies across the three dynamic models. Looking first at the results for the USA region, in two of the three dynamic models, ADAGE and GCAM, the corn crop yield response to the corn ethanol shock is strongest in 2030, the time step in which the shock reaches its peak. The yield response diminishes thereafter over time, likely reflecting the fact that reference case yields continue to improve in both of these models beyond 2030. The GLOBIOM results show a different pattern. However, because all of these changes are fairly small compared to the reference case corn yield, it is difficult to read much into the trends over time. Outside of the USA region, none of the four models show a substantial change in corn yield. These responses are consistent with the changes in corn area in each of the three models, described in Figure 6.6-2 further below.

[185] Average commodity prices for non-USA regions in GTAP results were not available for this exercise.

Figure 6.5-3: Difference in corn yield in the corn ethanol shock relative to the reference case in 2014 (GTAP) and over time from 2020 to 2050 (ADAGE, GCAM, GLOBIOM)



While the corn crop yield change results may appear to be somewhat different across models based on Figure 6.5-3, when compared to reference case corn yields in each model they are all relatively small. In ADAGE, GCAM, and GLOBIOM the percent differences in corn yields in 2030 in the corn shock relative to the reference case are all less than one percent for the USA and non-USA regions. We can observe from these results that the four economic models generally agree that, in the specific scenarios modeled for this exercise, yields are not projected to improve substantially in response to the corn ethanol shock. However, it is also notable that even these small changes in corn yield are responsible for a small but notable percentage of the additional corn produced to meet the shock.

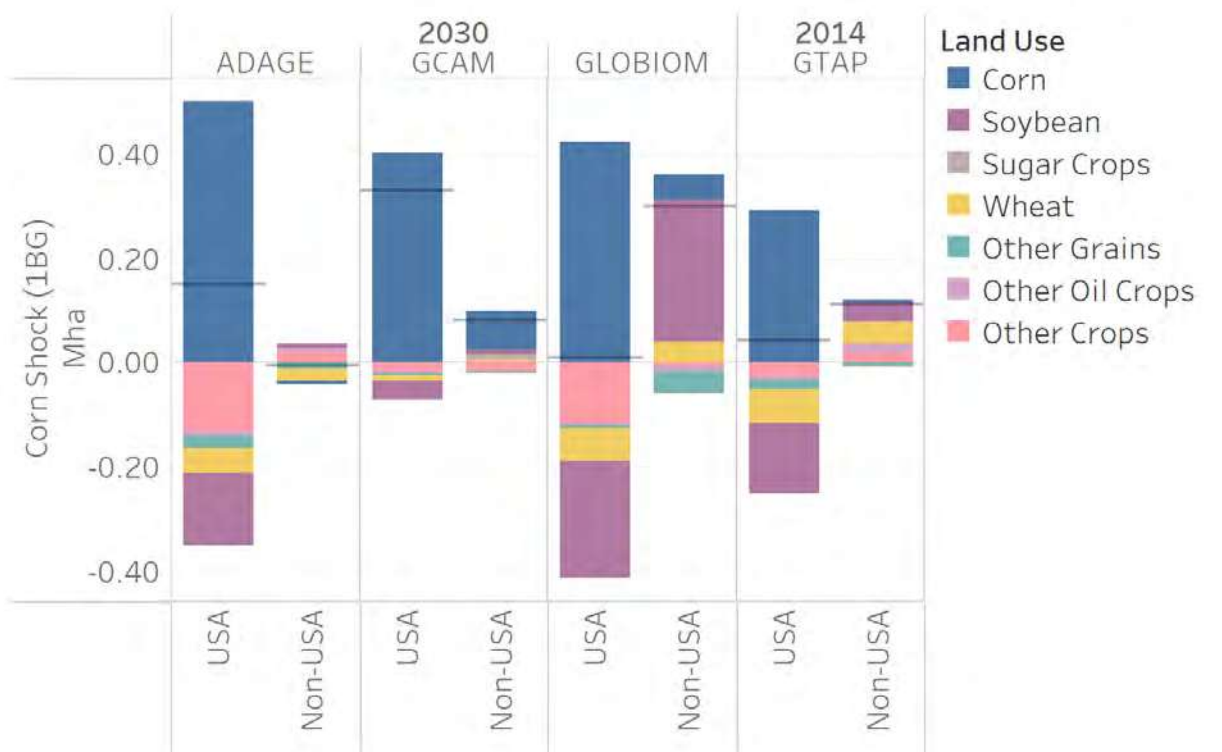
From this exercise however, we cannot draw any firm conclusions from this yield comparison regarding whether one method is superior to the others. All four of the models seem to behave reasonably in these yield results. Sensitivity analysis may reveal the degree to which GHG emissions results change when the underlying assumptions about crop yield responsiveness to price are changed. This may indicate areas for further research.

6.6 Land Use

As described in Sections 6.1 and 6.3, in the ADAGE, GCAM, GLOBIOM, and GTAP results, some of the corn ethanol shock is met by increased corn production, which comes from a mix of cropland shifting from other crops to corn, land use change from other land types to cropland, and changes in corn yield. As shown in Figure 6.6-1, corn cropland in the USA region increases by 0.3 Mha in GTAP (2014) and 0.4-0.5 Mha in ADAGE, GCAM, and GLOBIOM (2030). All of these model results show some amount of shifting of other crops to corn, but the amount of crop shifting varies. Model results also show differences in the impact on non-USA regions.

In the GTAP and GLOBIOM results, most of the new corn cropland in the USA region comes from shifting of other crops. In these model results, the area of soybean and wheat increases in non-USA regions to make up for the loss of production of these crops in the USA region. In both the GTAP and GLOBIOM results, the total cropland increases more in non-USA regions than in the USA region, even though the corn for the corn ethanol shock is coming from the USA region. In the ADAGE results there is some cropland shifting in the USA region, but a larger net increase in cropland area in the USA region than seen in the GTAP or GLOBIOM results. ADAGE has small amounts of cropland shifting in non-USA regions, with minimal changes in total non-USA cropland. In the GCAM results, a much smaller fraction of the new corn cropland is coming from crop shifting, and the net increase in cropland in the USA region is higher than in the other models. The GCAM results also show an increase in corn cropland in non-USA regions, reflecting the increased corn production in non-USA regions to meet the shock.

Figure 6.6-1: Difference in cropland area by crop type (million hectares) in the corn ethanol shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[186]



[186] Horizontal lines show the net change in cropland. Cropland area shown represents land cultivated for row crops in ADAGE and GCAM and harvested area in GLOBIOM and GTAP. When a single unit of land is harvested multiple times in a single year, the area is counted multiple times as "harvested area" but only a single time as "cultivated area."

Each model considered here categorizes land in somewhat different ways (summarized in Section 5.2), and each uses different methods for determining which land types, and how much of each, are converted in response to economic stimuli in scenario runs (summarized in Section 2). In addition, the historical data sources on which the models rely to estimate reference case land cover and land use differ in some ways, with data primarily coming either from FAO or from the GTAP database.

The four economic models all choose to expand cropland to some degree to meet growing crop demands in the corn ethanol shock, which subsequently causes changes in the area of other land types in each model (Figure 6.6-2). In the ADAGE results for the corn ethanol shock, most of the new cropland converted in the USA region comes from managed pasture. Due to the land rent and net primary production (NPP)[187] assumptions in ADAGE, that is the most profitable conversion option. Very little land is converted outside the USA region in these ADAGE results.

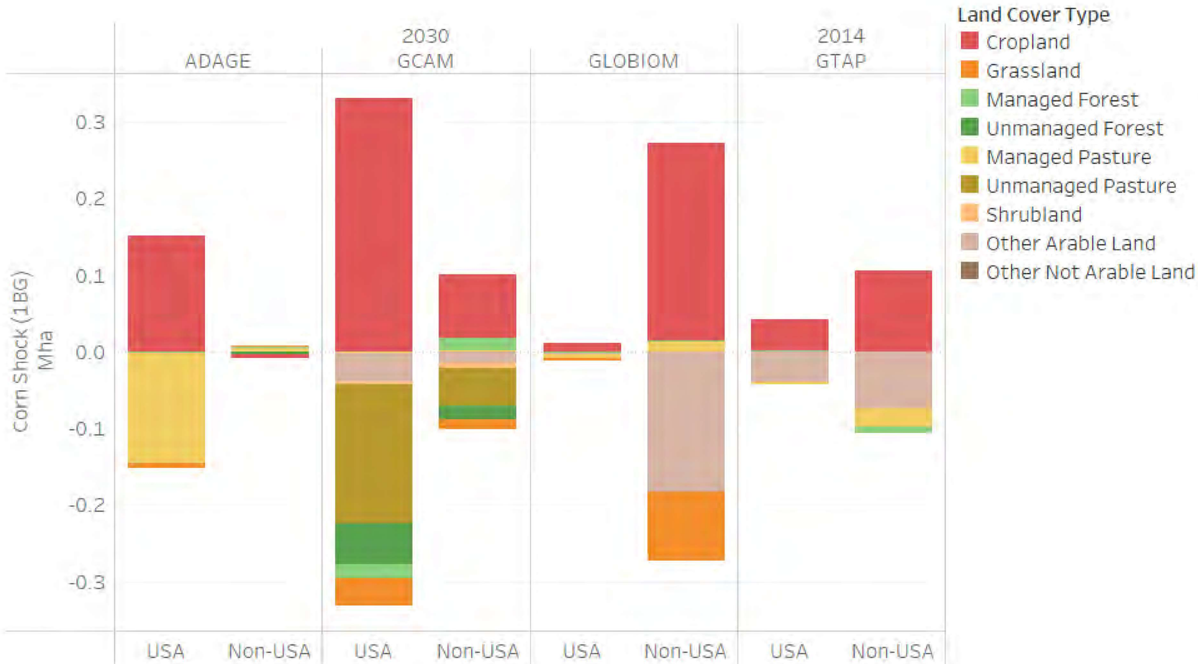
The GCAM results for the corn ethanol shock show decreasing cover for a mix of land types in both USA and non-USA regions, with the largest shift in land use estimated to come from unmanaged pasture. The change in USA land use is approximately three times greater than the non-USA change in use. In the GLOBIOM results, very little new cropland is created in the USA region; what change does occur comes largely from managed pasture. In the non-USA region, the area of other arable land and grassland decreases relative to the reference case. As explained in Section 2, in these model runs GLOBIOM does not allow forest conversion in the USA and EU regions and restricts natural land conversion. The restriction on natural land conversion may be a significant explanatory factor behind the observation in these GLOBIOM results that the new corn cropland is mostly coming from crop shifting, rather than from a net increase in cropland.

In the GTAP results, most of the new cropland comes from other arable land, which includes the land types categorized in the GTAP results as “cropland pasture” and “unused cropland.” In the GTAP results, in the USA region, about 75 percent of the increase in harvested area is explained by a reduction in cropland pasture area (land that fluctuates between cropland and pasture and was unharvested in the reference case), 16 percent by a reduction in unused cropland, 7 percent by a decrease in pasture, and 4 percent by an increase in multi-cropping. In the GTAP results, in the non-USA regions, cropland pasture is once again the main source for new harvested area (54 percent), followed by pasture (21 percent), unused cropland (12 percent), forest (7 percent) and increased multi-cropping (6 percent). The GTAP results show no change in unmanaged forest, grassland or pasture as these are not land categories in the GTAP model.

Each of the models has different assumptions about the carbon stock of different land types in different regions. As shown in more detail in Section 6.7, the type and amount of land converted and the carbon stock of the land types will factor in to the emissions from land use change.

[187] Net primary production is a measure of the rate of increase in plant biomass.

Figure 6.6-2: Difference in land use (million hectares) in the corn ethanol shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[188]



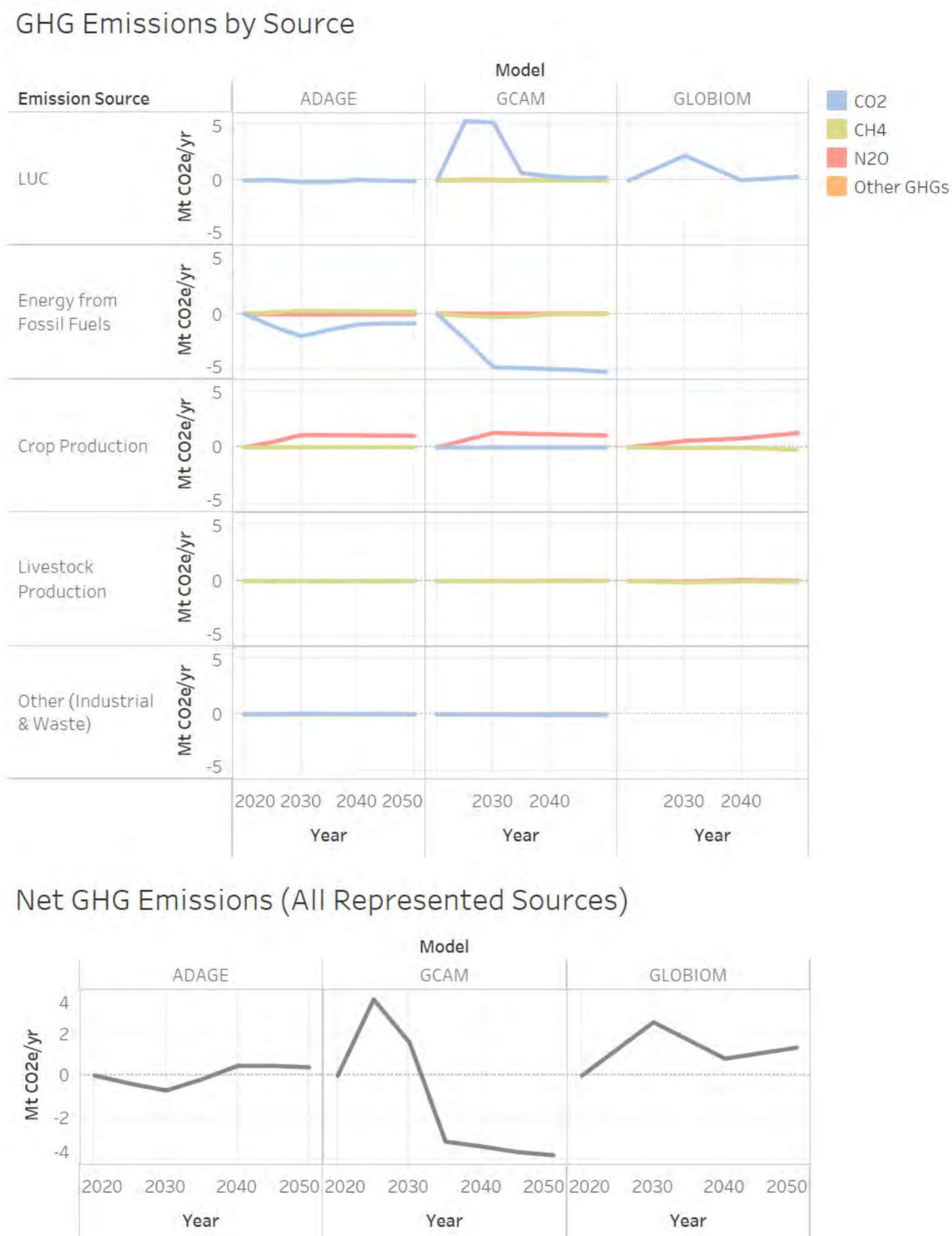
Following the trends observed in the crop production results, the models show variation in both the magnitude and location of land use change. As might be expected given their differences in land competition structure and land categorization, these four models also present diverse estimates regarding what types of land might be converted to cropland in response to greater demand for corn ethanol. The models show some consistency in that they all convert a significant share of the new cropland from pasture lands. Beyond this, some models convert some generally smaller amount of forest land while others convert some amount of natural grassland. Some of this uncertainty appears to be spatial in nature, that is, the models have different estimates regarding where in the world cropland will expand. However, a significant portion also appears attributable to differences in land conversion flexibility across the models. Both factors are areas ripe for sensitivity and uncertainty analysis. As discussed in detail in Sections 8 and 9, we have conducted some analyses of this sort for this exercise, but this remains an area of potential for future research.

6.7 Emissions

The modeled results of energy consumption, crop production, and land use change described above come together in the modeled greenhouse gas emissions. As shown in Figure 6.7-1, the modeled GHG emissions over time vary by model.

[188] In Figure 6.6-2 and 7.6-2, "Cropland" area in GTAP represents land cultivated for row crops (calculated as the change in harvested area minus the change in multicropping), while cropland pasture, and other unused cropland have been reassigned to "Other Arable Land." This differs from Figure 5.2-1, in which cropland pasture and other unused cropland are reported under the "Cropland" category.

Figure 6.7-1: Difference in global greenhouse gas emissions in the corn ethanol shock relative to the reference case[189]



[189] GTAP is not included in this figure because it does not represent emissions over time, and due to time constraints, we do not have GTAP GHG emissions by gas for the source categories used in this figure. For comparison, for GTAP, in the corn ethanol scenario relative to the reference case (2014), LUC emissions = 0.46 Mt CO_2e, fossil fuel combustion and industrial CO_2 emissions = -1.15 Mt, and other GHGs emissions from all covered sources = 0.085 Mt CO_2e, of which N_2O = 0.41 Mt CO_2e, CH4 = -0.28 Mt CO_2e, fluorinated gases = 0.001 Mt CO_2e, and other CO_2 = -0.045 Mt CO_2e; net total GHG emissions = -0.61 Mt CO_2e. GREET is not included in this figure because it does not represent scenario-based emissions over time. See Table 6.7-1 for carbon intensity values.

Emissions from land use change show different patterns in the GCAM, ADAGE, and GLOBIOM results due to the type of land use change occurring relative to the reference case and to the carbon stock assumptions in each model. In the ADAGE results, most of the land use change emissions that occur are attributable to the conversion of pasture to cropland. ADAGE assumes that the soil carbon stock of cropland in the USA region is higher on a per-hectare basis than the soil carbon stock of pasture.[190] Therefore, the conversion of pasture to cropland causes net carbon sequestration, and the emissions over time are less than in the reference case, but close to zero. In GCAM, most of the cropland change is estimated to convert from land types with relatively low carbon stocks, such as pasture and grassland. However, some of the land use change is attributable to reduced future afforestation relative to what GCAM estimates would occur in the future in the reference case. Even though the amount of change in future forest land is small compared to the amount of change in other land types, the relatively higher carbon stocks of forest compared to other land types lead to higher overall land use change emissions in these GCAM results, relative to the other models. GLOBIOM shows conversion of cropland from grassland and the other arable land aggregate category, which results in estimated LUC emissions in between those of ADAGE and GCAM. The GCAM and GLOBIOM results show land use change emissions peaking in 2030. This is because land conversion to cropland happens primarily from 2020-2030 as more land is needed to increase corn production to meet the corn ethanol shock.

"Energy from Fossil Fuels" (or "fossil fuel emissions") includes emissions associated with producing biofuels (e.g., from consuming natural gas or electricity for process energy), direct emissions associated with on-farm energy use to produce feedstock, and transporting both biofuel feedstocks and finished fuels, as well as emissions from indirect impacts on the energy sector, including displaced gasoline use for transportation that is replaced by corn ethanol. Of the three models shown in Figure 6.7-1, these emissions are reported by ADAGE and GCAM. In the corn ethanol results from these models, emissions from fossil fuels are lower than in the reference case. Fossil fuel emissions reductions in the GCAM results become larger until 2030, and then stay relatively constant through 2050. In the ADAGE results, emissions reductions become larger until 2030 but then become smaller from 2030 to 2050 (while staying below the reference case emissions). As shown in Section 6.2, fossil fuel consumption decreases in the corn ethanol shock scenario relative to the reference case. GCAM results show the most reduction in fossil fuel consumption, leading to a greater emissions reduction in the GCAM results than in the ADAGE results. The drivers of these varying results in fossil fuel consumption are discussed in Section 6.2 above.

Crop production emissions are higher than the reference case in the ADAGE, GCAM, and GLOBIOM results. Changes in crop production emissions relative to the reference case are due to changes in the types and quantities of crops grown in the models, and primarily come from changes in N_2O emissions, driven by both increased fertilizer use and direct nitrogen fixation by soybeans. As shown in Section 6.3, ADAGE, GCAM, and GLOBIOM results all show increases in corn production, with smaller changes in the production of other crops. GLOBIOM results also show shifts in the location of soybean production. The increase in crop production emissions is small in all of these model results. In the GLOBIOM results, the crop

[190] These assumptions are based on an area-weighted average of carbon stocks from an earlier version of GCAM (GCAM 3.2).

production emissions increase over time. In the ADAGE and GCAM results, the crop production emissions peak in 2030, and then decrease slightly until 2050. The change in emissions relative to the reference case from the livestock sector and from industrial and waste management sectors is very small.

The total change in GHG emissions across all sources over time varies across the models (Figure 6.7-1). The ADAGE results show a net decrease in emissions from 2020-2040, primarily driven by the decrease in CO_2 emissions in the energy from fossil fuels category. From 2040-2050, emissions are higher than in the reference case because the increase in N_2O emissions from crop production becomes larger than the decrease in CO_2 emissions from fossil fuels. In the GCAM results, net GHG emissions are greater than the reference case from 2020-2030 and less than the reference case from 2035-2050, because the CO_2 emissions from land use change decline rapidly after 2030. In the GLOBIOM results, net emissions are greater than the reference case from 2020-2050, because the largest contributors to emissions (CO_2 from land use change and N_2O from crop production) are greater than the reference case over this time period.

There are a few commonalities across the ADAGE, GCAM, and GLOBIOM results of emissions over time. All of these model results show small but positive emissions from crop production relative to the reference case. The model results also all show very small emissions from livestock production, waste management, and industry. There are also some key differences in the emissions. Although GCAM and ADAGE both consider indirect impacts on the energy sector, the emissions over time from the energy sector are very different. Future research could explore the factors that determine the extent of refined oil displacement in each model through sensitivity analysis. Additionally, there are large differences across the model results in the amount of land use change emissions, due to differences in both the types of land converted and the carbon stock assumptions. A sensitivity analysis of the carbon stock assumptions in GCAM is shown in Section 9.2 below, and a sensitivity analysis of the land conversion elasticities in ADAGE is shown in Section 9.3. Future research could focus on the impact of carbon stock assumptions in other models, or on other model parameters that determine the types of land converted.

As a next step in considering the lifecycle greenhouse gas emissions associated with the corn ethanol shock in these model results, we calculated a carbon intensity (CI) for each category of emissions. A CI is an estimate of the emissions per unit of fuel, which we express here in $kgCO_2eq/MMBTU$. The CI calculated from a model run depends on the particular scenario and model assumptions used. To calculate a CI for the ADAGE, GCAM, and GLOBIOM results, we summed the emissions relative to the reference case from 2020 to 2050 to get the difference in total cumulative emissions relative to the reference case. Then, we summed the difference in corn ethanol consumption in the USA region (i.e., the corn ethanol shock) over 2020 to 2050 to get the total cumulative biofuel consumption difference relative to the reference case. Finally, we divided the cumulative emissions difference by the cumulative biofuel consumption difference to estimate a CI. The calculated CI depends on the time horizon included in the calculation, because the annual emissions vary over time. For example, emissions in the corn ethanol scenario relative to the reference case may be higher from 2020-2030 than in later time steps, as is the case in these GCAM and GLOBIOM results (Figure 6.7-1), or lower in 2020-2030 than in later time steps, as is the case in these ADAGE results. Calculating a CI using only the results from 2020-

2030 would result in a higher CI than considering emissions from 2020-2050 for GCAM and GLOBIOM in this case. The opposite would be true for ADAGE in this case. For GTAP results, we divided the emissions difference by the biofuel consumption difference in the USA region in the single 2014 time step. GTAP emissions are given for a single year, but these results are amortized over a 30 year time period. Results from GREET are already given as carbon intensities, i.e., this is the metric GREET is designed to estimate.

When interpreting the ADAGE, GCAM, GLOBIOM, and GTAP CI results, a CI of zero means that global GHG emissions are equal in the shock case and the reference case, a positive CI means a greater quantity of GHGs are emitted globally relative to the reference case, and a negative CI means a smaller quantity of GHGs are emitted globally relative to the reference case. Importantly, a negative CI from one of these four models does not necessarily represent GHG sequestration, but rather is best interpreted as a lower rate of emissions. Conversely, because GREET is an attributional rather than consequential approach, a CI of zero means that the supply chain for the fuel is estimated to not produce any emissions, a positive CI means that the supply chain is estimated to release net GHG emissions, and a negative CI means that the supply chain is estimated to achieve net GHG sequestration.[191]

Table 6.7-1 shows the CI of corn ethanol calculated using the emissions reported by each model. Models are divided between those frameworks with energy markets (in the left side columns) and models without energy markets (in the right side columns). This division is made to reflect important differences in the sectors represented and the difficulty of direct comparability between models on the left with models on the right. ADAGE, GCAM, and GTAP include global emissions from every economic sector, including indirect, market-mediated impacts. GREET includes detailed emissions estimates from fuel production, transport, and use, but, as it is not a consequential model, it does not estimate the net change in GHG emissions resulting from a change in biofuel consumption. Rather it estimates the emissions directly attributable to the biofuel supply chain. GLOBIOM does not include any energy sector emissions, but does include market impacts on crop production and the livestock sector.

Because of the differences outlined above, it would be inappropriate to compare all of the emissions estimates across all of the models, but we can make several meaningful comparisons. Results from the three models with energy markets (ADAGE, GCAM, GTAP) can be directly compared, with the caveat that GTAP is representing 2014 while the other models are representing a 2020-2050 scenario. Furthermore, we can compare the land use change emissions estimates for all of the models, as GREET uses a consequential approach for this category of emissions, again with proper caveats about temporal differences. We can also compare crop production and livestock sector emissions estimates from ADAGE, GCAM and GLOBIOM.[192] In the table below, we report emissions from "Agriculture, forestry and land use" for all five

[191] This sentence about interpreting GREET CI estimates applies for biofuel pathways, such as corn ethanol and soybean oil biodiesel, produced from "primary" feedstocks, but not for all pathways made with waste, byproduct or residue feedstocks. For the waste, residue, and byproduct pathways, GREET sometimes considers emissions relative to a baseline/counterfactual scenario, in which case a negative CI cannot always be interpreted as a net GHG sequestration.

[192] GTAP can also report emissions disaggregated into these source categories, but due to time constraints we did not obtain such results from GTAP for this exercise.

models as the sum of emissions from these stages; however, the GREET estimate for this aggregate category is not directly comparable with the other models for reasons discussed below.

Energy sector emissions have a large impact on the CI in the ADAGE, GCAM, and GTAP results. The energy sector CI is much lower (more negative) for the GCAM results than for ADAGE and GTAP results, which is consistent with the greater cumulative global reduction of refined oil use (shown in Figure 6.2-3) and lower emissions from fossil fuels over time (shown in Figure 6.7-1). GREET reports the CI from fuel production and transportation but does not consider indirect impacts on the energy sector, such as the energy rebound effects shown in Section 6.2. The fuel production and transportation CI in the GREET results is based on the amount of process energy needed for corn ethanol production as well as the amount of energy needed to transport the feedstock and the fuel. This is why we use the label “Energy Sector” for the first row in Table 6.7-1 for the three models with energy markets, but the label “Biofuel Production” for this row for GREET.

Table 6.7-1: Carbon intensity of corn ethanol (kgCO$_2$eq/MMBTU) calculated using emissions reported by each model[193]

	Models with Energy Markets				Models without Energy Markets		
		ADAGE	GCAM	GTAP		GLOBIOM	GREET
Sector/stage-specific emissions	Energy from Fossil Fuels	-15	-65	-15	Biofuel Production	x	29
	Crop Production	14	16	1	Crop Production	9	x
					Feedstock Production	x	16
	Livestock Sector	0.1	0.3		Livestock Sector	-1	x
	Other	1	-1		Fuel Use	x	0.4
	Land Use Change	-1	31	6	Land Use Change	13	8
Totals	Agriculture, forestry, and land use	14	47	7	Agriculture, forestry, and land use	21	24
	Global GHG Impact	-1	-19	-8	Global GHG Impact	x	x
	Supply Chain GHG Emissions	x	x	x	Supply Chain GHG Emissions	x	53

The ADAGE and GCAM results show a similar CI from crop production. The crop production CI from the GLOBIOM results is lower than these models, consistent with the lower emissions over time in GLOBIOM relative to ADAGE and GCAM. GREET's feedstock production CI is based on the energy and chemical inputs required to produce the amount of corn needed for 1 MMBTU of ethanol. Unlike the other models, this value does not represent the change in crop production emissions associated with an increase in ethanol production; in other words, it does not include indirect impacts on the production of other types of crops. Livestock and other sectors (including waste management and other industrial sectors) have only minor impacts on the overall CI in ADAGE, GCAM, and GLOBIOM.

For the GTAP results, as discussed in Section 3.1.4, we have estimates of non-CO$_2$ emissions by greenhouse gas, but we do not have these emissions disaggregated by sector or

[193] "X" means that the model does not report that category. For GTAP, emissions from crop production, the livestock sector, and "other" are reported as an aggregated value of non-LUC, non-fossil fuel emissions. Negative values for ADAGE, GCAM, GTAP, and GLOBIOM mean that emissions are lower than the reference case, whereas positive values mean the emissions are higher than the reference case.

lifecycle stage. GTAP can also report emissions disaggregated into these source categories, but due to time constraints we did not obtain such results from GTAP for this exercise. The largest changes, by gas, are an increase in N_2O and a decrease in CH_4. We believe the bulk of the changes in these emissions are associated with changes in fertilizer N_2O and livestock CH_4, but more work would be needed to confirm our intuition. For these reasons, in Table 6.7-1, we report the aggregated non-CO_2 emissions estimate from GTAP across three rows combining Crop Production, Livestock Sector and Other. This aggregated emissions estimate from GTAP is lower than what the other models report for the sum of emissions from these three categories. We would need to do more research to disaggregate these emissions and understand why they are lower than estimates from the other models.

Land use change emissions are reported in all the models, and the CI results have wide ranges across the models. As explained above, these differences are due to the type of land use change and the carbon stocks of each land type in the models. GREET's LUC CI is based on Argonne's CCLUB translation of a preestablished GTAP run using a different shock size (11.59 billion gallons of corn ethanol) from a 2004 baseline. This earlier GTAP run estimated a global cropland area increase of 2.1 million hectares, with 47 percent of that additional land requirement coming from the USA region, and forest land making up about 11 percent of the land needed to convert to cropland.[194]

We can compare "Agriculture, forestry and land use change emissions" across four of the models (ADAGE, GCAM, GLOBIOM, GTAP). For GTAP, we include the non-CO_2 emissions in this category. For this category, the GCAM results include the highest emissions, driven by the land use change emissions. Although the ADAGE results include lower land use change emissions than the GTAP results, the aggregated agriculture and forest sector emissions are higher for the ADAGE results, due to the difference in crop production emissions.

The total global CI can be compared across ADAGE, GCAM, and GTAP, because all of these models represent the same sectors and include market impacts. The results from these models show a range in corn ethanol CI, primarily due to differences in the energy sector CI and land use change CI. For GLOBIOM and GREET, a total global CI cannot be calculated from the model results because these models do not include all the relevant sectors and/or do not include all the relevant market impacts. For GREET, we calculate the total supply chain CI. This is a different metric than the other models' CIs, since GREET primarily uses an attributional approach, coupled with consequential ILUC modeling from GTAP and CCLUB in lifecycle analysis rather than a consequential approach. This value does not include any displacement of fossil fuel consumption that would occur from the increased consumption of biofuels.[195]

[194] Taheripour, Farzad, Wallace Tyner, and Michael Wang. 2011. "Global Land Use Changes Due to the U.S. Cellulosic Biofuel Program Simulated with the GTAP Model." Argonne National Laboratory and Purdue University. https://greet.es.anl.gov/publication-luc_ethanol.

[195] GREET's ethanol CI estimates are often compared with GREET CI estimates for gasoline to derive a GHG percent reduction relative to gasoline. In our 2010 RFS analysis, we similarly compared ethanol CI estimates from models that do not include energy markets with a CI estimate for gasoline to calculate a percent reduction in emissions.

6.8 Summary of Corn Ethanol Estimates

Section 6 compares and contrasts the corn ethanol modeling estimates from ADAGE, GCAM, GLOBIOM, GREET, and GTAP produced for this exercise. These models source the corn ethanol required to meet the assumed shock in different ways in these results, but there are some commonalities. Across frameworks, the two primary model strategies are to source corn from new production and to divert corn from other uses. However, different models rely more on one of these sourcing strategies or the other. Because of these differences in sourcing strategy, the model results differ regarding the total additional corn production, crop trade, and land use change impacts of the shock. The model results also have some other notable similarities and differences. ADAGE, GCAM, GLOBIOM, and GTAP results all show a small amount of crop yield intensification. The results also show a displacement of corn for feed use with DDG, though there is disagreement regarding how much might be consumed in the USA region versus exported and consumed elsewhere in the world. The models which explicitly include the energy sector, ADAGE, GCAM, and GTAP, all show a decrease in refined oil consumption in the USA region in their results, and an increase in non-USA regions. But there are notable differences across these models in the total global displacement of refined oil. These factors all contribute to differences in the estimated GHG emissions and CI of corn ethanol across the models, with energy sector emissions and land use change emissions differing the most across the model results.

The previous sections also highlight potential areas for future research. Sensitivity analysis could better define the GHG emissions implications of model decisions regarding the location of additional DDG consumption. Further research and sensitivity analysis could also seek to better understand the parameters that influence land conversion to cropland. Furthermore, research and sensitivity analysis could seek to better understand why model results show a range in the reduction of refined oil consumption. These are only a few examples of the many research topics that could help to explain what is driving differences in these model results.

7 Comparison of Soybean Oil Biodiesel Estimates

In this section, we present the results of the soybean oil biodiesel shock. The results in this section show the difference between the soybean oil biodiesel shock and the reference case. We consider the following elements in turn:

- Sources of soybean oil biodiesel to meet the shock
- Energy market impacts from the shock
- Crop production and consumption
- Trade impacts
- Yield changes
- Land use impacts
- Emissions: the modeled results of energy consumption, crop production, and land use change described above come together in the modeled greenhouse gas emissions.

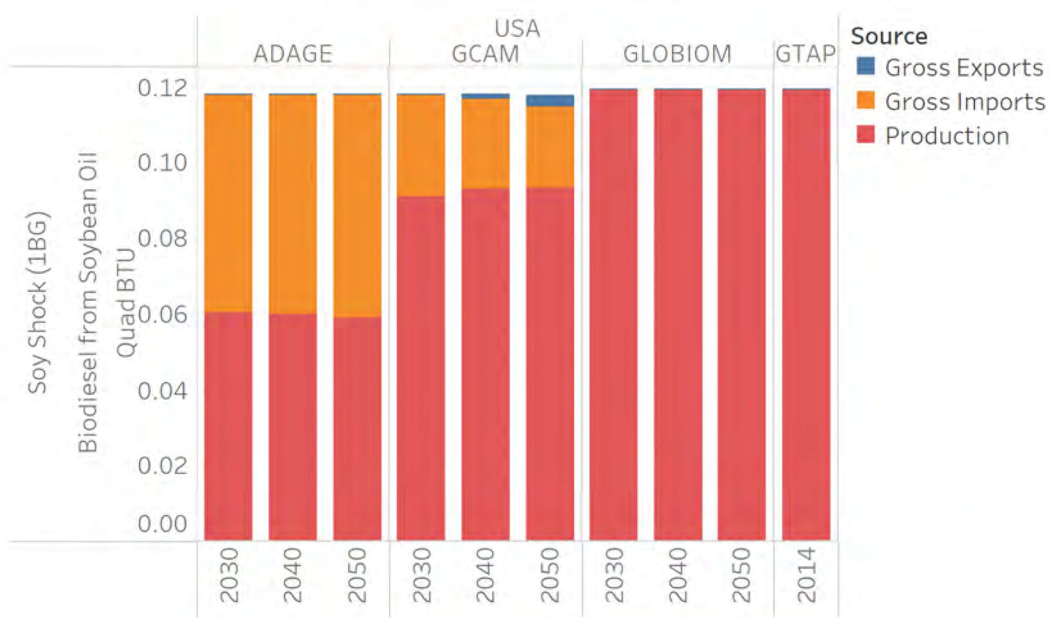
The majority of these comparisons include ADAGE, GCAM, GLOBIOM, and GTAP. Only the comparison of GHG emissions includes GREET. GREET is a supply chain LCA model that does not represent changes in agricultural and economic markets between reference and modeled scenarios, as the other models in this comparison exercise are designed to estimate.

7.1 Sourcing Overview

As in the corn ethanol runs, the models included in this analysis have many options available for meeting the soybean oil biodiesel consumption shock, including increased production of soybean oil biodiesel and changes in biodiesel imports and exports. Increased soybean oil biodiesel production could come from diversion of soybeans or soybean oil from other uses, increased crushing of existing soybean supplies, or increased production of soybeans. This section will give an overview of the extent to which the models rely on each of these options for meeting the soybean oil biodiesel consumption shock.

In the soybean oil biodiesel shock, the models show a range of solutions for meeting the shock (Figure 7.1-1). In the ADAGE soybean oil biodiesel results, around half of the shock is met by increased biodiesel production in the USA region, and half is met by increased gross imports to the USA region. In the GCAM results, 77-79 percent of the shock is met by increased soybean oil biodiesel production in the USA region, and 21-23 percent is met by a combination of increased imports and reduced exports of soybean oil biodiesel. In GLOBIOM and GTAP, the shock is met entirely by increased soybean oil biodiesel production in the USA region. GLOBIOM does not have an energy market and therefore cannot trade biofuels, making domestic biodiesel production the only option in this model.

Figure 7.1-1: Sources of additional soybean oil biodiesel consumed in the soybean oil biodiesel shock relative to the reference case[196]



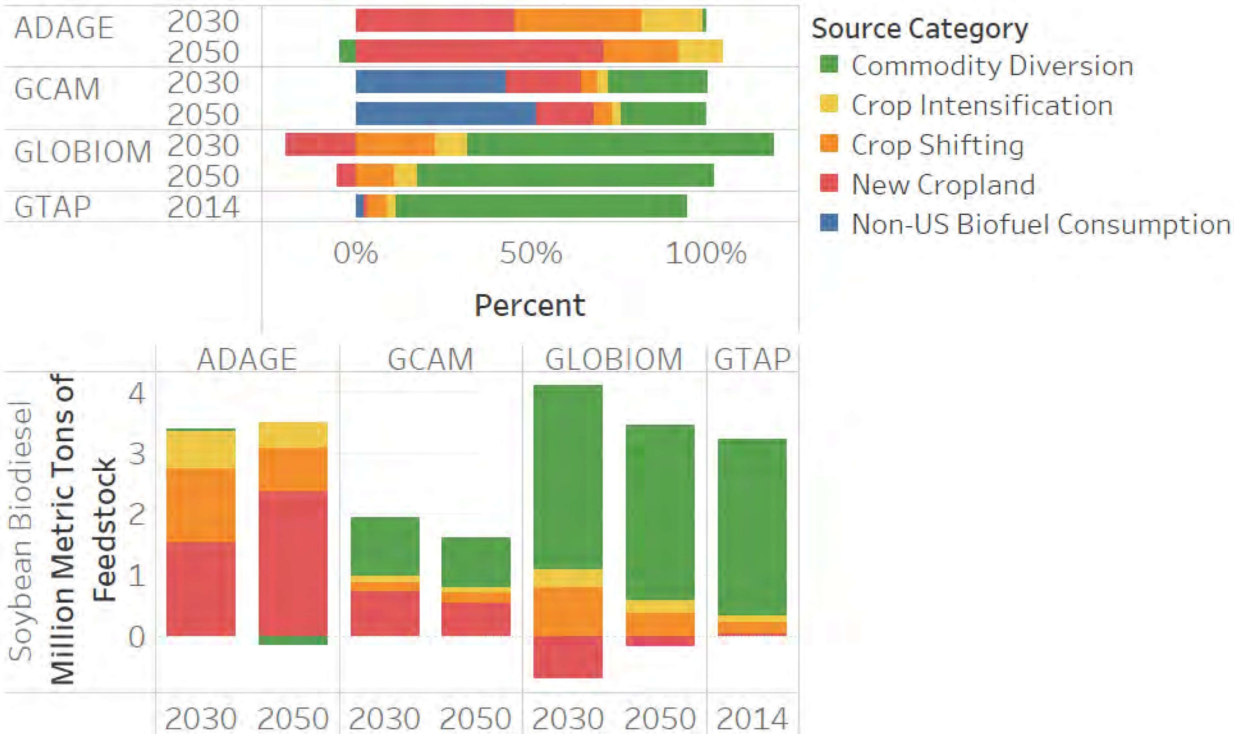
196 Red shows the contribution increased soybean oil biodiesel production in the USA region; orange shows the contribution from increased soybean oil biodiesel gross imports to the USA region; blue shows the contribution from reduced soybean oil biodiesel gross exports from the USA region.

Although the ADAGE and GCAM results both meet a large percentage of the shock through changes in soybean oil biodiesel imports, the impact on non-USA regions is very different. In the GCAM results, 43-52 percent of the shock is met by reduced soybean oil biodiesel consumption in non-USA regions (Figure 7.1-2). This latter share is larger than the share of biofuel trade noted in Figure 7.1-1 above. The estimate in Figure 7.1-2 also includes soybeans and soybean oil feedstock which are exported to the USA region rather than being processed into biodiesel in their region of origin and consumed domestically. In contrast, the ADAGE results do not show a reduction in soybean oil biodiesel consumption in other regions; instead the increased imports are sourced from increased soybean oil biodiesel production in non-USA regions. Energy market impacts are discussed further in Section 7.2.

ADAGE, GCAM, GLOBIOM, and GTAP meet the soybean oil biodiesel shock through different amounts of soybean and soybean oil diversion from other uses, crop intensification, crop shifting to soybean, and new cropland (Figure 7.1-2). Based on the assumed conversion factor of soybean oil to soybean oil biodiesel (Section 4), if all of the shock were met by new soybean oil biodiesel production, ADAGE, GCAM, and GLOBIOM would need 3.4 million metric tons of additional soybean oil for biodiesel in 2030 and 3.3 million metric tons of additional soybean oil for biodiesel in 2050 (bottom panel of Figure 7.1-2). GTAP would need 3.4 million metric tons of additional soybean oil for biodiesel in 2014. The GCAM results show much less additional soybean oil is needed for the soybean oil biodiesel shock than in the ADAGE, GLOBIOM, or GTAP results because soybean oil biodiesel consumption decreases in the non-USA region in GCAM. Because soybean crushing yields about 19 percent extractable soybean oil, if all of the additional soybean oil were coming from new soybean production, ADAGE, GCAM, and GLOBIOM would require additional production of 17.8 million metric tons of soybeans in 2030 and 17.6 million metric tons of soybeans in 2050. GTAP would require an additional 18.1 million metric tons of soybeans in 2014.

In the ADAGE soybean oil biodiesel shock results, less than 5 percent of the shock is met by commodity diversion, with the majority of the shock met by new soybean production. In the GCAM results, because so much of the shock is met by reduction of soybean oil biodiesel consumption in non-USA regions, much less additional soybean oil feedstock is needed than in the other models. Of the additional soybean oil feedstock sourced in GCAM, around half comes from commodity diversion, and half comes from new soybean production (primarily from new cropland). In GLOBIOM and GTAP, the majority of the shock is met through commodity diversion (85-88 percent and 83 percent, respectively). GTAP meets a small percentage of the shock (2 percent) through a reduction of soybean oil biodiesel consumption in non-USA regions. Commodity diversion and soybean production results are described more in Section 7.3, and land use results are described in more detail in Section 7.6.

Figure 7.1-2: Top panel: Percentage of the soybean oil biodiesel shock that is met by different categories in 2030 and 2050. Bottom panel: Million metric tons of additional soybean oil from new soybean production (red, orange, and yellow) and diversion from other uses (green)[197]



7.2 Energy Market Impacts

The energy market mechanisms at play in the corn ethanol shock generally hold for soybean oil biodiesel as well, though the magnitude and some of the detailed effects differ. We refer to Section 6.2 above for a discussion of those principles. As noted in that section, of the models considered under this model comparison exercise, ADAGE, GCAM, and GTAP include explicit representations of energy commodities and energy commodity trade, end use sectors, and energy market interactions.

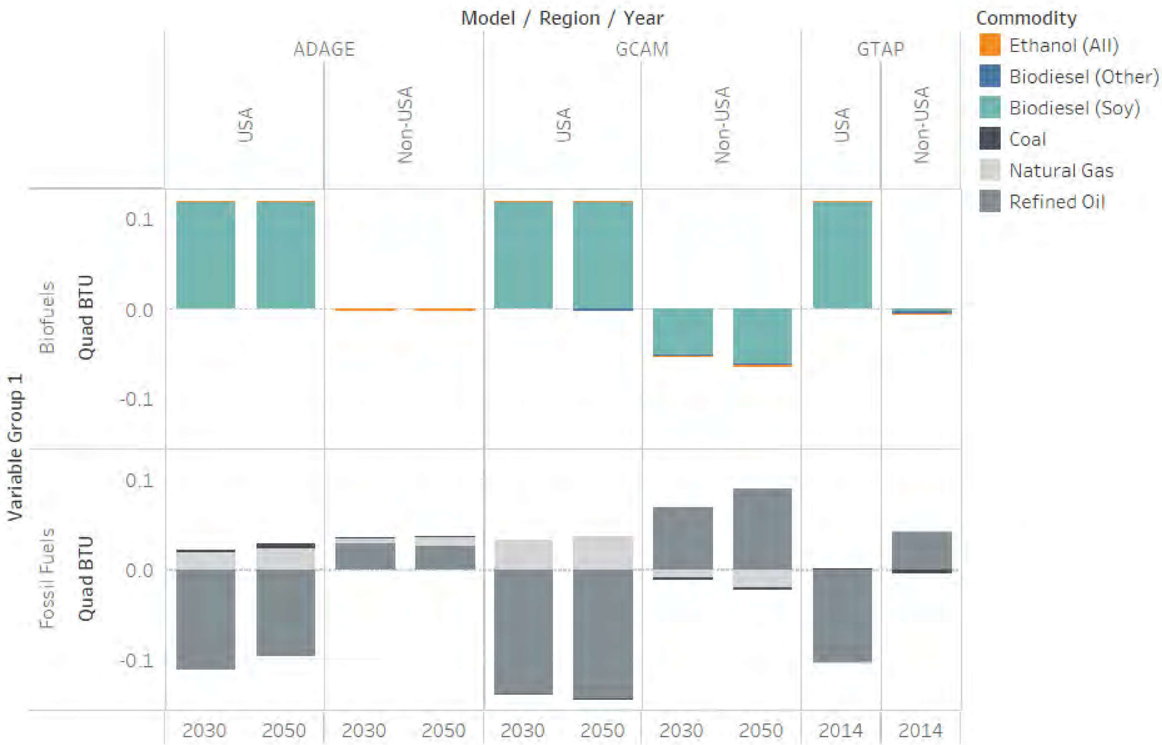
The impacts of the soybean oil biodiesel shock on consumption of refined oil[198] in the USA region in ADAGE, GCAM, and GTAP broadly mirror the impacts seen under the corn ethanol shock scenario; all three models show substantial displacement of refined oil use in the USA region, with displacement in GCAM being the highest, displacement in ADAGE starting somewhat less than in GCAM and declining over time, and GTAP having the smallest average displacement of refined oil consumption in the USA region. Displacement of consumption of

[197] A negative percent contribution means that there was decrease in soy production or an increase in non-fuel uses of soybean. ADAGE has a negative percent contribution from commodity diversion in 2050 because some additional soybeans were consumed for "other uses" – in this case, seed for additional soybean production. GLOBIOM has a negative percent contribution from new cropland because soy cropland area decreased in non-USA regions.

[198] In these models, refined oil is an aggregation of all refined petroleum products, including gasoline and diesel.

refined oil in the USA region results in reduced net imports of crude and refined oil, amounting to 93 percent and 101 percent of the reduced USA consumption of refined oil in 2030 in ADAGE results and GCAM results respectively.[199]

Figure 7.2-1: Difference in consumption of energy commodities (quadrillion BTUs) in the soybean oil biodiesel shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM) and 2014 (GTAP)

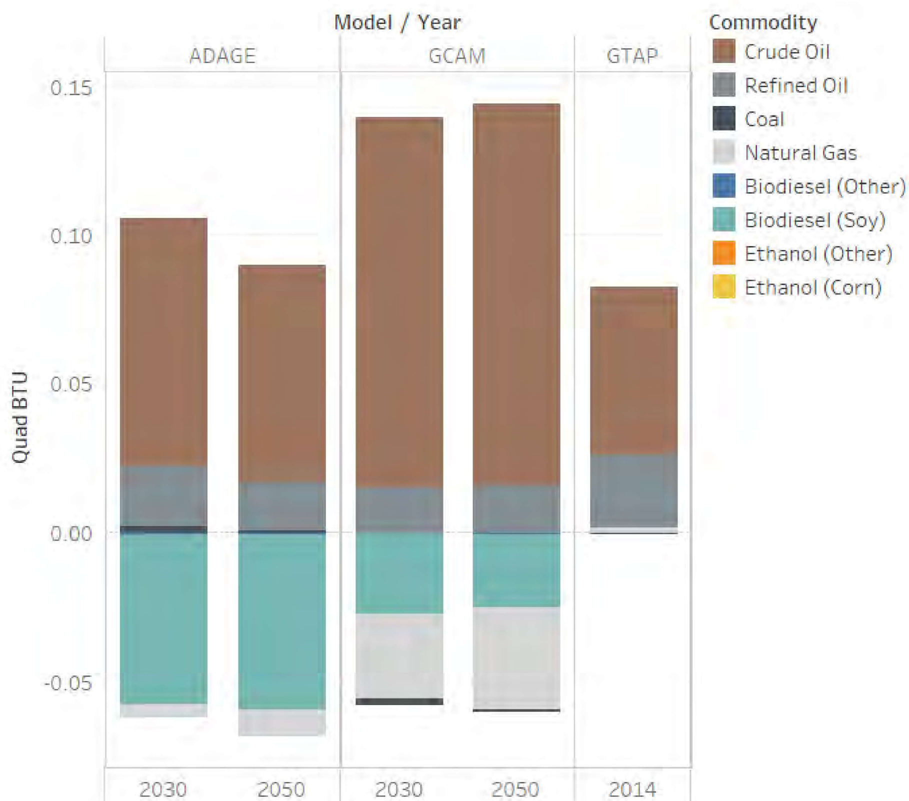


Trade in energy commodities plays a significant role in meeting the soybean oil biodiesel shock in results from several of the models considered (see Figures 7.1-1 and 7.2-1). In ADAGE and GCAM results, a substantial portion of the shock is met through greater net USA imports of soybean oil biodiesel (48 percent and 23 percent of the shock in 2030 in ADAGE and GCAM results respectively). In the ADAGE results, the increased net imports of soybean oil biodiesel in the USA region are constituted almost exclusively of an increase in gross exports from the Rest of Latin America region to the USA region. In the GCAM results, the increased net imports of soybean oil biodiesel in the USA region are constituted of changes in exports of biodiesel across multiple regions. It is notable that patterns of impacts of the soybean oil biodiesel shock on biofuel trade in ADAGE and GCAM reflect the theoretical representations of trade in the two models. In ADAGE, where trade is represented bilaterally and calibrated using historical trade data, impacts occur almost exclusively in a region with large historical exports of biodiesel to the USA. In GCAM, where commodities are exported to and imported from a global pool for each commodity, impacts are distributed across multiple regions with historical exports (regardless of destination) of biodiesel.

[199] Data on trade of crude oil in GTAP results were not available for this exercise.

We also note that GCAM's estimated reduction in consumption of soybean oil biodiesel in the non-USA regions is greater in magnitude than the increased volume of biodiesel exported to the USA region. This is because increased demand for soybeans and soybean oil puts upward pressure on their prices and further reduces consumption for fuel, food, and other uses in the non-USA regions.

Figure 7.2-2: Difference in U.S. net exports of energy commodities (quadrillion BTUs) in the soybean oil biodiesel shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM) and 2014 (GTAP)



Modeled changes in consumption of refined oil in non-USA regions are driven by two main mechanisms in the results from ADAGE, GCAM, and GTAP. First, increased use of soybean oil biodiesel in the USA region results in decreased consumption of refined oil in that region (i.e., "the displacement effect"). This puts downward pressure on the global prices of crude and refined oil, though the effect is small in absolute terms (between one and four hundredths of a percent) due to the relatively small size of the one billion gallon shock compared to global refined liquid fuel consumption. The result of this downward price pressure is some increased demand for refined oil in non-USA regions. This effect is present in, and a contributing factor to, the increased refined oil consumption seen in all three models in Figure 7.2-1. Second, if a portion of the soybean oil biodiesel shock in the USA region is met through increased net imports of soybean oil biodiesel, as is the case in ADAGE and GCAM, then the corresponding non-USA regions with increased exports of biofuels have to make up that deficit in their liquid fuel markets by "backfilling" with either a) increased consumption of biofuels, likely coming from increased production within those regions, or b) increased consumption of refined oil.

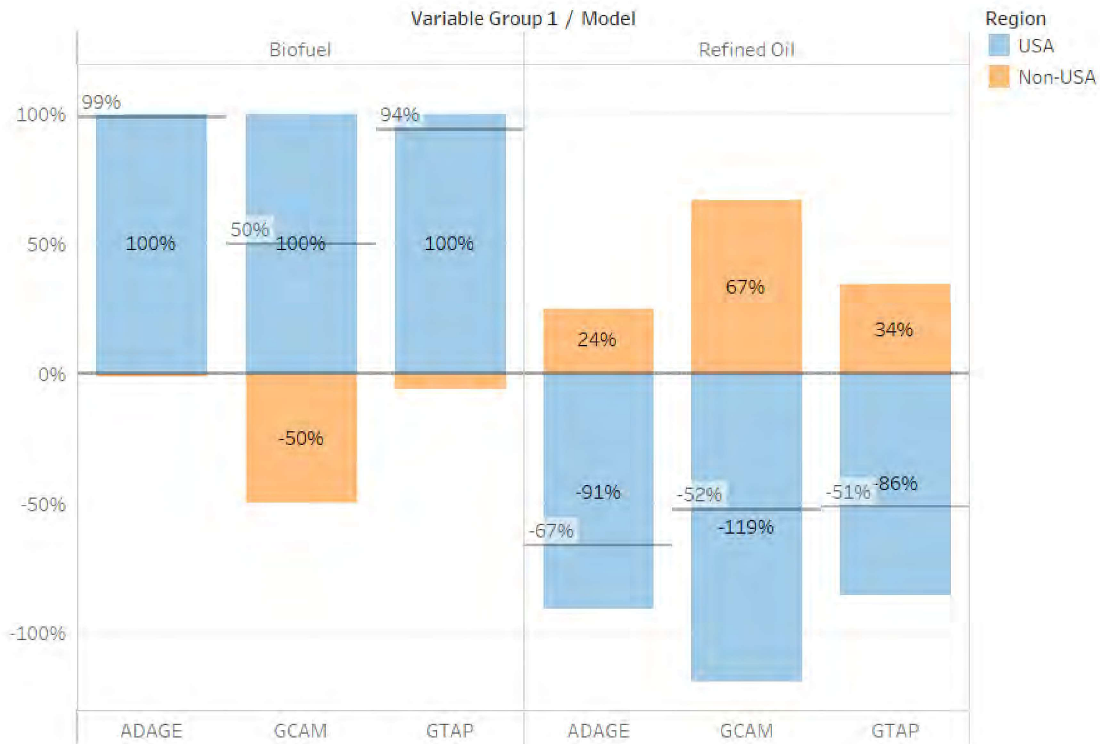
These two backfilling strategies are employed to different extents in ADAGE and GCAM results. In the GCAM results, multiple regions increase exports of soybean oil biodiesel to meet the increased demand in the USA region, but do not show commensurate increases in domestic biodiesel production. This results in reduced consumption of biodiesel in those regions which is backfilled with additional refined oil use. In contrast, in the ADAGE results, the increased exports of soybean oil biodiesel from the Latin America region are met with increased production, resulting in little impact on biofuel consumption in that region and obviating the refined oil backfill effect shown in the GCAM results.

In summary, these dynamics explain the differences between the models in increasing consumption of refined oil in non-USA regions. In GCAM results, deficits in liquid fuels markets in non-USA regions are backfilled with refined oil, reducing the net global displacement effect of the shock on refined oil consumption. In ADAGE results, deficits in liquid fuels markets in non-USA regions are backfilled with increased biofuel production. In GTAP results, there is little change in trade of biofuels, so there are no significant deficits in liquid fuel markets in non-USA regions.

Finally, ADAGE and GCAM show increased natural gas consumption in the USA region, albeit less than in the corn ethanol scenario, while GTAP shows little impact on natural gas consumption in any region. The smaller impact on natural gas in the soybean oil biodiesel scenario relative to the corn ethanol scenario is logical due to differences in the direct natural gas demands of their respective fuel production technologies. The corn ethanol dry mill process requires substantial natural gas for DDG drying, whereas the biodiesel transesterification production process requires relatively little natural gas.

As discussed in Section 6.2, cumulative measures of the changes in refined oil and biofuel consumption, relative to the size of the shock, are common and useful measures for summarizing energy market impacts. These cumulative measures, illustrated in Figure 7.2-3 reflect the story presented above on the impacts of the soybean oil biodiesel shock on consumption of other biofuels and refined oil globally.

Figure 7.2-3: Difference in liquid fuel consumption relative to the volume of the soybean oil biodiesel shock[200]



In the lefthand pane of this figure, we see that the cumulative change in biofuel consumption in the non-USA region amounts to one percent of the cumulative soybean oil biodiesel shock in ADAGE, and 50 percent of the cumulative soybean oil biodiesel shock in GCAM (largely attributable to reductions in soybean oil biodiesel consumption across a number of non-USA regions), and six percent of the 2014 soybean oil biodiesel shock in GTAP.

In the righthand pane, we see similar directional effects on refined oil consumption in the USA region as in the corn ethanol shock scenario discussed in Section 6.2; GCAM shows a greater reduction in USA consumption of refined oil than the cumulative energy content of the shocked biodiesel (119 percent), whereas ADAGE and GTAP show smaller reductions in USA consumption of refined oil than the energy content of the shock (91 and 86 percent, respectively). GCAM shows a much larger cumulative increase in non-USA refined oil consumption outside of the USA region, which is driven by backfill of reduced biodiesel consumption in the non-USA region.

The effect on cumulative net non-USA refined oil consumption – a commonly used definition of "oil rebound" in the literature – shows how global oil consumption changes as a

[200] Values in the figure represent the difference between the shock and reference case of the given fuel category (refined oil vs. liquid biofuels) and given region (USA region vs non-USA regions) divided by the difference in consumption of liquid biofuels in the USA region (i.e., the shock volume). For ADAGE and GCAM, this is calculated using cumulative volume differences between 2020 and 2050. For GTAP, which only estimates differences in a single time step, the calculation uses only the volume differences in 2014.

result of the shock. GCAM results show the largest increase in non-USA refined oil consumption (67 percent of the cumulative shock) due to backfilling for traded biodiesel, as discussed above. GTAP and ADAGE show more modest increases in non-USA refined oil consumption (34 and 24 percent respectively). The global net effect of the shock on refined oil consumption is that, on average, for every 100 BTUs of soybean oil biodiesel required to be consumed in the USA, 67 BTUs of global refined oil consumption are displaced in ADAGE, 52 BTUs of global refined oil consumption are displaced in GCAM, and 51 BTUs of global refined oil consumption are displaced in GTAP. Future research could be done to better understand the parameters and assumptions that lead to the range in reduction of refined oil consumption.

7.3 Crop Production and Consumption

As shown in Section 7.1, the ADAGE, GCAM, GLOBIOM, and GTAP results differ notably in how much of the soybean oil biodiesel shock they each estimate would be sourced from new soybean production. This is reflected in the estimated changes in soybean production shown in Figure 7.3-1. The ADAGE results show the largest increase in global soybean production, followed by GCAM, then GLOBIOM, and then GTAP. ADAGE and GCAM results estimate the increase in soybean production would be split between the USA and non-USA regions. In the GTAP results, the increase in production is estimated to occur almost entirely in the USA region. In GLOBIOM, soybean production is estimated to increase in the USA region but decrease in aggregate across the non-USA regions. ADAGE, GCAM, and GLOBIOM results all show a decrease in corn production in the USA region as some of the new soybean area displaces corn area.

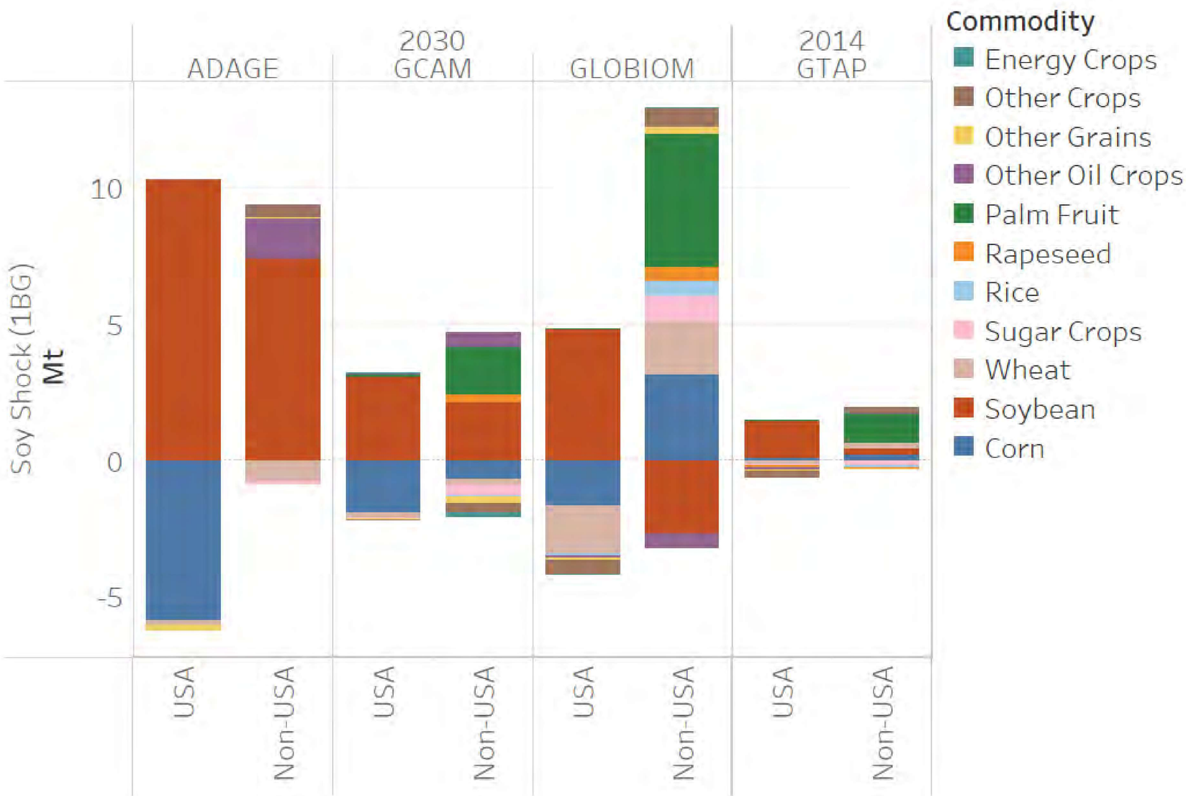
In the non-USA region, the model results show an increase in the production of oil crops. The ADAGE results show an increase in "other oil crop" production.[201] In the GTAP, GCAM, and GLOBIOM results, the increased oil crop production is primarily palm fruit. The GCAM results show decreased corn production in non-USA regions, whereas the GLOBIOM results show increased corn production in non-USA regions.

Globally, crop production increases in all four sets of model results.[202] However, there is much greater variation in the types and location of crop production across the models than there was in the corn ethanol results. All four sets of the model results show an increase in soybean production in the USA region, and a decrease in the production of other crops. There is substantial variation in the crop production in the non-USA regions, particularly for soybean production and palm fruit production. A comparison of Figures 6.1-2 and 7.1-2 lays plain one important first order reason for this greater variability. The models show much greater diversity in sourcing strategies for soybean oil biodiesel than they do for corn ethanol. This variation in sourcing for soybean oil biodiesel results in more complex economic and environmental outcomes than corn ethanol. Across the four economic models in this exercise, virtually all of the corn for ethanol is produced in the USA region. This is largely attributable to the monolithic role of the U.S. in historical global corn production and trade and to the fact that corn has no near-

[201] As explained in Section 5.1, ADAGE does not explicitly represent oil crops other than soybeans. Therefore, for ADAGE, "other oil crops" includes palm fruit.
[202] We also looked at forest product production for the models that are able to report it (ADAGE, GCAM, GLOBIOM), and the change relative to the reference case is negligible.

perfect substitutes. By contrast, soybean oil does have near perfect substitutes for many end uses, in the form of other vegetable oils. Additionally, soybean oil production and exports, and vegetable oil production and exports more broadly, are historically distributed across more regions. Marginal global demands for vegetable oil may reasonably be supplied from North America, South America, or Asia. Thus, for soybean oil biodiesel, the models have a wider range of options for the location of additional vegetable oil production. Also, soybean oil biodiesel production has more complex impacts on the consumption and production of other crops than corn ethanol production because of the wider range of end uses for soybean oil and meal, as described below. The location of additional soybean production and the impact on the production of other crops is a potential area for future research and sensitivity analysis.

Figure 7.3-1: Difference in commodity production (million metric tons) in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)



ADAGE, GCAM, GLOBIOM, and GTAP have slightly different pathways for producing soybean oil biodiesel. In GCAM, GLOBIOM, and GTAP, soybean oil biodiesel is produced from soybean oil. In ADAGE, soybean oil is not explicitly represented, and instead soybean oil is part of an aggregated vegetable oil commodity. Soybean oil biodiesel in ADAGE can be produced from vegetable oil or directly from soybeans.[203] Soybean oil biodiesel produced from soybeans produces oil crop meal (a generic vegetable meal commodity) as a coproduct.

[203] From a theoretical perspective, the latter strategy would represent a facility which co-locates crushing and biodiesel production plants. Such a facility inputs whole soybeans and outputs biodiesel and soybean meal.

The end use impacts of the soybean oil biodiesel shock are more complex than the impacts in the corn ethanol shock because soybean oil biodiesel production can impact oilseed markets, vegetable oil markets, and oil meal markets (Figure 7.3-2). The ADAGE, GCAM, GLOBIOM, and GTAP results all show an increase in soybean crushing in the USA region. This produces soybean oil and soybean meal in GCAM, GLOBIOM, and GTAP, and vegetable oil and oil crop meal in ADAGE. In the GCAM, GLOBIOM, and GTAP results, additional soybean oil is used for fuel production in the USA region. In the ADAGE results, some additional vegetable oil is used for fuel production in the USA region, and additional soybean is also used directly for fuel production. In the GCAM results, the additional soybean meal produced in the USA region largely displaces corn for domestic feed use. We observe a similar trend in the ADAGE results, where oil crop meal displaces corn for feed use in the USA region. In GTAP, the additional soybean meal produced in the USA region displaces other oil crop meal for domestic feed use. By contrast, all of the additional soybean meal produced in the USA region in the GLOBIOM results is exported; this increase in USA soybean meal exports in turn depresses non-USA production of feed crops, including soybeans. However, USA exports of DDG decrease and more DDG is consumed in the USA region, displacing corn for feed use. In the USA region, ADAGE, GCAM, and GLOBIOM results show only minimal impacts on food end uses. In contrast, the GTAP results show a reduction in soybean oil for food use and no increases in other types of crops for food use, implying a net reduction in food consumption. GTAP results also show a reduction in soybean oil for "other uses," which includes soybean oil that is industrially processed into other products.[204] "Other uses" of soybeans increases in the ADAGE results; this represents additional soybean seeds needed to grow more soybeans.

Non-USA regions show different impacts than the USA region. In the non-USA regions, the ADAGE results show an increase in soybean consumption for crushing, an increase in vegetable oil and soybean consumption for fuel production, an increase in soybean consumption for other uses (seed), and feed displacement of other crops with oil crop meal. In the GCAM, GLOBIOM, and GTAP results, there is an increase in oilseed crushing to make vegetable oil, including palm fruit (GCAM, GLOBIOM, and GTAP), rapeseed (GCAM and GLOBIOM), and other oil crops (GCAM and GTAP). ADAGE represents only two oil crop commodities, soybeans and "other oil crop." The ADAGE results show an increase in the consumption of the aggregated other oil crop for crushing. In the GLOBIOM results, the increased palm fruit crushing helps backfill for reduced soybean crushing, which is due to decreased soybean production in non-USA regions. In the ADAGE, GCAM, and GTAP results, the increased palm fruit, rapeseed, and other oil crop crushing is in addition to increased soybean crushing.

These results also show impacts on the food and feed markets in the non-USA region. In both the GCAM and GLOBIOM results, other vegetable oils replace soybean oil to at least some extent in the food market in non-USA regions.[205] GLOBIOM results show an overall reduction in food consumption in the non-USA regions. GCAM results show a small reduction in food consumption, but the overall change is close to zero. These food market impacts are smaller than

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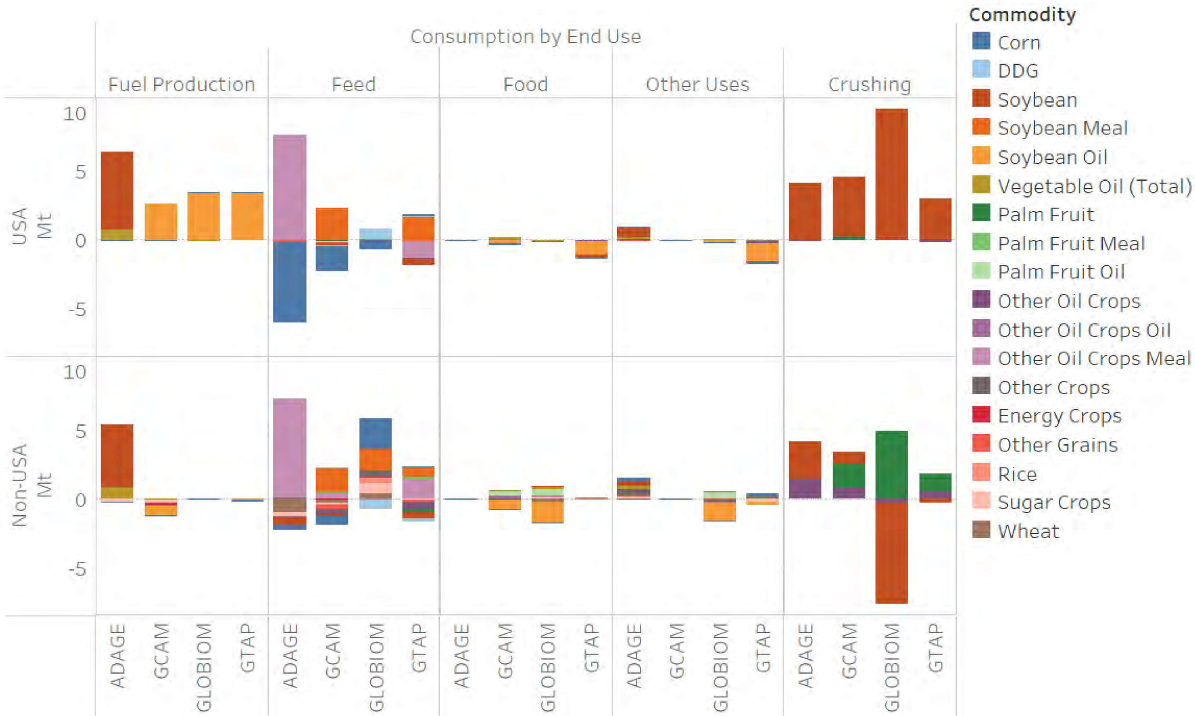
[204] The "other uses" of soybean oil in GTAP can include processing for food products, such as margarine or salad dressing, whereas the food end use includes soybean oil used directly for food, such as cooking oil.
[205] In GLOBIOM results, palm fruit oil replaces soybean oil. In GCAM results, a mix of palm fruit oil, rapeseed oil, and other oil crop oil replaces soybean oil.

the feed market impacts. The GLOBIOM results also show displacement of soybean oil with palm fruit oil for other uses (e.g., industrial uses such as cosmetics production) and an overall increase in feed consumption, primarily from corn, soybean meal, and other crops. GCAM and GTAP results show displacement of crops with soybean meal and other oil crop meal in the feed market. The degree of substitution among feed commodities and food commodities, particularly in the non-USA regions, is an area of difference across the model results.

Figure 7.3-2: Difference in consumption by end use (million metric tons) in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[206]

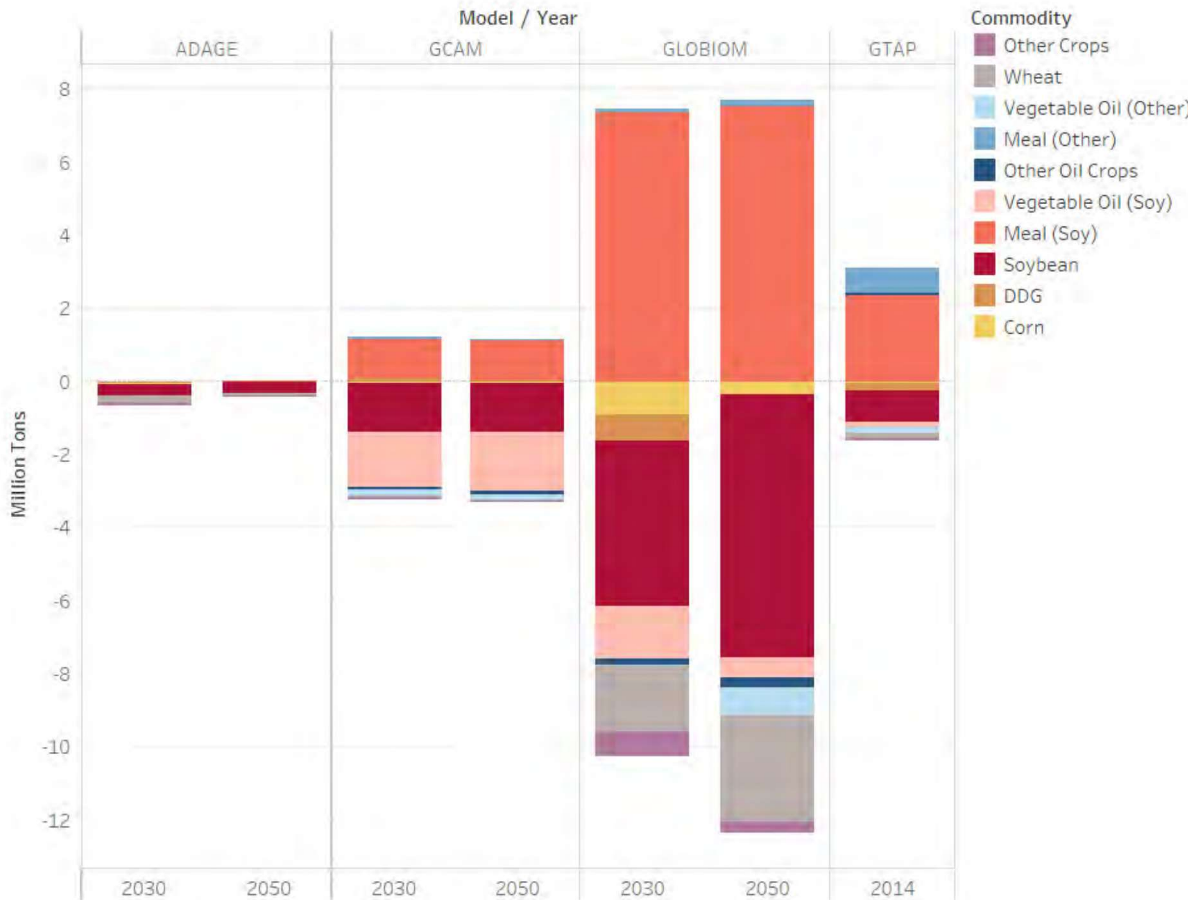


7.4 Trade of Agricultural Commodities

As discussed in Section 3.1.6, ADAGE, GCAM, GLOBIOM, and GTAP all specify commodity trade in somewhat different ways. From a theoretical perspective, we would expect this to be relevant to a soybean oil biodiesel consumption shock scenario in several ways analogous to those observed for corn ethanol in Section 6.4. Model results related to trade in soybeans and other crops would be expected to vary by model. In addition, the assumed elasticity of competition and degree of assumed fungibility between vegetable oils varies across these modeling frameworks and would be expected to produce somewhat different results across the models. Another consideration unique to soybean oil biodiesel scenarios is the treatment of soybean meal trade.

[206] Results are shown in million metric tons of each feedstock. Because soybeans contain 19 percent oil, 10 million metric tons of soybeans is equivalent to 1.9 million metric tons of soybean oil. ADAGE does not explicitly track soybean oil or soybean meal, and those are included in "Other Oil Crops Oil" and "Other Oil Crops Meal," respectively.

Figure 7.4-1: Difference in U.S. net exports of crops and secondary agricultural products (million metric tons) in the soybean oil biodiesel shock relative to the reference case in 2030 and 2050 (ADAGE, GCAM, GLOBIOM) and 2014 (GTAP)



In ADAGE, of the additional soybean oil biodiesel produced in the USA region, a sizeable portion is sourced from shifting cropland from corn production to soybean production. Reduced corn production coincides with reduced use of corn for livestock feed in the USA region, which is backfilled with the additional oilseed meal available in the soybean oil biodiesel shock scenario. This results in relatively little change in U.S. net exports of agricultural goods in ADAGE.

In GCAM, the USA region increases gross imports of soybean oil and decreases gross exports of whole soybeans in order to meet the soybean oil biodiesel shock targets. There is a smaller (relative to ADAGE) effect on crop production for non-soybean crops in the USA region, so the additional soybean meal produced to meet the shock is not needed to backfill deficits in livestock feed demand. A relatively small portion of the shock in GCAM (compared to ADAGE) is met through crop shifting in the USA region, so livestock feed demand met by corn and other crops is less affected by the soybean oil biodiesel shock. This results in increased gross exports of soybean meal from the USA region in the soybean oil biodiesel shock in GCAM.

GLOBIOM does not represent energy commodities nor their trade, so all of the biodiesel needed to meet the soybean oil biodiesel shock must be produced in the USA region in GLOBIOM. Additionally, GLOBIOM restricts the amount of natural land that can be converted to crop production, so the majority of the additional feedstock needed to meet the soybean oil biodiesel shock is sourced from either switching cropland from production of other crops to soybean production, or from changes in net trade of soybeans and soybean oil in the USA region. This results in reduced gross exports of soybeans and soybean oil and increased gross imports soybean oil in the USA region. Crop switching reduces production of other crops in the USA region, most notably corn, which results in decreased gross exports of corn and DDG, and wheat, which results in increased gross imports of wheat to meet demands for food.

The GTAP results include a reduction in soybean exports, but a larger increase in exports of soybean meal and other oilseed meals for livestock feed. Unlike the other models, the GTAP results include an overall increase in the mass of USA region net crop and secondary crop product exports. Relative to the other model results, the GTAP results include a smaller reduction in soybean oil and soybean exports. Instead of reduced exports, the GTAP results include reduced domestic consumption of soybeans and soybean oil for feed, food and other non-biofuel purposes.

7.5 Crop Yield

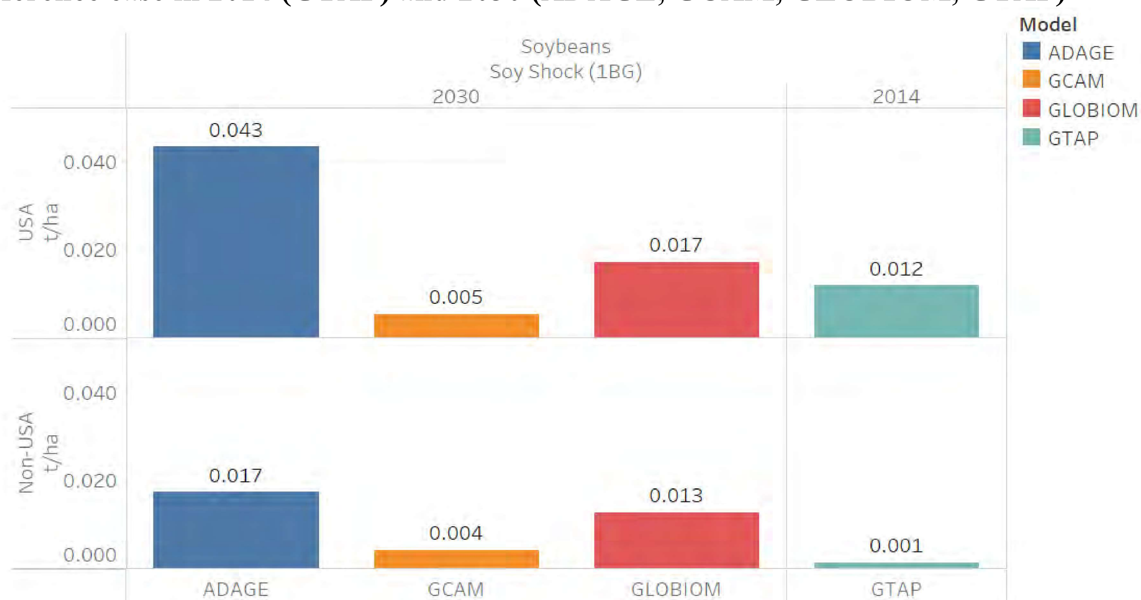
As was observed in Section 6.5 above regarding corn crop yield modeling results, the four economic models included in this comparison exercise all have the ability to increase crop yields in response to changes in crop price. However, while these models share some similar theoretical underpinnings regarding the economic logic of crop yield response to price, their mechanisms for simulating this response vary in structure. Further, these models represent additional methods of crop intensification beyond the ability to invest resources to increase yield per acre on existing cropland.

Reference case yield trends are also an important factor in understanding differences across models. As shown in Figure 5.3-1, reference case soybean crop yield trends across the four economic models are fairly similar in the historical periods of 2010 and 2015, though not identical. However, for the three dynamic models, ADAGE, GCAM, and GLOBIOM, the trends in reference case soybean yields diverge over time. Yields are calibrated to improve over time in all three models however, reflecting a shared assumption that agricultural technologies will continue to improve into the future. In reviewing the change in soybean yields in our shock scenario relative to the reference case shown by these dynamic models, the reader should keep in mind that yields are improving over time in both the USA and non-USA regions in both scenarios as they do in the reference case.

As shown in Figure 7.1-2 above, crop intensification contributes to the sourcing of soybean oil for the biodiesel shock to varying degrees across the models. In both of the biofuel volume shock scenarios modeled for this exercise, we observe that the contributions from intensification are a minority of the feedstock sourcing solution, accounting for 17 percent or less of the feedstock required. Intensification is a part of each model solution to at least some degree however, and we can make some useful observations about how this effect is similar and different across the models considered.

As shown in Figure 7.5-1, average USA region soybean yields increase in all four models in response to the soybean oil biodiesel shock. One can compare these results with the reference case yields presented in Figure 5.3-1 and observe that these improvements are generally less than a 1 percent increase relative to reference case yields, though in the case of ADAGE, USA region average yield does increase by 1.3 percent in 2030. While improvements may be larger in particular growing regions, the average yield across the USA region is instructive in understanding why intensification plays only a minor role in the sourcing of soybean oil for the biodiesel shock. As a collective, these four models estimate the soybean oil biodiesel shock modeled for this comparison does not induce much improvement in soybean yield relative to reference case yields. This small observed change in USA region soybean yields is reasonable in light of the crop price changes observed in these results. Figure 7.5-2 shows that the change in soybean price is also small, less than 2 percent in 2030. As discussed above, crop price is the primary driver of increased crop yields and intensification in general, and a small price change would be expected to induce a small yield response as well. These changes in soybean price are largely a function of the changes in soybean oil and soybean meal prices, shown in Figure 7.5-3.

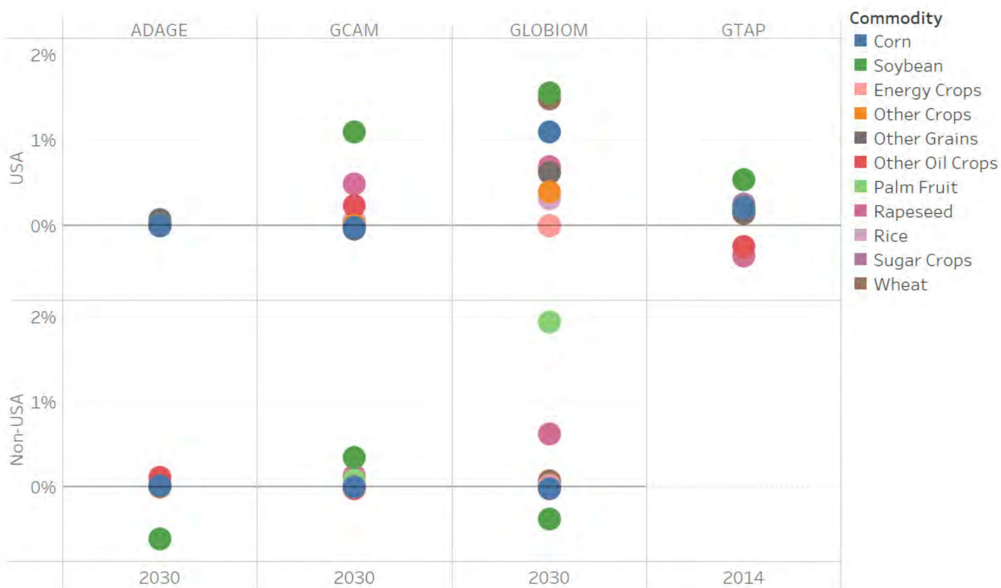
Figure 7.5-1: Difference in soybean yield in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM, GTAP)



Looking at the non-USA regions results, we see smaller average soybean yield responses from all four models. We observe more yield response in the ADAGE and GLOBIOM results than in the GCAM or GTAP results. ADAGE estimates the largest non-USA regional soybean production response of the four models, so it is perhaps unsurprising from that perspective that it also shows the strongest non-USA yield response. Soybean oil biodiesel produced in South America provides a substantial share of the shock in the ADAGE results. The increased demand of this new biodiesel production creates greater investment in soybean yields in this region. The GLOBIOM results tell a different story. In these results, soybean production declines outside the

USA region overall. As discussed in Section 7.3 above, the decline in non-USA soybean production is primarily a response to the influx of USA-produced soybean meal into global feed markets. However, it is notable that GLOBIOM appears to use intensification as a method for mitigating the reduction in soybean production, rather than a means of further boosting increased production, as is the case in the ADAGE results. Conversely, yields increase very little in GTAP and GCAM as these models appear to focus on other strategies for supplying the needed soybean oil. However, the responses from all four models are fairly small. These results, again, appear reasonable in light of the very small soybean price changes in the non-USA regions observed in Figure 7.5-2.

Figure 7.5-2: Percent difference in commodity prices in the soybean oil biodiesel shock relative to the reference case[207]



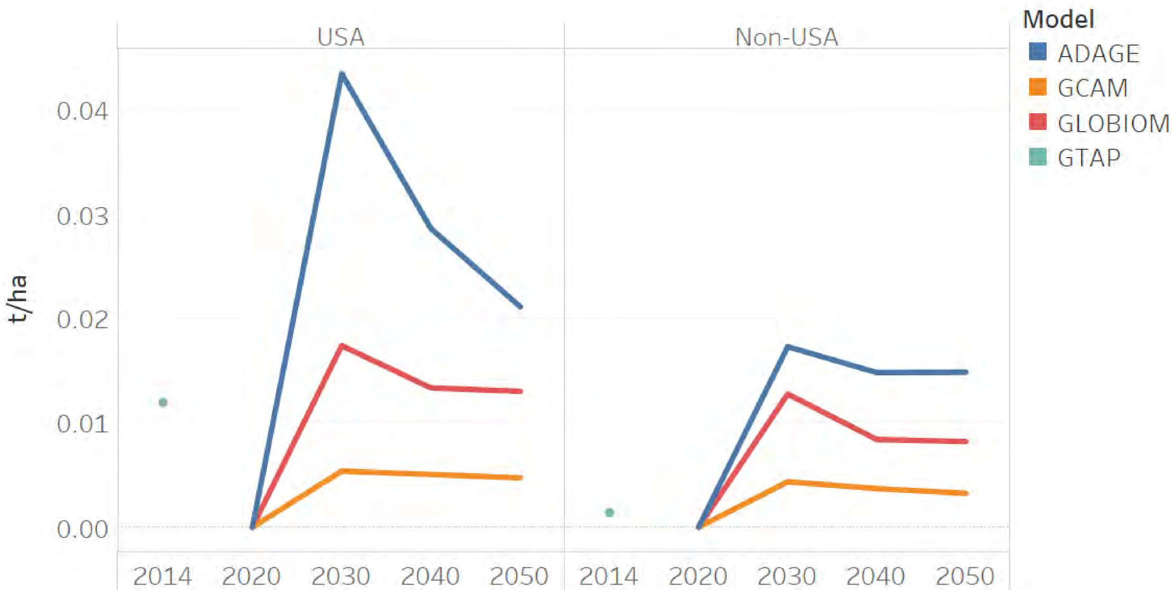
[207] Average commodity prices for non-USA regions in GTAP results were not available for this exercise.

Figure 7.5-3: Percent difference in coproduct prices in the soybean oil biodiesel shock relative to the reference case[208]

In the three dynamic models, ADAGE, GCAM, and GLOBIOM, we see somewhat similar patterns of yield change over time. Figure 7.5-4 shows that all four of the models estimate an increase in soybean yield in 2030 as the shock reaches its peak, both in the USA and non-USA regions though the magnitudes of these increases vary by region and model. By 2050, this increase tapers off in all models in both the USA and non-USA regions as well. The magnitude of this tapering varies as well and that magnitude appears to positively correlate to some degree with the magnitude of the 2030 increase in yield. In general, this tapering effect appears attributable to improving reference case soybean yields over time.

[208] Average commodity prices for non-USA regions in GTAP results were not available for this exercise.

Figure 7.5-4: Difference in soybean yield in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and over time from 2020 to 2050 (ADAGE, GCAM, GLOBIOM)



While the soybean crop yield change results may appear to be somewhat different across models based on the figures presented, they are all relatively small increases when compared to reference case soybean yields in each model The largest increase in soybean yields in 2030 is seen in the ADAGE results in the USA region – about 1.3 percent – while soybean yield changes in the other models and regions are all less than one percent in 2030. We can observe from these results that the four economic models generally agree that, in the specific scenarios modeled for this exercise, yields are not projected to improve substantially in response to the soybean oil biodiesel shock. However, it is also notable that even these small changes in soybean yield are responsible for a small but notable percentage of the additional soybean oil produced to meet the shock.

From this exercise however, we cannot draw any firm conclusions from this yield comparison regarding whether one method is better than the others. All four of the models seem to behave reasonably in these yield results. Sensitivity analysis may reveal the degree to which GHG emissions results change when the underlying assumptions about crop yield responsiveness to price are changed. This may indicate areas for further research.

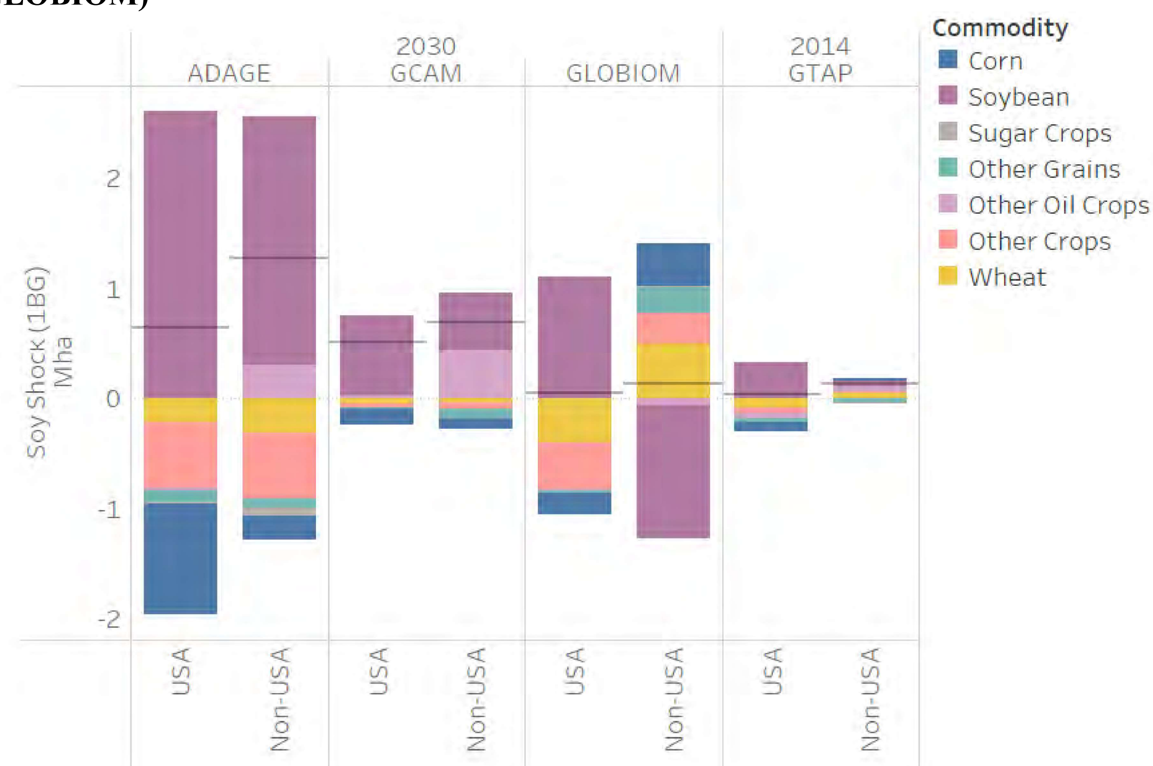
7.6 Land Use

The increased soybean production comes from a mix of cropland shifting from other crops to soybeans, land use change from other land types to cropland, and changes in soybean yield. As shown in Figure 7.6-1, soybean cropland in the USA region increases by 0.3 Mha in GTAP (2014), 2.7 Mha in ADAGE (2030), 0.7 Mha in GCAM (2030), and 1.1 Mha in GLOBIOM (2030). In the non-USA regions, soybean cropland increases by 0.02 to 2.1 Mha in

GTAP, ADAGE, and GCAM, and decreases by 1.2 Mha in GLOBIOM. All of these models show some amount of shifting of other crops to soybeans, but the amount of crop shifting varies.

In the GTAP and GLOBIOM results, most new soybean cropland in the USA region comes from shifting of other crops. In the GLOBIOM results, there is a shift in the non-USA region from soybean cropland to corn, wheat, other grains, and other crops, to make up for the lost production of these crops in the USA region. In both models, the total cropland increases more in non-USA regions than in the USA region. In the ADAGE results, there is some cropland shifting in the USA and non-USA regions, but a larger net increase in cropland area than in GTAP or GLOBIOM. In the GCAM results, even though there is much less new soybean cropland than in ADAGE, there is a similar net increase in total new cropland (horizontal line in Figure 7.6-1) because there is less cropland shifting than in ADAGE.

Figure 7.6-1: Difference in cropland area by crop type (million hectares) in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[209]



The net increase in cropland causes changes in the area of other land types in each model (Figure 7.6-3). As described in Sections 2 and 6.6, the type of land use change in each model depends on the model structure and constraints. In ADAGE, most of the increase in cropland in the USA region is coming from managed pasture. In contrast, non-USA regions show large

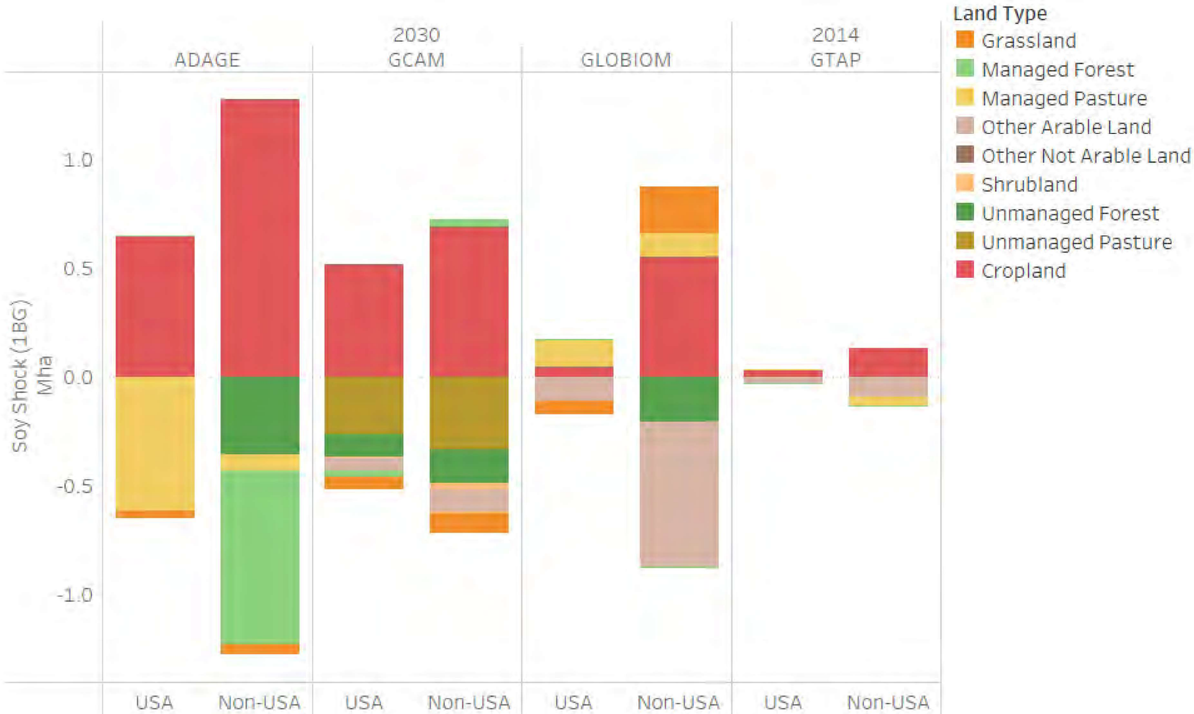
[209] Horizontal lines show the net change in cropland. Cropland area shown represents land cultivated for row crops in ADAGE and GCAM and harvested area in GLOBIOM and GTAP. When a single unit of land is harvested multiple times in a single year, the area is counted multiple times as “harvested area” but only a single time as “cultivated area.”

decreases in managed and unmanaged forest. In the non-USA region, the soybean production and land use change are occurring the Rest of Latin America region. In the Rest of Latin America region in ADAGE, the model assumes that forest productivity decreases over time, which impacts land prices, and causes the reduction of forest area. GCAM results show a decrease in a mix of land types in both the USA and non-USA regions, with the largest impact on unmanaged pasture, similar to the corn shock. In the GLOBIOM results, the area of other arable land and managed forest decreases relative to the reference in non-USA regions. The restriction on natural land conversion in GLOBIOM could drive the result that the new soybean cropland in the USA region comes from crop shifting, rather than land use change.

In the GTAP results, there is very little change in land use in the USA region, but in the non-USA regions, cropland increases and other arable land decreases. In GTAP, in the non-USA regions cropland pasture is the main source for new harvested area (53 percent), followed by pasture (30 percent), unharvested cropland (11 percent), increased multi-cropping (5 percent), and forest (1 percent). Because GTAP only represents managed land, the results show no conversion of unmanaged forest, grassland, or unmanaged pasture.

Each of the models has different assumptions about the carbon stock of different land types in different regions. As shown in more detail in Section 7.7, the type and amount of land converted and the carbon stock of the land types will factor into the emissions from land use change.

Figure 7.6-2: Difference in land use (million hectares) in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM)[210]



Following the trends observed in the crop production results, the models show variation in both the magnitude and location of land use change. As might be expected given their differences in land competition structure and land categorization, these four models also present diverse estimates regarding what types of land might be converted to cropland in response to greater demand for soybean oil biodiesel, in particular the extent of forest loss. Some of these differences appear to be related to where in the world the results show that cropland will expand. The differences also appear to be attributable to differences in land conversion flexibility across the models. These are areas for potential future sensitivity and uncertainty analysis.

7.7 Emissions

The modeled results of energy consumption, crop production, and land use change described above come together in the modeled greenhouse gas emissions. As shown in Figure 7.7-1, the modeled GHG emissions over time vary by model.

[210] In Figure 6.6-2 and 7.6-2, "Cropland" area in GTAP represents land cultivated for row crops (calculated as the change in harvested area minus the change in multicropping), while cropland pasture, and other unused cropland have been reassigned to "Other Arable Land." This differs from Figure 5.2-1, in which cropland pasture and other unused cropland are reported under the "Cropland" category.

Figure 7.7-1: Difference in global greenhouse gas emissions in the soybean oil biodiesel shock relative to the reference case[211]

[211] GTAP is not included in this figure because it does not represent emissions over time, and due to time constraints, we do not have GTAP GHG emissions by gas for the source categories used in this figure. For comparison, for GTAP, in the soybean oil biodiesel scenario relative to the reference case (2014), LUC emissions = 1.1 Mt CO_2e, fossil fuel combustion and industrial CO_2 emissions = -5.5 Mt, and other GHGs emissions from all covered sources = -0.70 Mt CO_2e, of which N_2O = 0.13 Mt CO_2e, CH_4 = -0.72 Mt CO_2e, fluorinated gases = 0.01 Mt CO_2e, and other CO_2 = -0.13 Mt CO_2e; net total GHG emissions = -5.1 Mt CO_2e. GREET is not included in this figure because it does not represent scenario-based emissions over time. See Table 7.7-1 for carbon intensity values.

Emissions from land use change show different trends in ADAGE, GCAM, and GLOBIOM results, due primarily to two factors: variation in the type(s) of land use change occurring relative to the reference case, and variation in the underlying carbon stock data sets and assumptions used in each model. In the ADAGE results, land use change emissions are the highest of the models shown here. These emissions peak in 2030 in ADAGE and are higher than the reference case throughout the entire model period. In the ADAGE results, the non-USA region has a large amount of forest converted to cropland. Because forests have a higher carbon stock than other land types, the ADAGE results show high land use change emissions. In addition, emissions continue after 2030 because the assumptions and structure in ADAGE make it cost effective to continue to convert land after 2030.

In the GCAM and GLOBIOM results, land use change emissions estimates are higher than the reference case from 2020 to 2040, peaking in 2030. From 2040-2050, emissions are slightly lower than the reference case. Emissions in the GCAM results are higher than in the GLOBIOM results. In the GCAM results, most of the land use change is coming from lower carbon land types, such as pasture and grassland. However, some of the land use change is attributable to reduced amounts of estimated future afforestation relative to the reference case. Even though the amount of change in forest land is small compared to the amount of change in other land types, the high carbon stocks of forest land leads to higher land use change emissions. The GLOBIOM results have less forest conversion than ADAGE and GCAM, and therefore lower land use change emissions, especially earlier in the modeled period.

The "Energy from Fossil Fuels" (or "fossil fuel emissions") category includes emissions associated with producing biofuels (e.g., from consuming natural gas or electricity for process energy), direct emissions associated with on-farm energy use to produce feedstock, and transporting both biofuel feedstocks and finished fuels, as well as emissions from indirect impacts on the energy sector, including displaced diesel use for transportation that is replaced by soybean biodiesel. In the soybean oil biodiesel results, ADAGE and GCAM show lower fossil fuel emissions than in the reference case.[212] In these results, the reduction in emissions from fossil fuels becomes larger until 2030. From 2030-2050, fossil fuel emissions in the GCAM results are relatively constant. In the ADAGE results, from 2030-2050 the reduction in emissions becomes smaller, but emissions stay lower than in the reference case. As shown in Section 7.2, refined oil consumption decreases in the soybean oil biodiesel shock scenario relative to the reference case. Globally, the refined oil consumption decreases more in the ADAGE results than the GCAM results. However, ADAGE results show a larger increase in global natural gas consumption than the GCAM results, and an increase in coal consumption, rather than the decrease seen in the GCAM results. The higher consumption of natural gas and coal in the ADAGE results leads to a lower reduction in fossil fuel emissions in the ADAGE results than the GCAM results.

Crop production emissions are higher than the reference case in the ADAGE, GCAM, and GLOBIOM results, with GCAM results showing the largest increase. Changes in crop production emissions relative to the reference case are due to changes in the types and quantities of crops grown in the models, and primarily come from changes in N_2O emissions, driven by both increased fertilizer use and direct nitrogen fixation by soybeans. As shown in Section 7.3,

[212] Emissions from "Energy from fossil fuels" are not reported by GLOBIOM.

the ADAGE, GCAM, and GLOBIOM results all show increases in soybean production. These results also show increased production of palm fruit and other oil crops. ADAGE and GCAM results show a decrease in corn production, whereas GLOBIOM results show a shift in corn production from the USA region to the non-USA regions. The crop production emissions are small in all of these model results. Emissions peak in 2030 in the GCAM and GLOBIOM results, and in 2040 in the ADAGE results, and then decrease until 2050. The change in emissions relative to the reference case from the livestock sector and from industrial and waste management sectors is very small.

The total change in GHG emissions across all sources over time varies across the models (Figure 7.7-1). The ADAGE results show higher emissions than in the reference case from 2020-2050, which is dominated by CO_2 emissions from land use change. In the GCAM results, GHG emissions are higher than in the reference case from 2020-2030 and lower than the reference case from 2035-2050, because the CO_2 emissions from land use change decline rapidly after 2030. In the GLOBIOM results, emissions are higher than in the reference case from 2020-2050, and are dominated by CO_2 emissions from land use change.

There are a few commonalities across the ADAGE, GCAM, and GLOBIOM results of emissions over time. All of these model results show small but positive emissions from crop production relative to the reference case. The model results also all show very small changes in emissions from livestock production, waste management, and industry. The GCAM and ADAGE results both show lower emissions from fossil fuel than the reference case, but there are differences in the amount of fossil fuel emissions reduction. Future research could explore the factors that determine the extent of refined oil displacement in each model through sensitivity analysis. Additionally, there are large differences across the model results in the amount of land use change emissions, due to differences in both the types of land converted and the carbon stock assumptions. A sensitivity analysis of the carbon stock assumptions in GCAM is shown in Section 9.2 below, and a sensitivity analysis of the land conversion elasticities in ADAGE is shown in Section 9.3. Future research could focus on the impact of carbon stock assumptions in other models, or on other model parameters that determine the types of land converted.

As explained in Section 6.7, we calculated a CI for each category of emissions, in $kgCO_2eq/MMBTU$ (Table 7.7-1). We also consider CI results from GREET. As explained in Section 6.7, the models report emissions from different sectors. Models are divided between those frameworks with energy markets (in the left side columns) and models without energy markets (in the right side columns). This division is made to reflect important differences in the sectors represented and the difficulty of direct comparability between models on the left with models on the right. ADAGE, GCAM, and GTAP include global emissions from every economic sector, including indirect, market-mediated impacts. GREET includes detailed emissions assumptions from fuel production, transport, and use, but, as it is not a consequential model, it does not estimate the net change in GHG emissions resulting from a change in biofuel consumption. Rather it estimates the emissions directly attributable to the biofuel supply chain. GLOBIOM does not include any energy sector emissions but does include market impacts on crop production and the livestock sector.

Because of the differences outlined above, it would be inappropriate to compare all of the emissions estimates across all of the models, but we can make several meaningful comparisons. Results from the three models with energy markets (ADAGE, GCAM, GTAP) can be directly compared, with the caveat that GTAP is representing 2014 while the other models are representing a 2020-2050 scenario. Furthermore, we can compare the land use change emissions estimates for all of the models, as GREET uses a consequential approach for this category of emissions, again with proper caveats about temporal differences. We can also compare crop production and livestock sector emissions estimates from ADAGE, GCAM and GLOBIOM. In the table below, we report emissions from "Agriculture, forestry and land use" for all five models as the sum of emissions from these stages; however, the GREET estimate for this aggregate category is not directly comparable with the other models for reasons discussed below.

Like in the corn ethanol shocks, energy sector emissions have a large impact on the CI of soybean oil biodiesel in the ADAGE, GCAM, and GTAP results. The energy sector CI is higher (less negative) for the ADAGE results than for the GCAM and GTAP results, which is consistent with the smaller emissions reduction from fossil fuels over time shown in Figure 7.7-1, particularly in the later model years. GREET reports the CI from fuel production and transportation but does not consider indirect impacts on the energy sector, such as the energy rebound effects shown in Section 7.2. The fuel production and transportation CI in the GREET results is based on the amount of process energy needed for soybean oil biodiesel production as well as the amount of energy needed to transport the feedstock and the fuel. This is why we use the label "Energy Sector" for the first row in Table 7.7-1 for the three models with energy markets, but the label "Biofuel Production" for this row for GREET.

Table 7.7-1: Carbon intensity of soybean oil biodiesel (kgCO_2eq/MMBTU) calculated using emissions reported by each model[213]

	Models with Energy Markets				Models without Energy Markets		
		ADAGE	GCAM	GTAP		GLOBIOM	GREET
Sector/stage-specific emissions	Energy from Fossil Fuels	-28	-40	-46	Biofuel Production	x	13
	Crop Production	7	21	-6	Crop Production	11	x
					Feedstock Production	x	9
	Livestock Sector	0.7	-1.3		Livestock Sector	3	x
	Other	1	0		Fuel Use	x	0.4
	Land Use Change	295	62	10	Land Use Change	23	10
Totals	Agriculture, forestry, and land use	303	82	4	Agriculture, forestry, and land use	38	19
	Global GHG Impact	276	42	-42	Global GHG Impact	x	x
	Supply Chain GHG Emissions	x	x	x	Supply Chain GHG Emissions	x	32

The ADAGE, GCAM, and GLOBIOM results show a range of CI from crop production. The crop production CI from the GCAM results is higher than the other models, consistent with the higher emissions over time in the GCAM results relative to the ADAGE and GLOBIOM results. GREET's feedstock production CI is based on the energy and chemical inputs required to produce the amount of soybean oil needed for 1 MMBTU of biodiesel. Unlike the other models, this value does not consider indirect impacts on the production of other types of crops. Livestock and other sectors (including waste management and other industrial sectors) have only minor impacts on the overall CI in ADAGE, GCAM, and GLOBIOM.

For the GTAP results, we have estimates of non-CO_2 emissions by greenhouse gas, but we do not have these emissions disaggregated by sector or lifecycle stage. The largest change, by

[213] "X" means that the model does not report that category. For GTAP, emissions from crop production, the livestock sector, and "other" are reported as an aggregated value of non-LUC, non-fossil fuel emissions. Negative values for ADAGE, GCAM, GTAP, and GLOBIOM mean that emissions are lower than the reference case, whereas positive values mean the emissions are higher than the reference case. For further discussion of how to interpret positive and negative values, see Section 6.7.

gas, is a decrease in CH_4 emissions. We believe the bulk of the changes in these emissions are associated with changes livestock CH_4, but more work would be needed to confirm our intuition. In Table 7.7-1, we report the aggregated non-CO_2 emissions estimate from GTAP across three rows combining Crop Production, Livestock Sector and Other. GTAP shows a negative CI in this aggregated category. We would need to do more research to understand why these emissions are lower than estimates from the other models.

Land use change emissions are reported across all the models, and the CI results show wide differences, consistent with the large differences in emissions shown in Figure 7.7-1. As explained in Section 7.6, ADAGE results show conversion of forest land to cropland to grow soybeans in non-USA regions, which results in a high estimated LUC CI. In contrast, GTAP results show very little land use change, and therefore this model estimates a low LUC CI. Here again, GREET's LUC CI is based on a GTAP run[214] using a different shock size (0.812 billion gallons of soybean oil biodiesel) using a 2004 baseline where around 13 percent of crop land cover demand comes from forest land, and the remainder comes from land previously having been pastureland.[215]

We can compare "Agriculture, forestry and land use change emissions" across four of the models (ADAGE, GCAM, GLOBIOM, GTAP). For GTAP, we include the non-CO_2 emissions in this category. For this category, the ADAGE results include the highest emissions, followed by GCAM. These differences are driven by the land use change emissions.

The total global CI can be compared across ADAGE, GCAM, and GTAP, because all of these models represent the same sectors and include market impacts. The results from these models show a range in soybean oil biodiesel CI, primarily due to differences in the land use change CI. For GLOBIOM and GREET, a total global CI cannot be calculated from the model results because these models do not include all the relevant sectors and/or do not include all the relevant market impacts. For GREET, we calculate the total supply chain CI. This is a fundamentally different metric than the other models' CIs, since GREET primarily uses an attributional approach to lifecycle analysis rather than a consequential approach. This value does not include any displacement of fossil fuel consumption that would occur from the increased consumption of biofuels.[216]

7.8 Summary of Soybean Oil Biodiesel Estimates

Section 7 compares and contrasts the soybean oil biodiesel modeling estimates from ADAGE, GCAM, GLOBIOM, GREET, and GTAP produced for this exercise. These models source the soybean oil biodiesel required to meet the assumed shock in different ways in these

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[214] We present the default soybean oil biodiesel run from GREET's LUC CCLUB tool here, referred to as "Soy Biodiesel CARB Case 8"

[215] Chen, Rui, Zhangcai Qin, Jeongwoo Han, Michael Wang, Farzad Taheripour, Wallace Tyner, Don O'Connor, and James Duffield. 2018. "Life Cycle Energy and Greenhouse Gas Emission Effects of Biodiesel in the United States with Induced Land Use Change Impacts." Bioresource Technology 251 (March): 249–58. https://doi.org/10.1016/j.biortech.2017.12.031.

[216] GREET's biodiesel CI estimates are often compared with GREET CI estimates for diesel to derive a GHG percent reduction relative to diesel. In our 2010 RFS analysis, we similarly compared biodiesel CI estimates from models that do not include energy markets with a CI estimate for diesel to calculate a percent reduction in emissions.

results. Some models rely primarily on crushing of new soybean production to produce additional soybean oil feedstock. Other models rely primarily on diversion of soybean oil from other uses. Some models also show a contribution from reduced soybean oil biodiesel consumption in non-USA regions. In addition, the model results show differences in how much of the new soybean oil biodiesel is produced in the USA region versus the non-USA regions. Because of these differences in sourcing strategy, the model results differ regarding the amount and location of soybean oil production, vegetable oil and biodiesel trade, and land use change impacts of the shock. Notably, the amount and location of land use change, and the types of land converted to cropland, differ substantially across the range of model results. The model results also show differences in the impact on the food and feed markets, and different amounts of displacement of palm oil or other oils. The model results also have some notable similarities. ADAGE, GCAM, GLOBIOM, and GTAP results all show a small amount of crop yield intensification. The models which explicitly include the energy sector, ADAGE, GCAM, and GTAP, all show a decrease in refined oil consumption in the USA region in their results, and an increase in non-USA regions. But there are differences across these models in the total global displacement of refined oil. These factors all contribute to differences in the estimated GHG emissions and CI of soybean oil biodiesel across the models, with the differences in land use change emissions having the greatest impact on estimated CI.

The previous sections also highlight potential areas for future research. Sensitivity analysis could test the impact of different degrees of substitution in feed and food markets. Further research and sensitivity analysis could also seek to better understand the parameters that influence land conversion to cropland. Furthermore, research and sensitivity analysis could seek to better understand why model results show a range in the reduction of refined oil consumption. These are only a few examples of the many research areas that could help us to understand what is driving the variation in estimates across models.

Alternative Scenarios and Model Sensitivity Analysis

8 Alternative Volume Scenarios

To determine whether and how GHG emissions estimates from these models may vary based on the volume of biofuels assumed, we ran alternative volume scenarios through the models. The scenarios included half of the original soybean oil biodiesel shock (decreased to 500 million gallons) and a combined scenario in which both soybean oil biodiesel and corn ethanol consumption are each increased by 1 billion gallons simultaneously. These new volume scenarios were performed in ADAGE, GCAM, GLOBIOM, and GTAP using the same methods for the core corn ethanol and soybean oil biodiesel scenarios. The alternative shock size was chosen to compare how each model functions, and they are not necessarily meant to represent realistic biofuel shock sizes.

8.1 Soybean Oil Biodiesel 500 Million Gallons (MG) Scenario

The 500 MG soybean oil biodiesel shock results generally indicate a linear relationship between shock size and most output parameters. ADAGE, GCAM, and GTAP show a high degree of linearity between volume shock assumptions and output values, with scenario changes from the reference case for the 500 MG soybean oil biodiesel shock generally being half the size of those from the 1 BG shock. The GLOBIOM results show more nonlinear variability in output values, but these nonlinearities tend to be quantitatively minor. To examine these questions of model response linearity and for clarity of presentation, the 500 MG soybean oil biodiesel shock has been normalized to show impacts per 1 billion gallons of soybean oil biodiesel in the results presented in this section.

8.1.1 Energy Market Impacts

The models that include energy market impacts, ADAGE, GCAM, and GTAP, show a linear relationship between shock size and global energy consumption. The size of the energy sector impacts, expressed in quad BTUs per billion gallons (of shocked biodiesel), are generally equal across the 500 MG and 1 BG soybean oil biodiesel scenarios, as illustrated in Figure 8.1.1-1. GLOBIOM does not represent the energy sector and as such was not included in this section of the analysis.

Figure 8.1.1-1: Difference in global energy consumption (Quad BTUs per BG of shocked soybean oil biodiesel consumption) in the 500 MG and 1 BG soybean oil biodiesel shocks relative to the reference case in 2030 (ADAGE and GCAM) and 2014 (GTAP)

8.1.2 Crop production and consumption

Similar to energy consumption, ADAGE and GCAM show a generally linear relationship between shock size and global commodity production impacts in the 500 MG soybean oil biodiesel shock. GTAP also shows a generally linear relationship between commodity production and shock size. GLOBIOM results have slight differences in production of corn and soy between the 500 MG and 1 BG soybean oil biodiesel shocks, but these differences are minor.

Global commodity consumption by end use indicates a generally linear relationship with respect to shock size across ADAGE, GCAM, and GLOBIOM in the year 2030, and there are not any notable changes between the 500 MG and 1 BG soybean oil biodiesel scenarios. GTAP also shows a generally linear relationship between global commodity consumption and shock sizes in 2014.

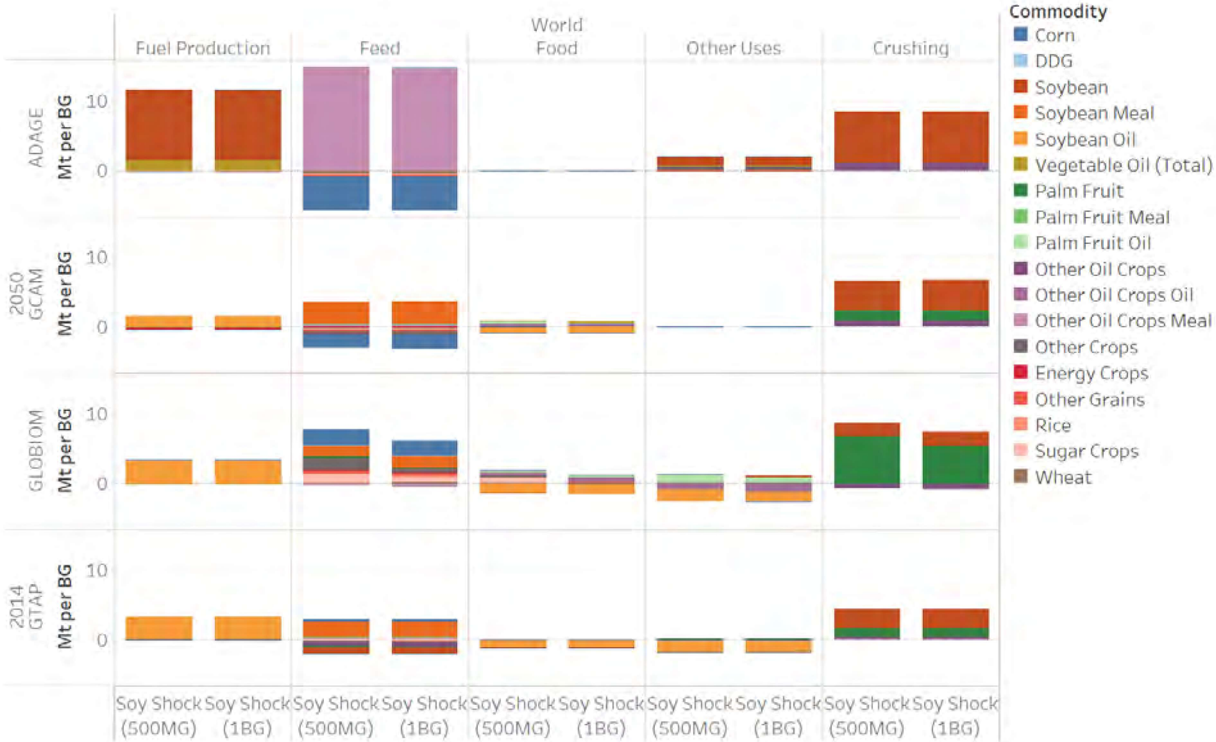
However, in the 2050 time step, GLOBIOM results show nonlinearities in the global crushing of palm fruit and the consumption of sugar crops and other crops for feed, with the 500 MG shock showing higher consumption per billion gallons.[217] The nonlinearity for palm fruit is attributable to the commodity substitution dynamics of GLOBIOM. As a commodity becomes scarcer on the global market (soybean oil in this case), the price of that commodity increases and there is increasing incentive to substitute less expensive alternatives (palm oil in this case). However, that substitution becomes more expensive, i.e., the price of the substitute good increases as greater quantities of the substituted product are demanded. In both the 500 MG and 1 BG soybean oil biodiesel shocks, increasing U.S. demand for soybean oil to produce biodiesel leads to lower availability of soybean oil in other countries and higher prices for soybean oil and soybeans. This shortfall is partly addressed with increased palm oil supply from Southeast Asia. However, substitution of palm oil for soybean oil grows more costly per unit as demand rises. For this reason, this substitution effect is less pronounced in the 1 BG case than in the 500 MG case, where the total volume of additional palm oil demanded is smaller.

Regarding feed crops, the economic dynamics at play are somewhat similar. The 500 MG soybean oil biodiesel shock generates less additional soybean meal than the 1 BG case, and U.S. soybean meal prices are depressed by a smaller amount. This smaller price depression leads to a less than proportional increase of the use of the meal as livestock feed abroad. The nonlinear change in consumption of other feed products in the 500 MG case is related to the fact that, unlike the other models considered in this exercise, GLOBIOM explicitly accounts for the need for animal feed diets to be balanced nutritionally. Increasing consumption of one feed product, in this case soybean meal, means that consumption of other complementary feed products must also increase to maintain nutritional balance for livestock. In the 500 MG soybean oil biodiesel case relative to the 1 BG case, the smaller increase in Non-USA consumption of soybean meal, relative to the size of the shock, means that increased consumption of these other feed products is also proportionally smaller. Figure 8.1.2-1 illustrates the differences in global commodity

[217] In the 500 MG scenario results from GLOBIOM, consumption of palm fruit for crushing was 6.8 Mt per BG, consumption of sugar crops for feed was 1.2 Mt per BG, and consumption of other crops for feed was 1.8 Mt per BG. In the 1 BG scenario, consumption of palm fruit for crushing was 5.3 Mt per BG, consumption of sugar crops for feed was 0.8 Mt per BG, and consumption of other crops for feed was 0.6 Mt per BG.

consumption by end use in the 2050 time step for ADAGE, GCAM, and GLOBIOM, as well as the 2014 time step for GTAP.

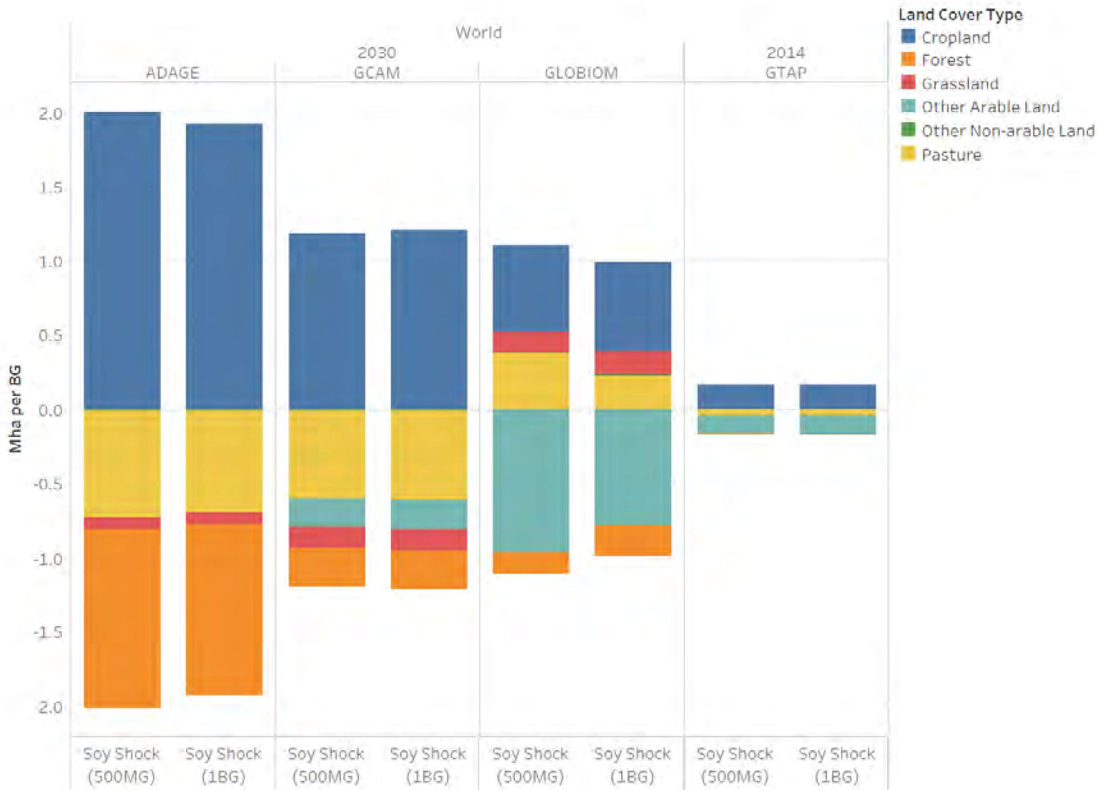
Figure 8.1.2-1: Difference in global commodity consumption by end use (Mt per BG of shocked soybean oil biodiesel consumption) in the 500 MG and 1 BG soybean oil biodiesel scenarios relative to the reference case in 2050 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)



8.1.3 Land Use

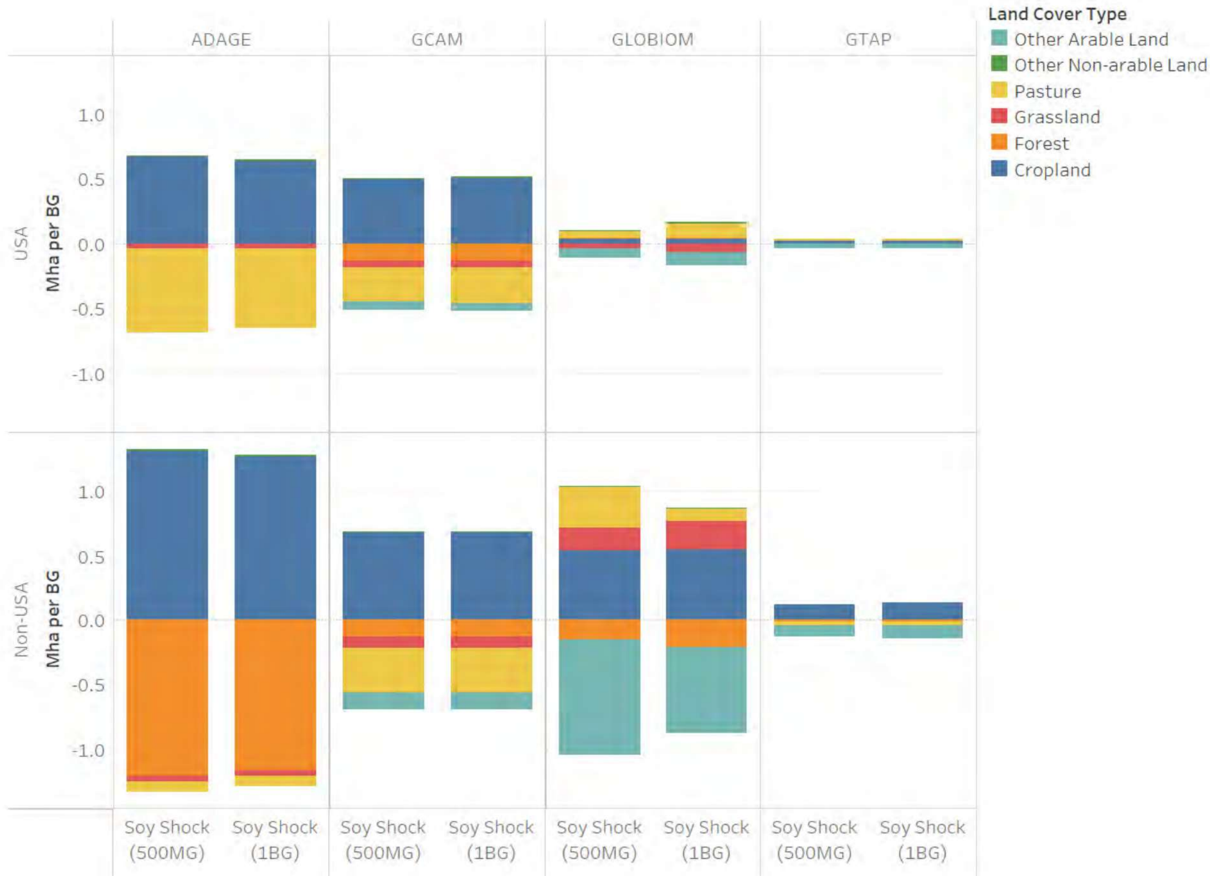
The global land use change by land cover type in the 500 MG soybean oil biodiesel shock has a relatively linear relationship in ADAGE, GCAM, and GTAP results, as seen in Figure 8.1.3-1. However, GLOBIOM results show an increase in global land converting to pasture per billion gallons in the 500 MG shock (0.383 Mha per BG) relative to the 1 BG shock (0.233 Mha per BG). Soybean meal and pasture are both livestock inputs and they are in competition with each other to some extent to provide nutrition to livestock. When soybean meal prices fall as a result of a supply influx, as occurs in the soybean oil biodiesel shocks, this reduces the competitiveness of alternative forms of livestock nutrition, i.e., grazing on pasture land. In the smaller 500 MG shock, soybean meal prices decrease less, which improves the competitiveness of pasture relative to the larger 1 BG shock. As overall livestock demand rises in both of the soybean oil biodiesel scenarios, pasture therefore captures a larger share of the nutrition supply in the scenario where it is more competitive, i.e., the 500 MG shock. GLOBIOM results also show a larger decrease in other arable land per billion gallons in the 500 MG shock (-0.964 Mha per BG) compared to the 1 BG shock (-0.778 Mha per BG).

Figure 8.1.3-1: Difference in land use (Mha per BG of shocked soybean oil biodiesel consumption) for the 500 MG and 1 BG soybean oil biodiesel shocks relative to the reference case in 2030 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)



The GLOBIOM 500 MG results also show differences in where LUC occurs relative to the 1 BG results (Figure 8.1.3-2). In the USA region, GLOBIOM results show a larger increase in land conversion to pasture per billion gallon in the 500 MG scenario (0.325 Mha per BG) in comparison to the 1 BG scenario (0.110 Mha per BG) and a larger decrease in other arable land (-0.897 Mha per BG) compared to the 1 BG scenario (-0.666 Mha per BG). Forest has a smaller decrease in land conversion in the 500 MG scenario (-0.145 Mha per BG) compared to the 1 BG scenario (-0.21 Mha per BG) in GLOBIOM as well. In the non-USA regions, the 500 MG GLOBIOM results show a greater increase in pasture and a greater decrease in other arable land per billion gallons than the 1 BG results.

Figure 8.1.3-2: Difference in land use by region (Mha per BG of shocked soybean oil biodiesel consumption) for the 500 MG and 1 BG soybean oil biodiesel shocks relative to the reference case in 2030 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)



8.1.4 Emissions

In the 500 MG scenarios, ADAGE, GCAM, and GTAP results indicate a relatively linear relationship between shock size and global GHG emissions. These models estimate a slight percentage decrease in total cumulative GHG emissions in the 500 MG scenarios relative to the 1 BG scenarios, but these results are quantitatively minor (Table 8.1.4-1). In comparison to ADAGE, GCAM, and GTAP, GLOBIOM results estimate a larger percentage decrease in global cumulative emissions in the 500 MG soybean oil biodiesel scenario compared to the 1 BG soybean oil biodiesel scenario.

Table 8.1.4-1: Percent difference in global accumulated GHG emissions per billion gallons of soybean oil biodiesel shock in the 500 MG shock scenario relative to the 1 BG shock scenario

	ADAGE	GCAM	GLOBIOM	GTAP
Percent Difference (TOTAL GHG)	-2%	-2%	-24%	-6%
Percent Difference (LUC Only)	0%	-2%	-21%	-1%

When examining global GHGs over time, in the 500 MG scenario, GLOBIOM results estimate an increase in N_2O emissions in 2050 compared to the 1 BG scenario (Figure 8.1.4-1). While the accumulated GHGs in ADAGE remain relatively linear by the year 2050, when examining emissions over time, ADAGE has more variability in each time step. This includes a smaller increase in CO_2 emissions in the year 2040 and conversely a larger increase in the year 2045 for the 500 MG shock in comparison to the 1 BG shock. GCAM indicates a generally linear relationship between both the accumulated GHGs and the emissions over time.

Figure 8.1.4-1: Difference in global GHG emissions ($MtCO_2eq$ per BG of shocked soybean oil biodiesel consumption) in the 500 MG and 1 BG soybean oil biodiesel shocks relative to the reference case from 2020 through 2050[218]

Global GHG emissions by source also show a linear relationship over time. The patterns between the 500 MG and 1 BG shocks tend to mirror each other in each model. However, in the 500 MG scenario, GLOBIOM shows a decrease in livestock production emissions in the year 2050 compared to the slight increase in livestock emissions in the 1 BG scenario.

8.1.5 Summary

Overall, the soybean oil biodiesel 500 MG shock results indicate a linear effect between shock size and most output values for ADAGE, GCAM, and GTAP results. GLOBIOM results show somewhat more nonlinearity with shock size for certain output parameters, which leads to differences in the GHG emissions. But the nonlinearities observed in the GLOBIOM results tend to be minor. GLOBIOM's global commodity consumption by end use estimates an increase in palm fruit used for crushing per billion gallon, as well as an increase in sugar crops and other

[218] GTAP is not included in this figure as it doesn't represent emissions over time. See Table for carbon intensity values.

crops used for feed in the 500 MG scenario relative to the 1 BG scenario. The most notable difference in land use change is the increase in pasture and decrease in other arable land in the non-USA region in the GLOBIOM 500 MG results relative to the 1 BG results. GLOBIOM also estimated a decrease in global CO_2 emissions in the 500 MG soybean oil biodiesel shock, compared to the 1 BG shock. However, we can observe that, across ADAGE, GCAM, and GTAP, the size of the biofuel shock does not appear to cause significant changes in the modeled global GHG emissions results.

8.2 Combined Shock Volumes

In addition to the 500 MG soybean oil biodiesel scenario, a combined shock of 1 billion gallons each of soybean oil biodiesel and corn ethanol was also performed. In the core scenarios for corn ethanol and soybean oil biodiesel, presented in Section 6 and Section 7 respectively, some models estimated an inverse relationship between corn and soybean production. For instance, when we shocked the model with 1 BG of corn ethanol, soybean commodity production would go down, as seen in Figure 6.3-1. However, historically volumes of corn ethanol and soybean oil biodiesel consumption have grown alongside one another, though often at somewhat different annual rates. This has resulted historically in simultaneous increases in demand for corn starch and soybean oil from the biofuel sector. It is therefore worth considering whether modeled LUC and emissions impacts in particular might differ from our core scenario results if the models conduct a scenario where both corn ethanol and soybean oil biodiesel consumption in the USA are assumed to increase simultaneously. The combined scenario was performed to examine what would happen if both biofuels shocked the models.

There are a few general hypotheses regarding what impact such a combined volume shock scenario might have relative to our core scenarios. One hypothesis is that the impacts will be "additive", that is, the results will be approximately the sum of adding together impacts from the corn ethanol and soybean oil biodiesel core scenarios. Another hypothesis is that increasing demand for both fuels at the same time will create greater stress on the agricultural system than either core scenario in isolation, since it will not be possible to simply decrease USA soybean production in response to greater corn ethanol demand, or decrease USA corn production in response to soybean oil biodiesel demand, as is estimated to occur in most of the core scenario results. Such a result would be expected to create greater-than-additive modeled impacts on LUC, crop production, and the resulting GHG emissions. The third hypothesis is that there could be a counterbalance within variables with the combined shock, where the increase in one variable could decrease another. We find the land and emissions estimates in the combined scenario have a mostly additive effect in which modeling results in combined scenario are generally equal in magnitude to the sum of the individual corn ethanol (1 BG) and soybean oil biodiesel (1 BG) core scenarios.

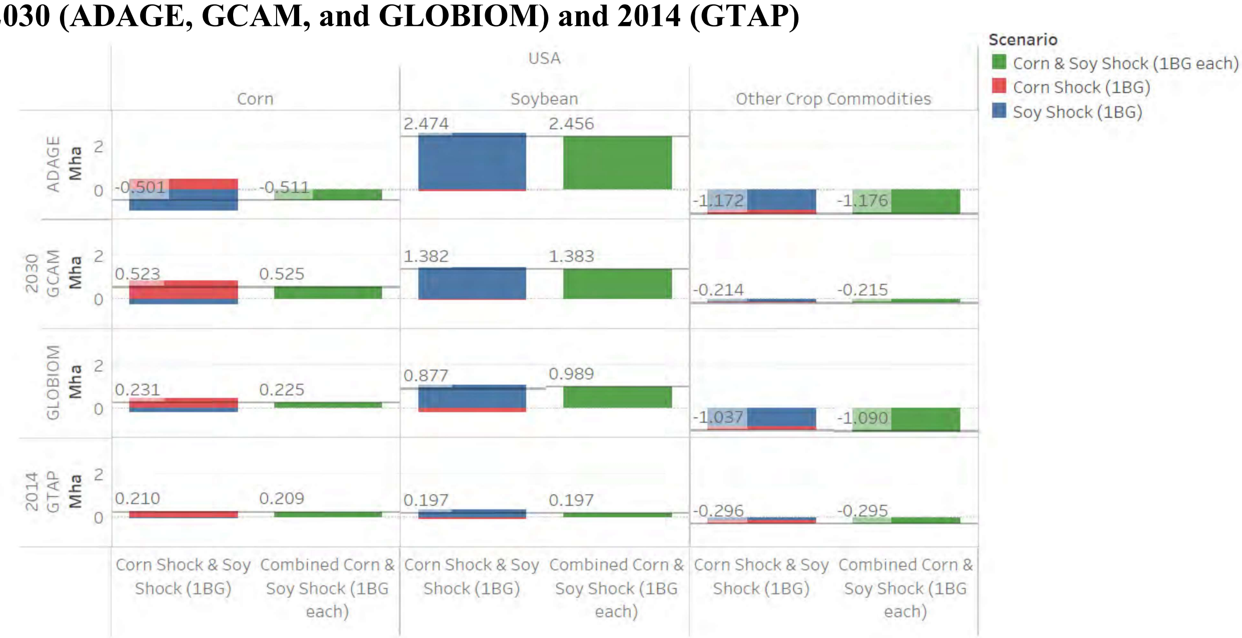
8.2.1 Land Use

The combined scenario provides insight into how each of the models account for the impact on other crop commodities when both corn ethanol and soybean oil biodiesel consumption are increased simultaneously. Figures 8.2.1-1 and 8.2.1-2 illustrate the USA and non-USA regional land use change by crop commodity in the years 2030 (ADAGE, GCAM, and

GLOBIOM) and 2014 (GTAP). The 1 BG corn ethanol and 1 BG soybean oil biodiesel core scenarios are stacked together in the left-hand columns of each commodity type with a line indicating the sum of the two scenarios, and the combined scenario is on the right-hand side of the columns with the line indicating the total from this scenario. To the extent the results of the combined scenario are additive, we would expect the pair of lines for each crop commodity to be similar in magnitude.

The figures below do in fact show each model estimates a generally additive relationship between the corn and soy shocks, meaning that the sum of the impact magnitudes from the core scenarios generally equals the total magnitude of the combined scenario. The most notable difference is that GLOBIOM has a slightly larger increase in USA regional soybean land cover as well as a slightly larger decrease in the non-USA regional soybean land cover in the combined shock.[219] Interestingly, we do not observe any notable changes in land cover for any other crop commodities.

Figure 8.2.1-1: Difference in cropland area by crop in the corn ethanol shock, soybean oil biodiesel shock, and combined shock relative to the reference case in the USA region in 2030 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)



[219] The detailed livestock feed market representation in GLOBIOM provides some explanation for this observation. In the corn shock scenario, GLOBIOM estimates greater DDG production would displace some soybean meal used for animal feed in the USA region, reducing the demand for soybeans and decreasing cropland used for soybeans. In the combined shock scenario, demand for soybeans is driven by the soybean oil biodiesel target, and the displacement effect of DDG in animal feed markets has less impact on cropland used for soybeans. This results in surplus soybean meal in the USA region in the combined shock scenario, which is exported and displaces some soybean production in non-USA regions.

Figure 8.2.1-2: Difference in cropland area by crop in the corn ethanol shock, soybean oil biodiesel shock, and combined shock relative to the reference case in non-USA regions in 2030 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)

8.2.2 Emissions

To compare how the combined shock affects GHG emissions results in each model, we analyzed the percent change from the combined shock relative to the sum of the core corn ethanol and soybean oil biodiesel scenarios. ADAGE, GCAM, and GTAP estimate that the combined scenario would results in relatively similar emissions to the sum of the individual 1 BG corn ethanol and soybean oil biodiesel core scenarios (Table 8.2.2-1). Similar to the soybean oil biodiesel 500 MG scenario sensitivity, GLOBIOM estimates a larger percentage decrease than the other models in cumulative LUC and total GHG emissions in the combined scenario.

Table 8.2.2-1: Percent difference in global accumulated emissions between the combined shock scenario and the sum of the corn ethanol shock and soybean oil biodiesel shock

	ADAGE	GCAM	GLOBIOM	GTAP
Percent Difference (TOTAL GHG)	0%	3%	-27%	2%
Percent Difference (LUC Only)	0%	1%	-45%	5%

8.2.3 Summary

In this section we compared LUC and GHG emissions impacts from the combined scenario to the sum of the core corn ethanol and soybean oil biodiesel scenarios. Overall, across each of the models (ADAGE, GCAM, GLOBIOM, and GTAP), the results from the combined scenario show an additive effect in which the combined scenario generally equals the sum of the two core scenarios across many output values and parameters. GLOBIOM estimates slightly more variability or nonlinearity in output values than the other models. The most notable nonlinearity is the decrease in cumulative LUC emissions in the combined scenario. The results from these scenarios did not support the hypothesis that shocking the models with 1 BG corn ethanol and 1 BG soybean oil biodiesel simultaneously creates greater stress on the agriculture systems of these models.

9 Parameter Sensitivities

Sensitivity analysis assesses how uncertainty in the output of a model can be apportioned to different sources of uncertainty in the model input.[220] The NASEM (2022) study on LCA Methods for transportation fuels recommends sensitivity analysis in several areas of the report. For example, the report says, "LCA studies used to inform transportation fuel policy should be explicit about the feedstock and regions to which the study applies and to the extent possible should explicitly report sensitivity of results to variation in these assumptions."[221] Following these recommendations, we have conducted multiple sensitivity analyses as part of our model comparison exercise.

When we model the environmental and economic impacts of biofuel production, uncertainties arise in multiple forms. One type of uncertainty is model uncertainty, which is related to the structure of the model employed. Two models with different structures and/or solution techniques that otherwise are comparable in scope and use the same input data may produce different results. One motivation for this model comparison exercise is to study model uncertainty by comparing results of common scenarios from multiple models. The effect of different models on GHG estimates is discussed above.

Another form of uncertainty is parameter or input uncertainty. Parameter uncertainty naturally results as inputs to a model are not exactly known and/or the values of these inputs cannot be exactly inferred.[222] This section focuses on the effects of parameter uncertainty within a given model. We performed multiple sensitivity analyses to study the influence of parameter uncertainty on biofuel GHG emissions estimates. These sensitivity analyses are discussed in this section. First, we performed stochastic sensitivity analysis, where input parameters are assigned probability distributions, with GCAM, GLOBIOM and GREET. Second, we tested changes in the soil organic carbon input data in GCAM. Third, we tested changes in land conversion assumptions in ADAGE.

[220] Saltelli, A. (2002), Sensitivity Analysis for Importance Assessment. Risk Analysis, 22: 579-590. https://doi.org/10.1111/0272-4332.00040

[221] National Academies of Sciences, Engineering, and Medicine 2022. Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States. Washington, DC: The National Academies Press. https://doi.org/10.17226/26402. Recommendation 4-6. Other relevant recommendations include but are not limited to: 2-1, 2-2, 4-2, 4-4, 4-9, 4-10.

[222] Related to parametric uncertainty is the concept of parametric variability which relates to the fact that even if perfectly knowable, there is variability in values corresponding to parameter values in these systems. Models are simplifications of reality and do not capture all the variability naturally occurring over time, space, and changing conditions.

9.1 Stochastic Parametric Sensitivities

9.1.1 GCAM

We ran a Monte Carlo simulation (MCS) with GCAM to explore the influence of a range of parameters on the LCA estimates. The goals of the MCS are to test the behavior of the model, evaluate the overall sensitivity of the CI estimates to variations in the input parameters, and to test which parameters tend to have the largest influence on the results for this specific model.

We conducted this analysis using methods and software consistent with the MCS described in Plevin et al. (2022).[223] We ran the MCS by applying random values drawn from distributions across 50 parameters. In this case, we use the term parameter to refer to a set of related values in GCAM's input files. For example, for this analysis we call biomass carbon density of grassland one parameter, even though GCAM uses independent grassland biomass carbon input values for each water basin region. For each of the three MCE scenarios (i.e., reference, corn ethanol shock, soybean oil biodiesel shock), we ran 1,000 trials (3,000 total model runs). The same set of randomly drawn parameter values were used for each of the three scenarios. We consulted with the GCAM developers to determine the likely range of legitimate values for each parameter and then set selected distributions for each parameter based on our own subjective judgements. In some cases we were able to leverage previous research to determine empirically based distribution shapes. Table 9.1.1-1 describes the parameters and distributions used in our MCS.

Table 9.1.1-1: GCAM Monte Carlo Simulation Parameter Distributions[224]

Name	Distribution	Description
bd-biomassOil-coef	Triangle(0.95, 1, 1.05)	The EJ of biomass oil required to produce an EJ of biodiesel.
Corn-etoh-corn-coef	Triangle(0.98, 1, 1.02)	The Tg of corn required to produce an EJ of corn ethanol.
Crop-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of cropland.
Grass-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of unmanaged grass land.
Mgd-forest-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of managed forest land.
Mgd-pasture-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of managed pasture.
Other-arable-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of "other arable" land.
Shrub-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of shrubland.
Unmgd-forest-biomass-c	Triangle(0.7, 1, 1.3)	Biomass carbon density of unmanaged forest land.
Unmgd-pasture-biomass-c-linked	Linked(grass-biomass-c)	Biomass carbon density of unmanaged pasture (linked with grass-biomass-c).

[223] Plevin, R. J., Jones, J., Kyle, P., Levy, A. W., Shell, M. J., & Tanner, D. J. (2022). Choices in land representation materially affect modeled biofuel carbon intensity estimates. Journal of cleaner production, 349, 131477. Section 2.5 describes the MCS.

[224] Unless the parameter name includes an asterisk, the draws from the given distributions were multiplied by the GCAM default values to produce values for each trial. For parameter names with an asterisk, values from the distribution were used directly, replacing the default values.

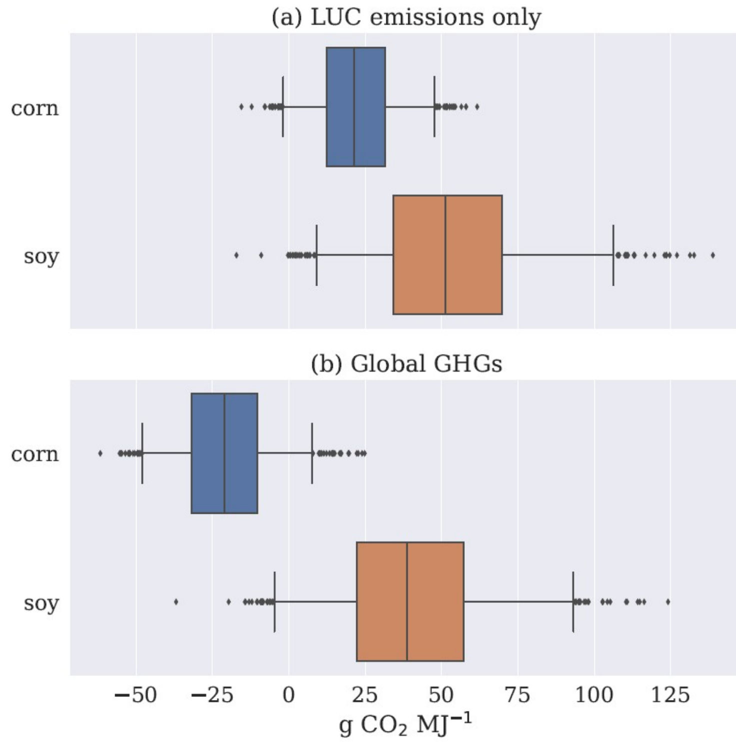
crop-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of cropland.
Grass-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of unmanaged grass land.
Mgd-forest-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of managed forest land.
Mgd-pasture-soil-c-linked	Linked(grass-soil-c)	Soil carbon density of managed pasture.
Other-arable-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of "other arable" land.
Peat-CO2-emissions	Uniform(0.5, 2.0)	CO_2 emissions from peatland conversion.
Peat-CO2-emissions-linked	Linked(peat-CO2-emissions)	CO_2 emissions from peatland conversion on unmanaged land.
Shrub-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of shrubland.
Unmgd-forest-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of unmanaged forest land.
Unmgd-pasture-soil-c-linked	Linked(grass-soil-c)	Soil carbon density of unmanaged pasture (linked with grass-soil-c).
N-fertilizer-rate	Triangle(0.7, 1, 1.3)	Quantity of N fertilizer required per mass of crop harvested.
Ag-energy-coef	Triangle(0.7, 1, 1.3)	Energy consumption coefficient for crop production.
Ag-energy-freight-coef	Triangle(0.5, 1.0, 3.0)	Energy consumption coefficient for transport of ag and energy commodities.
Crop-productivity	Triangle(0.7, 1, 1.3)	Annual change in agricultural productivity (yield).
Irrig-rainfed-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between irrigated and rainfed land.
Mgmt-level-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between high and low crop management levels.
N2o-emissions	Triangle(0.5, 1, 2.0)	N_2O emissions intensity of agricultural production.
Veg-oil-demand-logit-exp	Triangle(0.333, 1, 3.0)	Controls substitution among types of vegetable oil
water-wd-price	Triangle(0.333, 1, 3.0)	The price of withdrawn water.
Non-staples-demand-share-logit*	Uniform(-5.0, 0.0)	Logit exponent controlling shifting between non-staple foods. Standard value is 0 in all regions.
Agro-forest-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between forest-grass-crop and pasture.
Cow-sheepgoat-feed-logit	Triangle(0.5, 1, 2.0)	Logit exponent controlling competition between Beef, Dairy, and SheepGoat, which determines the sharing between Mixed and Pastoral subsectors.
Crop-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition among crops.
Forest-grass-crop-logit-exp	Triangle(0.1, 1.0, 3.0)	Logit exponent controlling competition among forest, grassland, and cropland.
Forest-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between managed and unmanaged forest.
Pasture-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between managed and unmanaged pasture.
Regional-crop-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition between imports and domestic ag products.
Traded-commodity-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition in traded ag commodities.
Traded-commodity-subsector-logit-exp	Triangle(0.333, 1, 3.0)	Logit exponent controlling competition among exports in each traded commodity sector

ng-upstream-ch4	Uniform(0.9, 1.3)	CH_4 emissions upstream from natural gas production processes and transport.
Population-factor*	Triangle(0.0, 0.5, 1.0)	Defines a path between the lower and higher bounds of the UNDP 95 percent confidence interval around population projections.
Resource-energy-coef	Triangle(0.5, 1, 1.5)	Energy consumption coefficient for producing energy commodities.
Biodiesel-competition-logit-exp	Triangle(0.5, 1, 2.0)	Controls substitution among types of biodiesel
pass-road-ldv-4W-logit-exp	Triangle(0.5, 1, 2.0)	Logit exponent controlling substitution among Compact Car, Midsize Car, Large Car, Light Truck and SUV.
Pass-road-ldv-4W-vehicle-logit-exp	Triangle(0.5, 1, 2.0)	Logit exponent controlling substitution among 4WD vehicle fuel technology options include BEV, FCEV, Hybrid liquids, Liquids, and NG.
pass-road-ldv-logit-exp	Triangle(0.5, 1, 2.0)	Logit exponent controlling substitution between 2- and 4-wheel light-duty vehicles.
Ref-fuel-enduse-ex-US	Triangle(0.333, 1, 3.0)	Controls substitution in supplies of refined fuel for "end use" outside the USA.
Staples-price-elast*	empirical	Price elasticity of demand for staple foods
non-staples-price-elast*	empirical	Own price elasticity of non-staple food demand.
Non-staples-income-elast*	empirical	Income elasticity of non-staple food demand.

In some cases, combinations of parameters push the model beyond its ability to match supply and demand in all markets simultaneously, in which case the model fails to solve. As shown in the table above, we primarily used triangular distributions to reduce the likelihood, relative to normal distributions, of outlier parameter draws, thus reducing the number of model failures. Nonetheless, some of the trials failed to solve; the actual number of reference case/shock pairs completed for each model version was 916 for corn ethanol (91.6 percent) and 918 for soybean oil biodiesel (91.8 percent). We investigated the source of failures and found the parameter perturbations most likely causing the failures are some combination of: *crop-logit-exp*, *staples-price-elast*, *agro-forest-logit-exp*, *veg-oil-competition-logit-exp* and *forest-grass-crop-logit-exp*. The purpose of the MCS is to understand the model's response to parameter variation. We could reduce the failure rate by narrowing the distributions for these parameters, but this would come at the cost of gaining insights about how wider distributions influence the model. Furthermore, evaluating which parameters tend to cause model failures provides valuable information about the model. For these reasons, we did not to adjust our MCS setup to reduce the failure rate.

The following figure presents the results of our MCS experiment with GCAM as distributions of CI estimates for corn ethanol and soybean oil biodiesel. Although the figure presents the MCS results in probabilistic terms, the actual probability of any given GHG emissions impact cannot be determined from this analysis. Our sensitivity analysis only reveals the likelihood of an outcome *given all of the inputs into our analysis*, such as the version of GCAM, the reference parameter values, the solution technique, the definitions chosen for the parameters evaluated, and the distributions for the parameters evaluated. Although the figure does not tell us the actual probability of a given outcome, it provides information about the general tendency of the model and the variance of results due to parametric uncertainty.

Figure 9.1.1-1: Distribution of GCAM (a) land use change carbon intensity and (b) overall carbon intensity estimates for corn ethanol and soybean oil biodiesel based on the MCS[225]



In the above figure, we present the distribution of land use change CI separately from the distribution of overall CI. We extract the land use change CI to facilitate comparisons with other studies or models that only report land use change emissions. While we do this separation to facilitate comparison, we caution against considering the land use change estimates in isolation, without considering the influence of scenario design and other sectors on the land use change estimates. For example, in many of the soybean oil biodiesel trials, non-USA biodiesel consumption decreases relative to the reference case, which tends to decrease land use change emissions but tends to increase overall emissions because it is associated with greater use of refined oil.

Based on the above figure, we observe that GCAM tends to estimate higher CI for soybean oil biodiesel than corn ethanol, for both land use change and overall. The majority of overall CI estimates for corn ethanol are less than zero, meaning that over the 2020-2050 period considered, the modeled corn ethanol shock tends to result in a decrease in global GHG

[225] Boxes indicate interquartile range; whiskers indicate 5th and 95th percentiles; vertical line indicates median value. For corn ethanol, the median land use change carbon intensity is 22 gCO_2e/MJ with 95 percent interval from 2 to 48 gCO_2e/MJ. For corn ethanol, the median overall carbon intensity is -21 gCO2e/MJ with 95 percent interval from -48 to 8 gCO_2e/MJ. For soybean oil biodiesel, the median land use change carbon intensity is 53 gCO_2e/MJ with 95 percent interval from 9 to 106 gCO_2e/MJ. For soybean oil biodiesel, the median overall carbon intensity is 40 gCO_2e/MJ with 95 percent interval from -5 to 93 gCO_2e/MJ.

emissions, inclusive of reductions in refined oil consumption. Conversely, a large majority of the overall CI estimates for soybean oil biodiesel are greater than zero. The overall CI distributions for the two fuels overlap, but in every trial (i.e., each set of runs with identical parameter values) the overall CI of corn ethanol is at least 24 gCO_2e MJ^{-1} smaller than that of soybean oil biodiesel. This is explained by the fact that that the most influential parameters have the same directional effect on the CI estimates for both corn ethanol and soybean oil biodiesel. Finally, the figure shows that the interval spanning the central 95 percent of CI estimates is about twice as wide for soybean oil biodiesel relative to corn ethanol, indicating a higher level of parameter uncertainty for soybean oil biodiesel.

As part of the MCS experiment, we identified the parameters most strongly influencing the variance in GHG emissions results. We did this by computing the rank correlations between the values for each random variable and the resulting GHG emissions across all MCS trials. The rank correlations are squared and normalized to sum to one to produce an approximate "contribution to variance." In the tornado charts below, the sign of the correlation is applied after normalization. These figures show the strength of the influence of the 15 most influential input parameters on the variance in the output (GHG emissions), in descending order, with the magnitude and direction corresponding to the strength and direction of the correlation respectively. A contribution to variance further from zero indicates that the parameter is more influential. A positive contribution to variance indicates that as the parameter value increases or decreases the CI estimates tend to move in the same direction. A negative contribution to variance indicates the opposite. Following the figures, we discuss our interpretation of the findings.

Figure 9.1.1-2: Tornado chart of most the influential parameters on corn ethanol land use change carbon intensity estimates with GCAM

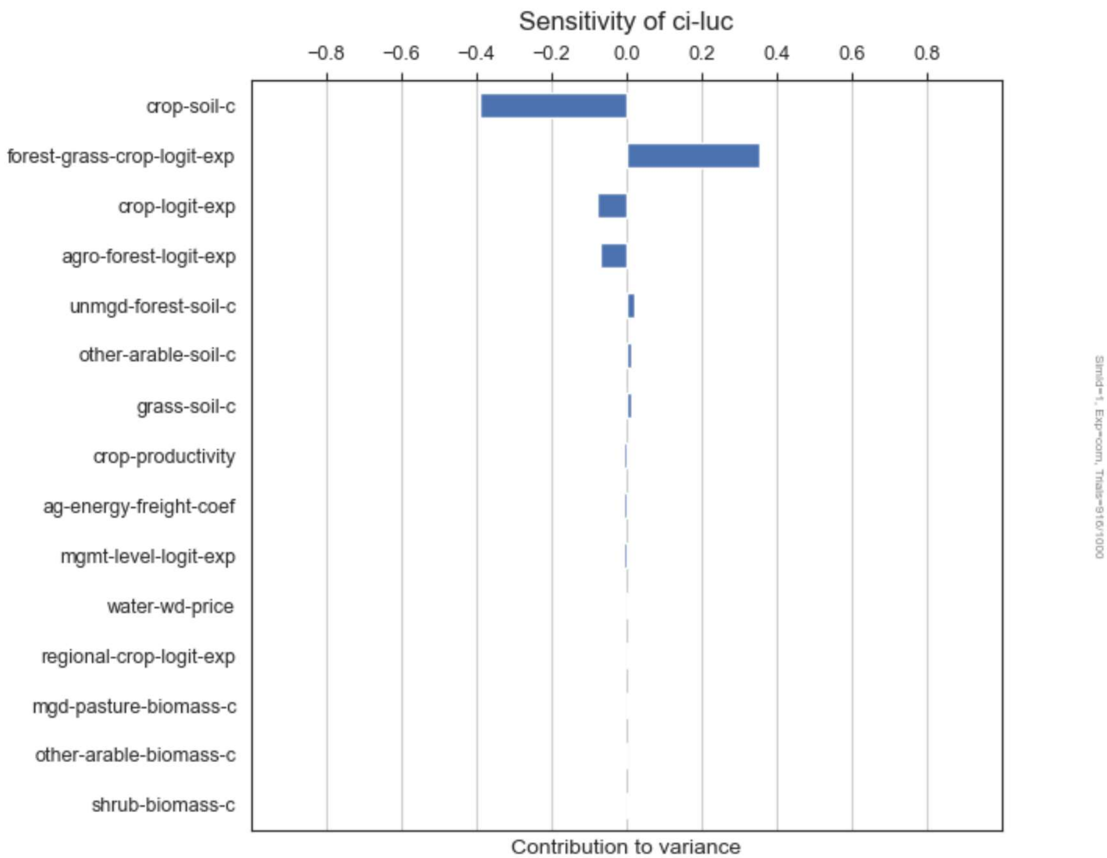


Figure 9.1.1-3: Tornado chart of most the influential parameters on corn ethanol overall carbon intensity estimates with GCAM

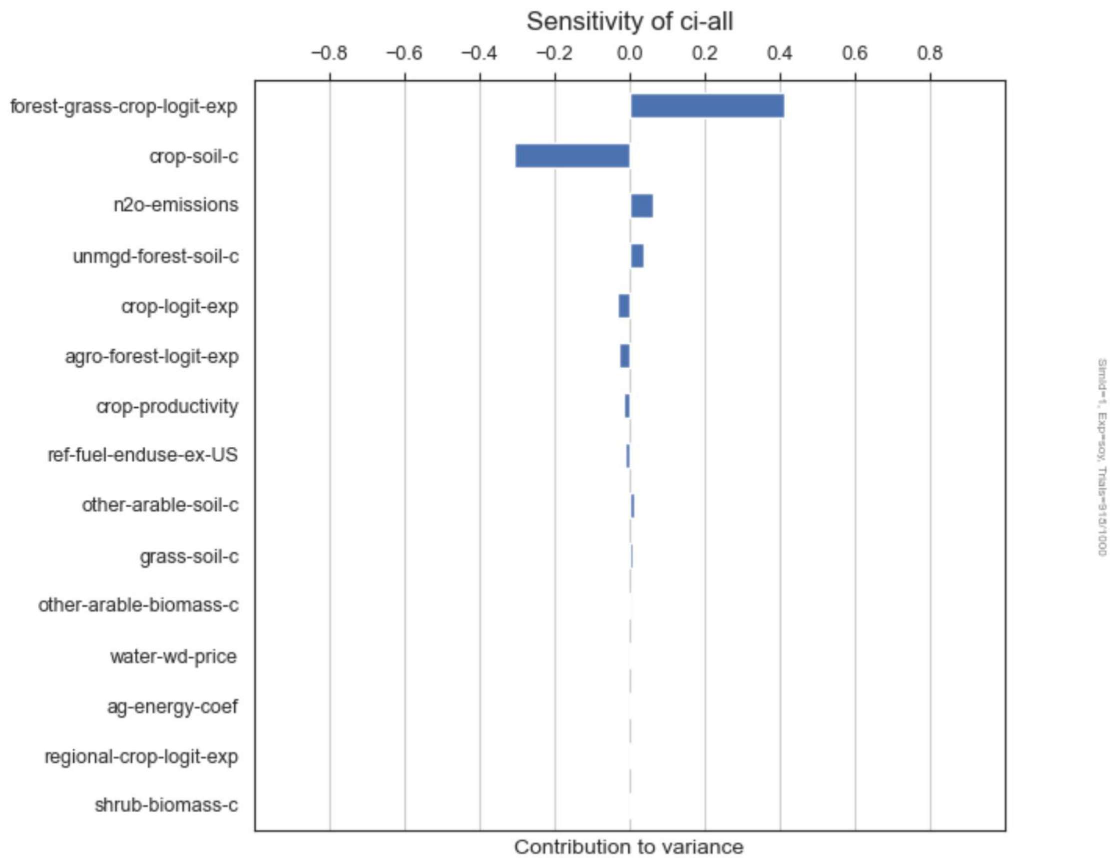


Figure 9.1.1-4: Tornado chart of most the influential parameters on soybean oil biodiesel land use change carbon intensity estimates with GCAM

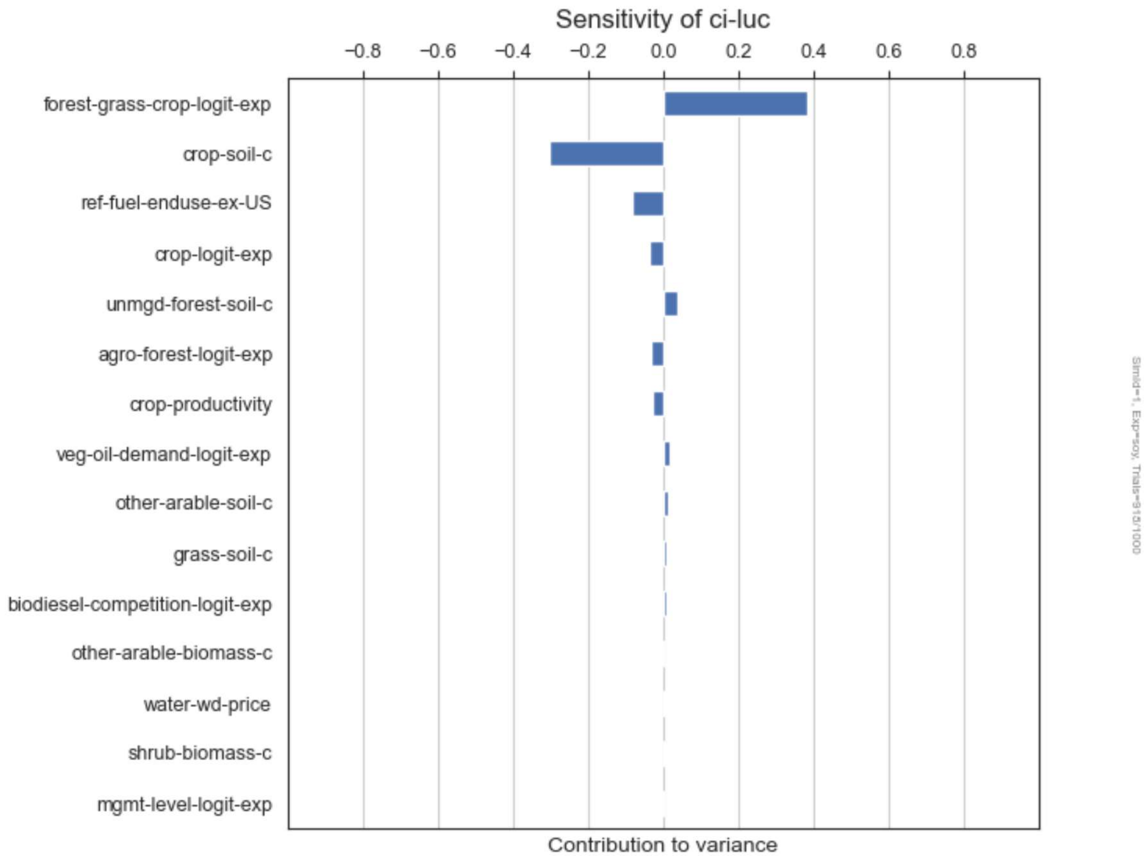
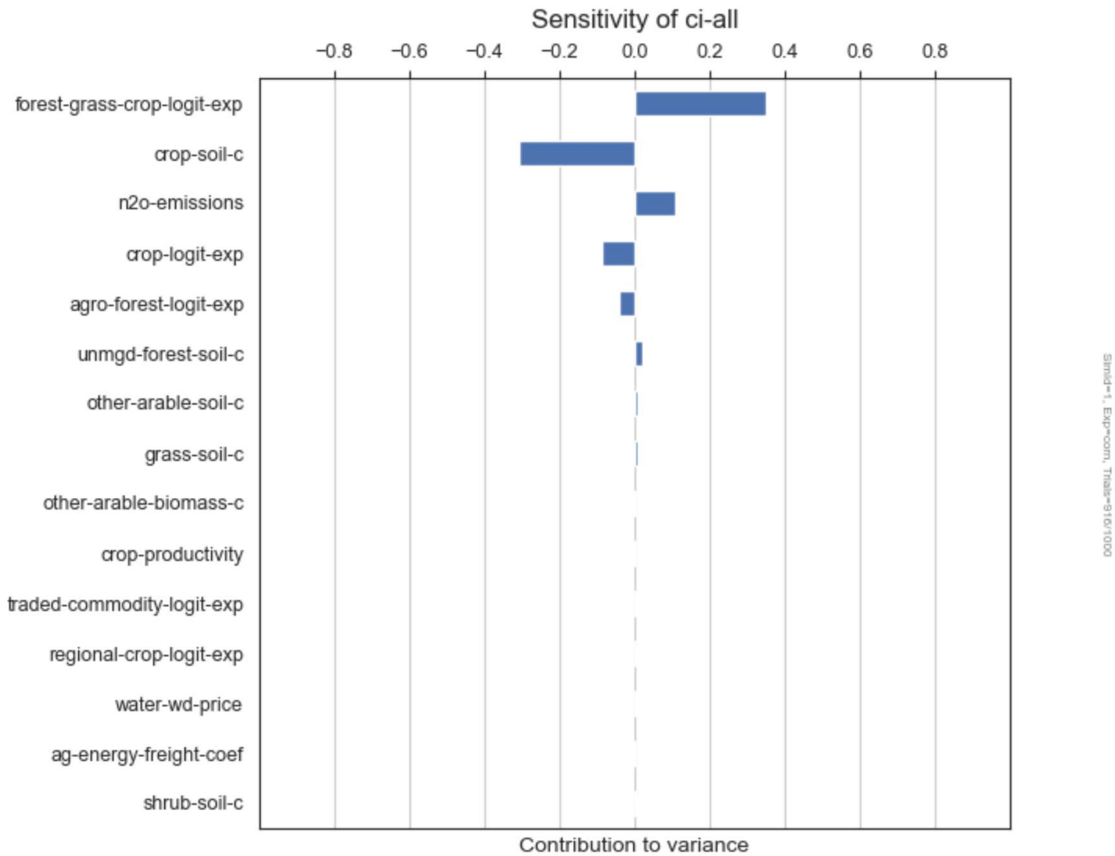


Figure 9.1.1-5: Tornado chart of most the influential parameters on soybean oil biodiesel overall carbon intensity estimates with GCAM



For overall CI, the tornado charts show that, for this MCS experiment, about 6 parameters have an outsized influence on the estimates. This does not mean the other parameters have no effect, but rather that their influence is overwhelmed by the 6 most influential parameters. The 6 most influential parameters for corn ethanol CI are also the 6 most influential parameters for soybean oil biodiesel, with minor differences in their rank order. All of the 6 most influential parameters for overall CI are directly related to emissions from land use and land use change.

For both fuels, the most influential parameter is *forest-grass-crop-logit-exp*, the parameter controlling the flexibility of competition among forest, grassland, and cropland. Higher values for this parameter mean more flexibility for price-driven land use changes among these land categories. For example, given an increase in crop prices, higher values for this parameter will translate to larger increases in crop area at the expense of grassland and forest area. This finding helps to clarify that land conversion flexibility is not only a source of uncertainty for GHG emissions impacts of biofuels between models, as we observe in Sections 6.6 and 7.6 above. It is also a source of uncertainty within models, at least for GCAM.

The other most influential parameters for both fuels are: 1) *crop-soil-c*, the soil carbon density of cropland, 2) *n2o-emissions*, the N_2O emissions intensity of agriculture, 3) *crop-logit-*

exp, the flexibility of competition among crops, 4) *agro-forest-logit-exp*, the flexibility of competition between forest, grassland, cropland and pasture, and 5) *unmgd-forest-soil-c*, the soil carbon density of unmanaged forest land.

When we look at the most influential parameters on the CI of land use change, we see almost the same group of influential parameters, but with two exceptions. First, the *n2o-emissions* parameter is absent from the tornado charts for land use change CI. N_2O emissions are an important component of crop production emissions in the GCAM results. This parameter is only absent because we define land use change CI as the projected global change in CO_2 emissions from LUC per unit of additional corn ethanol production, with both quantities summed annually from 2021 through 2050 (i.e., it excludes N_2O emission). The second exception is that *ref-fuel-enduse-ex-US* parameter shows up as one of the most influential parameters for soybean oil biodiesel land use change CI. This parameter controls substitution in supplies of refined fuel outside the USA. For example, it controls substitution between biodiesel and petroleum diesel in non-USA regions. As discussed above, in GCAM the soybean oil biodiesel shock tends to reduce biodiesel consumption outside the USA, which increases petroleum diesel consumption and requires less land for biodiesel feedstocks. Thus, higher values for *ref-fuel-enduse-ex-US* tends to result in lower land use change emissions, but increases other emissions, resulting in a small net effect on overall CI.

Overall, our MCS experiment with GCAM provides several insights. Parameter uncertainty is an important factor for CI estimates of corn ethanol and soybean oil biodiesel with GCAM. Based on this experiment, CI estimates for soybean oil biodiesel are more sensitive to parameter uncertainty than such estimates for corn ethanol. Parameters related to land use change have the most influence on CI estimates. In particular, parameters related to soil carbon densities and ease of substitution between land categories are highly influential, and thus warrant special attention.

9.1.2 GLOBIOM

We ran a Monte Carlo simulation (MCS) with GLOBIOM to explore the influence of a range of parameters on land use change carbon intensity (LUC CI) for soybean oil biodiesel.[226] The goals of the GLOBIOM MCS mirror those of the GCAM MCS discussed in Section 9.1.1; to test the behavior of the model and to evaluate the overall sensitivity of the CI estimates to variations in the input parameters.

The approach used in the GLOBIOM MCS was similar to that used in the GCAM MCS described in Section 9.1.1. We ran the MCS by applying random values drawn from distributions defined for 11 parameters. For each of two cases (i.e., a reference case and a soybean oil

[226] The GLOBIOM MCS was conducted prior to the initiation of this MCE and, as such, differs somewhat in its scenario design and assumptions. Differences between the version of GLOBIOM used in the MCE include some minor updates of corn food consumption trends to better match historic development (2010, 2020) in a number of different regions represented in GLOBIOM. The changes shift upward the food demand projections in both the reference and shock scenarios. Additionally, the shock scenario in the MCS was specified as one billion *gallons gasoline equivalent* of soybean oil biodiesel above reference case levels, whereas the shock in the MCE was specified as one billion *wet gallons* of soybean oil biodiesel consumption above reference case levels.

biodiesel shock), we ran 1,000 trials (2,000 scenario runs total). The same set of randomly drawn parameter values were used for both of the two cases.

The eleven identified parameters were chosen by GLOBIOM developers based on expert knowledge and previous research.[227,228,229] These include seven economic parameters and four biophysical parameters. The parameters and distributions used in the GLOBIOM MCS are described below in Table 9.1.2-1. Each parameter distribution below represents a set of related input values in GLOBIOM which are adjusted simultaneously based on the drawn value of the parameter in a given trial. For example, a value drawn for the parameter labeled "Demand elasticity (vegetable oils)" in Table 9.1.2-1 below is a multiplicative scalar which simultaneously adjusts the demand elasticity for each vegetable oil and each region represented in GLOBIOM.

Three of the parameters in Table 9.1.2-1 represent collections of inputs which each have independently drawn scalar values from the identical distribution. These parameter groups are indicated with bold names and described in the Description column. When accounting for these parameter groups, 72 separate values are drawn for each of 1,000 trials in the MCS.

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[227] Valin, H., D. Peters, M. van den Berg, S. Frank, P. Havlik, N. Forsell & C. Hamelinck (2015) The land use change impact of biofuels consumed in the EU. Quantification of area and greenhouse gas impacts. *Ecofys, Utrecht (the Netherlands)*.
[228] Nelson, G. C., H. Valin, R. D. Sands, P. Havlik, H. Ahammad, D. Deryng, J. Elliott, S. Fujimori, T. Hasegawa, E. Heyhoe, P. Kyle, M. Von Lampe, H. Lotze-Campen, D. Mason d'Croz, H. van Meijl, D. van der Mensbrugghe, C. Muller, A. Popp, R. Robertson, S. Robinson, E. Schmid, C. Schmitz, A. Tabeau & D. Willenbockel (2014) Climate change effects on agriculture: economic responses to biophysical shocks. *Proc Natl Acad Sci U S A*, 111, 3274-9. https://doi.org/10.1073/pnas.1222465110
[229] Valin, H., R. D. Sands, D. van der Mensbrugghe, G. C. Nelson, H. Ahammad, E. Blanc, B. Bodirsky, S. Fujimori, T. Hasegawa, P. Havlik, E. Heyhoe, P. Kyle, D. Mason-D'Croz, S. Paltsev, S. Rolinski, A. Tabeau, H. van Meijl, M. von Lampe & D. Willenbockel (2014) The future of food demand: understanding differences in global economic models. *Agricultural Economics*, 45, 51-67. https://doi.org/10.1111/agec.12089

Table 9.1.2-1: GLOBIOM Monte Carlo simulation parameter distributions[230,231]

Name	Distribution	Description
Demand elasticity (vegetable oils)	Log-uniform(0.5, 2)	Own-price and cross-price elasticities of demand for vegetable oils. Determines adjustments in food uses of vegetable oils.
Demand elasticity (animal products)	Log-uniform(0.5, 2)	Own-price and cross-price elasticities of demand for animal products (meat and dairy). Determines adjustments in food uses of animal products.
Trade elasticity (vegetable oils)	Log-uniform(0.75, 4)	Response of bilaterally traded quantities of vegetable oils to changes in market prices. Separate scalar values are drawn from identical distributions for each of the four vegetable oils represented in GLOBIOM.
Substitution elasticity (vegetable oils)	Log-uniform(0.75, 4)	Substitutability of vegetable oils for all uses, given a change in their market price. Separate scalar values are drawn from identical distributions for each of 58 different global regions represented in GLOBIOM.
Cropland and pasture expansion into natural vegetation	Log-uniform(0.5, 2)	Extent to which cropland and grazing pasture can expand into natural land uses, represented by land transition costs. Separate scalar values are drawn from identical distributions for cropland and grazing pasture.
Yield elasticity (corn and soybean)	Log-uniform(0.9, 1.1)	Changes in corn and soybean yields in response to changes in crop prices.
Yield projection (corn and soy)	Log-uniform distribution between SSP3 and SSP5 assumptions.	Exogenous yield change over time for corn in the USA region and soybeans in the USA, Brazil, and Argentina regions.
Expansion response of palm into peatland	Uniform(0.5, 1.5)	Degree of expansion of palm plantation into peatland in Indonesia and Malaysia.[232]
Peatland emission factor on undisturbed forest*	Lognormal distribution on range of 49 to 8549 tCO_2 ha^{-1} yr^{-1}	Peatland emission intensity per unit of area converted in Indonesia and Malaysia.
Emission factor for carbon sequestration in biomass on palm plantations	Normal(0.59, 1, 1.41)	Carbon sequestration (as CO_2) in palm plantations in Indonesia and Malaysia per unit of area. Range based on (IPCC 2019).[233]
Emission factors from forest biomass loss	Normal(0.5, 1, 1.5)	Emissions per unit of area due to forest clearing.

[230] **Bold parameter names** indicate related groups of parameters. Unless the parameter name includes an asterisk, the draws from the given distributions were multiplied by the GLOBIOM default values to produce values for each trial. For parameter names with an asterisk, values from the distribution were used directly, replacing the default values.

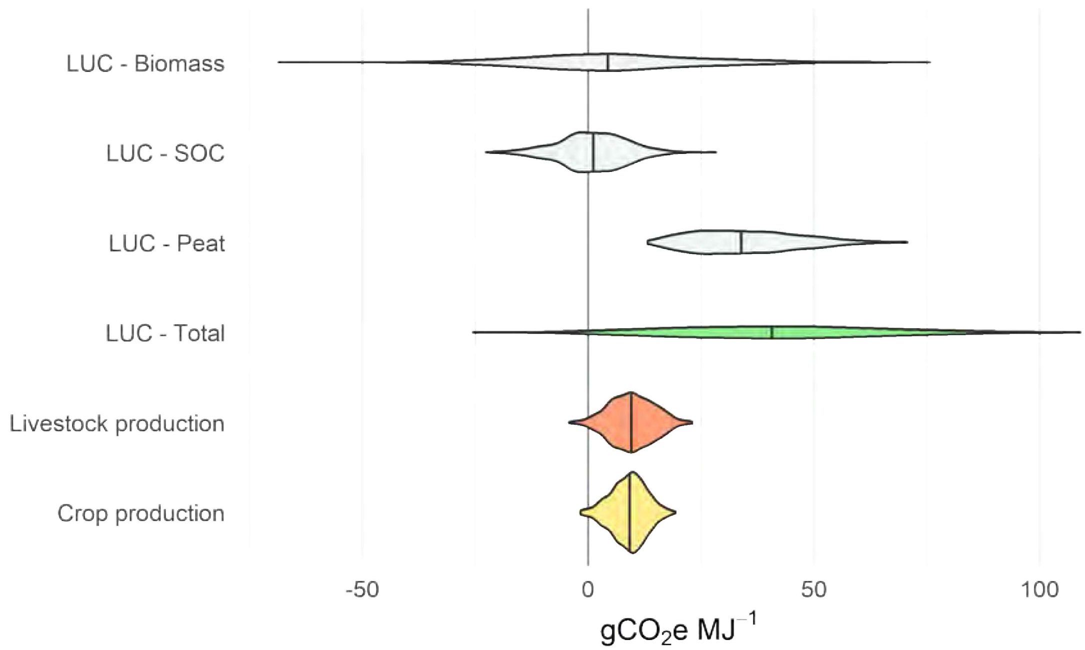
[231] Note that some of the scalar distributions in this MCS are not balanced around the central value (scalar of 1). For example, in the distribution for trade elasticity of vegetable oils (Log-uniform(0.75, 4)), roughly 17 percent of the draws would be expected to be below one, and thus decrease the value of the given vegetable oil trade elasticity, and roughly 83 percent of the draws would be expected to be above one, and thus increase that elasticity.

[232] In GLOBIOM, expansion of palm plantations is assumed to occur in peatland and non-peatland at a fixed ratio, which we adjust stochastically in this MCS analysis.

[233] IPCC. 2019. 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. Volume 4: Agriculture, Forestry and Other Land Use. Geneva (Switzerland): Intergovernmental Panel on Climate Change.

Figure 9.1.2-1 below presents distributions of carbon intensity factors for a number of different emissions categories, after excluding trials considered outliers.[234] Although the figure presents the MCS results in probabilistic terms, the actual probability of any given GHG emissions impact cannot be determined from this analysis. Our sensitivity analysis only reveals the likelihood of an outcome *given all of the inputs into our analysis*, including the version of GLOBIOM, the reference parameter values, and the distributions for the parameters evaluated. Although the figure does not tell us the actual probability of a given outcome, it provides information about the general tendency of the model and the variance of results due to parametric uncertainty.

Figure 9.1.2-1: Distributions of carbon intensities from different categories of emissions for soybean oil biodiesel based on the GLOBIOM MCS.[235]



The MCS produced a range of LUC CI results (9.5, 40.6, and 73.5 gCO_2e/MJ for the 10th percentile, mean, and 90th percentile respectively), with variation in emissions from biomass loss accounting for a substantial portion of the variability in total LUC emissions. Note that the mean value of total LUC CI for the GLOBIOM MCS is larger than the LUC CI estimate from the

[234] Outliers are identified in these results based on the so-called "1.5 rule", assuming that the distribution of emissions factors follows a normal distribution. According to this rule, a data point is considered an outlier if it is less than (Q1 - 1.5*IQR) or greater than (Q3 + 1.5*IQR), where IQR is the interquartile range and Q1 and Q3 are the first and third quartiles of the distribution, respectively. Outlier trials were identified using this rule for each of three emissions categories – total land use change, crop production, and livestock production – after which all identified outlier trials were excluded from the following results analysis. In total, 42 outlier trials were excluded using this procedure.

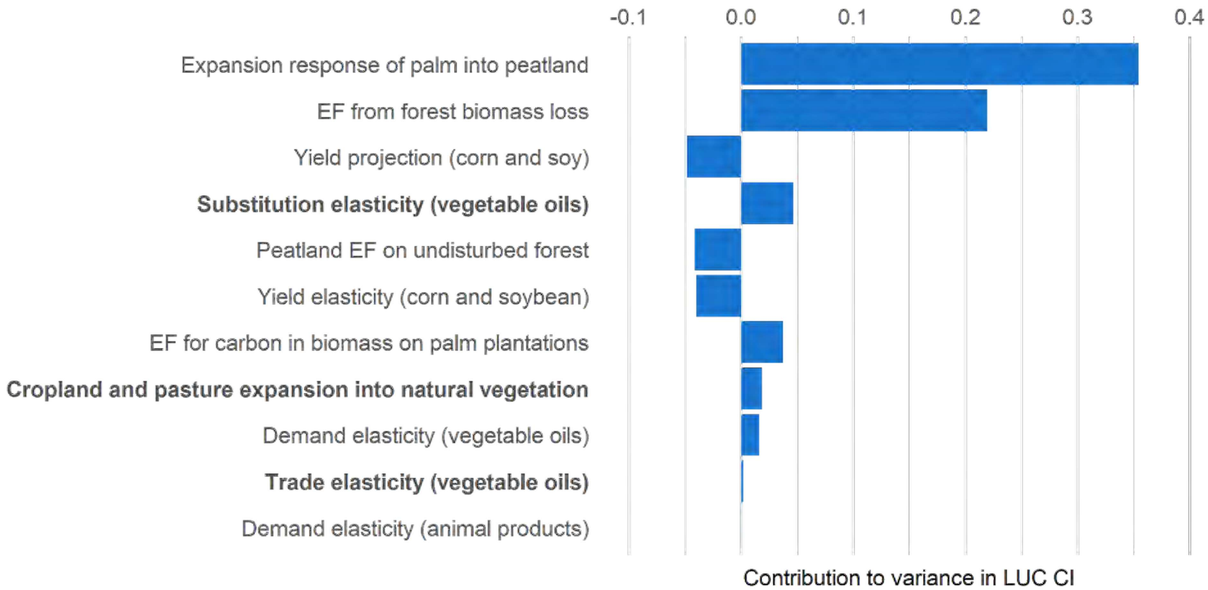
[235] Vertical lines within distributions represent mean values. "LUC – Biomass" includes emissions changes from biomass loss from land use change, changes in agricultural biomass, natural reversion of land, and carbon sequestered in harvested wood products. "LUC – SOC" emissions are land use change emissions from soil organic carbon. "LUC – Peat" emissions are land use change emission from oxidation of peatlands. "LUC – Total" is the sum of the above land use change emissions categories.

soybean oil biodiesel shock scenario in the MCE. This difference arises for two reasons; 1) the version of GLOBIOM used in the MCE was a more recent version of the model, with several updated assumptions (see footnote above); and 2) some of the distributions of scalar values applied to the parameters are weighted towards increasing the value of the parameter, which may result in more trials showing CI values on one side of the central MCS scenario than the other. This difference illustrates the limitation discussed above, but worth reiterating; distributions of CI values produced through this MCS analysis are dependent on the inputs of the analysis and should not be interpreted as representative of the probability of a given GHG emissions impact.

However, there are still meaningful observations we can make using these results. GLOBIOM's estimates of GHG emissions from land use change, particularly emissions from biomass loss but also from other subcategories of estimated LUC emissions, appear to be more sensitive to parametric variations, at least for the parameters and distributions included in this study, than estimates of emissions from livestock production and from crop production. This observation reinforces the importance of continued study of model assumptions affecting LUC and LUC CI and of considering uncertainty in LUC CI estimates.

In a process similar to that used in the GCAM MCS described in Section 9.1.1 above, we identified the parameters most strongly influencing the variance in LUC CI. We did this by computing the rank correlations between the values for each random variable and the resulting LUC CI estimate across all MCS trials. The rank correlations are squared and normalized to sum to one to produce an approximate "contribution to variance." In Figure 9.1.2-2 below, the sign of the correlation is applied after normalization. This figure shows the strength of the influence of each input parameter on the variance in the output (LUC CI), in descending order, with the magnitude and direction corresponding to the strength and direction of the correlation respectively. A contribution to variance further from zero indicates that the parameter is more influential. A positive contribution to variance indicates that as the parameter value increases or decreases the CI estimates tend to move in the same direction. A negative contribution to variance indicates the opposite.

Figure 9.1.2-2: Tornado chart of most the influential parameters in GLOBIOM MCS on soybean oil biodiesel land use change carbon intensity.[236]



The two parameters found to have the largest contribution to variance in LUC CI were the expansion response of palm into peatland and the emissions factor from forest biomass loss. The positive correlation of these parameters with LUC CI is logical; larger values of the first result in greater expansion of palm plantations into peatland in response to the increased demand for vegetable oils imposed under a soybean oil biodiesel shock. Larger values of the second increase the emissions associated with forest loss in response to the shock. The sensitivity of GHG emissions estimates to these parameters highlights the importance of further examination of all of the models' parameterizations of land transitions, carbon fluxes, and representation of peat lands.

The parameter with the third largest contribution to variance of LUC CI is the assumed yield growth of corn and soy throughout the duration of the GLOBIOM run, which is negatively correlated with LUC CI. Again, this relationship is logical; lower yield growth results in lower yields in the future, which means that producing feedstock (soybeans) to meet the shock requires additional cropland area and results in greater areas of land use change. The relative impact of this parameter highlights the importance of considering the impact of assumptions about baseline trends and how they continue into the future.

Finally, we note the relative importance (4th in Figure 9.1.2-2) of the substitution elasticity of vegetable oils. Increasing the assumed substitutability of vegetable oils allows the model to backfill more easily for deficits in soybean oil use with other oilseed oils, including

[236] For parameters which represent groups of independently adjusted model inputs (indicated in bold), the contributions to variance across all inputs within a given parameter group are summed. For all three of the grouped parameters, this results in some cancellation because the signs of the calculated contributions to variance differ among the inputs within a group. An alternative MCS design which instead used a single value applied to all model inputs within these parameter groups may be expected to increase the relative contribution to variance of these parameters.

from palm and rapeseed. This results in increased diversion of soybean oil from food and other uses. The impacts of this substitution on land use change and emissions are not straightforward, vary by region and type of vegetable oil substitution, and interact with other parameters perturbed in this MCS.[237] This complicating layer of market interaction contributes to the wider range of estimated GHG emissions impacts of soybean oil biodiesel relative to corn ethanol.

9.1.3 GREET

We worked with Argonne to develop the lifecycle GHG emissions analyses presented in Section 6.7 and Section 7.7. These analyses rely on many input values from many sources including government (e.g., USDA, EPA, DOE), academia, and industry. All these input values are subject to some level of variation and uncertainty. We worked with Argonne to conduct multiple sensitivity analyses with the GREET model[238] to explore the influence of the inputs and assumptions in the model framework on the results. This exercise allowed us to observe some of the most influential and important factors to consider for further research to address uncertainty. We conducted three sensitivity analyses, where we varied one parameter or assumption at a time, and one stochastic sensitivity analysis (Section 9.1.3.4) where we varied all of the input parameters simultaneously based on random draws from statistical distributions. Each of these analyses are described in this section.

9.1.3.1 Parameter Input Data

To support our parametric sensitivity analyses we used data that Argonne has previously collected from various sources. These data provide information about the variation in some of the key input values to GREET. For farming input data, the main source of the variation is geographic, and the source of variation for ethanol production data is differences among individual corn ethanol facilities. The value and ranges for these parameters were used in both the sensitivity and stochastic (Section 9.1.3.4) analyses discussed below. The tables below list the parameter values and their ranges for corn ethanol and soybean oil biodiesel. The tables also indicate the shape of the distribution used for each parameter for the stochastic analysis. For parameters where Argonne had a relatively large data set on variation they used a normal distribution, whereas they used a triangular distribution for parameters informed with less data on variation.

Most of the data used in support of corn ethanol sensitivities is documented in Lee et al. (2021).[239] For corn farming, that includes data from USDA datasets (National Agricultural Statistics Service [NASS], the Economic Research Service [ERS], and the Office of the Chief

[237] For example, the effect on GHG emissions of greater substitution of palm oil for soybean oil used for food and fuel production in Southeast Asia is amplified or muted by the parameters governing the expansion response of palm plantations onto peatland, emissions factors associated with forest biomass loss, and the carbon in biomass on palm plantations.

[238] Sensitivity analyses presented in this section were run using GREET-2022 for the 2021 time step. This is the default time step for the model. We decided to conduct sensitivity analyses for the 2021 time step as the data used to inform the parameter ranges is more representative of 2021 than 2030.

[239] Lee, Uisung, Hoyoung Kwon, May Wu, and Michael Wang (2021). "Retrospective Analysis of the US Corn Ethanol Industry for 2005–2019: Implications for Greenhouse Gas Emission Reductions." Biofuels, Bioproducts and Biorefining 15 (5): 1318–31.

Economist [OCE] reports). Ethanol production data relies heavily on a corn ethanol benchmarking and an agricultural consulting company that has conducted quarterly surveys of 65 dry mill ethanol facilities between 2005 – 2019 and includes ethanol yields (with corn inputs and ethanol production), energy inputs by type (natural gas, coal, and electricity), chemical inputs, and the yields of coproducts. Argonne used the 10th percentile (P10) and the 90th percentile (P90) values as the high and low bounds of the ranges for ethanol production parameters in this exercise. The full set of input parameters and their ranges for corn ethanol are shown below in Table 9.1.3-1.

Table 9.1.3-1: GREET Corn Ethanol Sensitivity and Stochastic Simulation Input Parameter Distributions for Model Year 2021

Name	Distribution[240]	Units
Farming: Corn yield	Normal (113, 178, 191)	bushels/acre
Farming: Corn yield (Nine states)[241]	Normal (153, 178, 191)	bushels/acre
Farming: N fertilizer	Normal (72, 158, 187)	lbs/acre
Farming: P fertilizer	Normal (33, 59, 89)	lbs/acre
Farming: K fertilizer	Normal (16, 60, 130)	lbs/acre
Farming: N_2O rate	Normal (0.8, 1.26, 1.6)	percent
Farming: Herbicide	Normal (0.0, 2.3, 3.2)	lbs/acre
Farming: Insecticide	Normal (0.0, 0.0, 0.2)	lbs/acre
Farming: Diesel	Normal (630,025; 927,625; 1,578,474)	BTU/acre
Farming: Gasoline	Normal (115,686; 143,155; 201,905)	BTU/acre
Farming: Natural gas	Normal (0; 85,504; 260,170)	BTU/acre
Farming: LPG	Normal (57,257; 183,004; 290,957)	BTU/acre
Farming: Electricity	Normal (72,741; 236,548; 950,459)	BTU/acre
Corn transportation distance	Normal (32, 40, 48)	miles
Ethanol: Yield	Triangular (2.7, 2.9, 3.0)	gal/bu
Ethanol: DGS yield	Triangular (3.7, 4.6, 5.5)	lbs/gal
Ethanol: Natural gas	Triangular (8,846; 22,386; 30,961)	BTU/gal
Ethanol: Electricity	Triangular (600; 2,098; 3,646)	BTU/gal

For soybean farming, the data informing the sensitivity analysis was mostly documented in Xu et al. (2022)[242] and primarily comes from USDA's National Agricultural Statistics Service (NASS) Quick Stats database.[243] Farm energy use data was obtained from USDA's ERS based on the Agricultural Resource Management Survey. The farming data covers 19 major soybean-

[240] In the parentheses, the first value is the P10 value, the middle value is the default assumption in GREET, and the third value is the P90 value.

[241] Corn is grown in many states in the United States but is primarily grown in the Midwest region across nine states. For this sensitivity analysis, we present both the fuller range of corn yields across the U.S., and this subset of nine primary corn growing states, which has a tighter range of corn yields.

[242] Xu, Hui, Longwen Ou, Yuan Li, Troy R. Hawkins, and Michael Wang. 2022. "Life Cycle Greenhouse Gas Emissions of Biodiesel and Renewable Diesel Production in the United States." Environmental Science & Technology 56 (12): 7512–21. https://doi.org/10.1021/acs.est.2c00289.

[243] USDA National Agricultural Statistics Service Quick Stats Database. Available at: https://quickstats.nass.usda.gov/

producing U.S. states. Parameter data on biodiesel production (e.g., chemical inputs, energy consumption, product yields) came from an Argonne-led industry survey conducted of biodiesel producers in 2021 with support from what was then known as the National Biodiesel Board (NBB) and is now known as Clean Fuels Alliance America as documented in Xu et al. The full set of input parameter values and their ranges for soybean oil biodiesel are shown below in Table 9.1.3-2.

Table 9.1.3-2: GREET Soybean Oil Biodiesel Sensitivity and Stochastic Simulation Input Parameter Distributions for Model year 2021

Name	Distribution[244]	Units
Farming: Soybean yield	Triangular (31.4, 50.6, 61.7)	bushels/acre
Farming: N fertilizer	Triangular (1.3, 4.9, 15.6)	lbs/acre
Farming: P fertilizer	Triangular (12.4, 23.2, 54.8)	lbs/acre
Farming: K fertilizer	Triangular (2.9, 36.8, 92.6)	lbs/acre
Farming: Herbicide	Triangular (1.5, 2.2, 3.8)	lbs/acre
Farming: Insecticide	Triangular (0.002, 0.03, 0.40)	lbs/acre
Farming: Energy use	Triangular (338,791; 694,421; 1,373,805)	BTU/acre
Biodiesel production: Methanol use	Triangular (926, 945, 964)	BTU/lb BD
Biodiesel production: Energy use	Triangular (437, 514, 592)	BTU/lb BD
Biodiesel production: Biodiesel yield	Triangular (0.133, 0.136, 0.138)	gal BD/lb oil
Oil extraction: Oil yield	Triangular (4.4, 4.6, 4.9)	dry lbs soybean/ lb soybean oil
Oil extraction: Energy use	Triangular (2,765; 3,073; 3,380)	BTU/lb oil
Biodiesel production: Glycerin yield	Triangular (0.09, 0.10, 0.11)	lb/lb BD

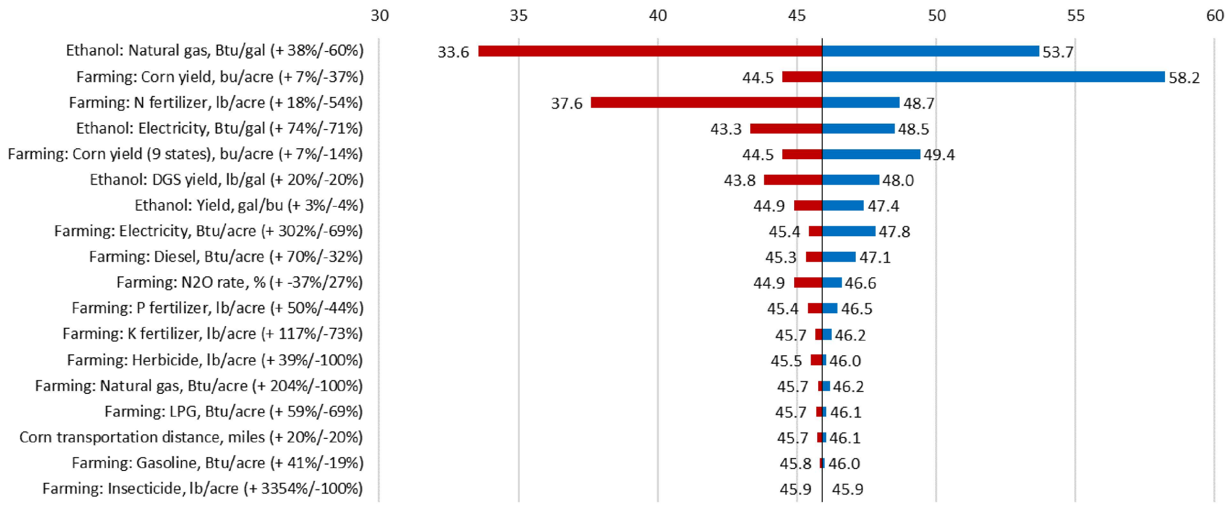
9.1.3.2 Parameter Sensitivity Scenario Analysis

The first set of parametric sensitivities presented here was developed with Argonne and assessed the modeling framework by considering variations and ranges of the key parameters shown above and their individual impacts on the carbon intensities of corn ethanol and soybean oil biodiesel produced in the United States. We conducted these sensitivity analyses by varying each major input parameter shown in Table 9.1.3-1 for corn ethanol and Table 9.1.3-2 for soybean oil biodiesel across their full range of values, each one at a time while keeping all the other parameter values constant. By varying one parameter at a time, while holding others constant, we can see the relative impact of each parameter on the final estimated LCA results. This is also informative for identifying areas of uncertainty and necessary further research. However, this "one at a time approach" provides less information than a stochastic analysis about the potential range of results stemming from parameter uncertainty. This is because one at a time analysis does not consider the effect of multiple parameters simultaneously varying from their default input values. For example, if corn yield is higher than the default input value and simultaneously the farming nitrogen fertilizer rate is actually lower than the default input value, the actual carbon intensity may be lower than any of the results depicted in the Figure 9.1.3-1.

[244] In the parentheses, the first value is the P10 value, the middle value is the default assumption in GREET, and the third value is the P90 value.

We used the parameter values in Table 9.1.3-1 for corn ethanol in GREET-2022 representing 2021 to conduct the sensitivity analysis of each individual parameter against a baseline CI value of 45.9 gCO_2/MJ derived using GREET's default assumptions (including coproduct allocation assumptions). This value excludes LUC impacts from GREET's separate CCLUB module that are discussed further below. Figure 9.1.3-1 shows the results of the sensitivity analysis for corn ethanol minus GREET's CCLUB derived LUC impacts. Parameters are ordered by their relative individual influence on the overall CI with the most impactful parameters at the top of the figure.

Figure 9.1.3-1: Sensitivity analysis results of USA corn ethanol carbon intensity values ranked by relative influence of each parameter's potential impact in GREET



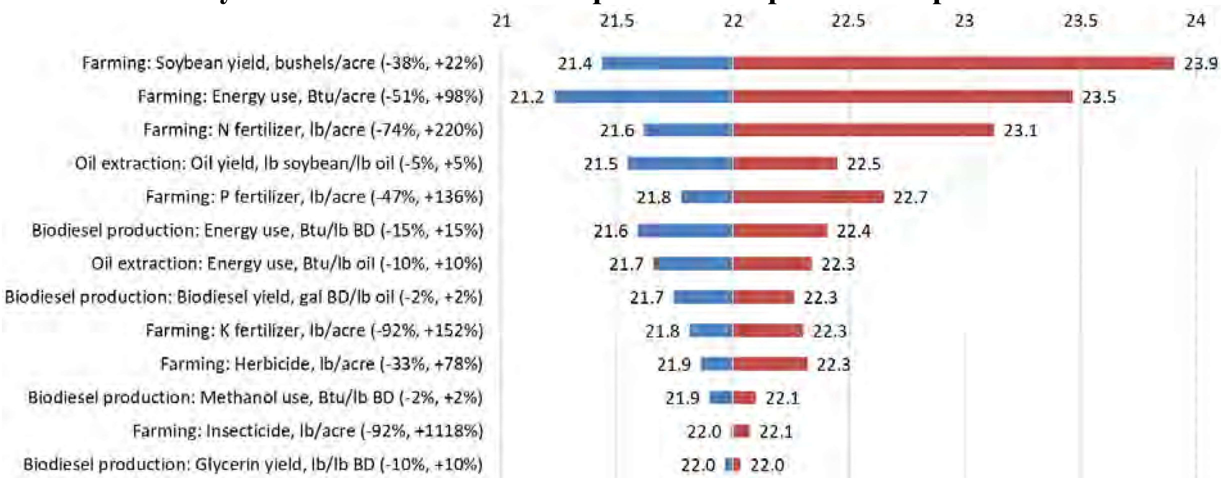
Based on the data provided, overall CI for corn ethanol saw the largest variation and influence in this exercise from the amount of natural gas used in processing and producing ethanol in facilities with a wide range of efficiencies representing a difference of roughly 20 grams of CO_2 per MJ of ethanol produced. Corn yields from farming corn was the next most important factor when considering the variation in growing corn across the country. A subset of these corn yields appears further down the list when considering only the nine states in the Midwest. These states represent the majority of corn production volume and have higher corn yields than most of the country. Corn farming and corn ethanol production do take place across many states outside the Midwest,[245] and we present both variations of this parameter for context. Nitrogen fertilizer used to obtain higher crop yields was the third highest parameter of importance in this sensitivity analysis.

We used the parameter values in Table 9.1-3 for soybean oil biodiesel in GREET-2022 representing 2021 to conduct the sensitivity analysis of each individual parameter against a baseline CI value of 22.0 gCO_2/MJ derived using GREET's default assumptions (including coproduct allocation assumptions). This value also excludes LUC impacts from GREET's separate CCLUB module that are discussed further below. Figure 9.1.3-2 shows the results of the

[245] Geographic Representation of Corn Ethanol Production Ethanol Facilities in The United States. EIA (2023). Available at: https://atlas.eia.gov/maps/3f984029aadc4647ac4025675799af90

sensitivity analysis for soybean oil biodiesel minus GREET's CCLUB derived LUC impacts. Parameters are ordered by their relative individual influence on the overall CI with the most impactful parameters at the top of the figure.

Figure 9.1.3-2: Sensitivity analysis results of USA soybean oil biodiesel carbon intensity values ranked by relative influence of each parameter's potential impact in GREET



Based on our input parameters and our GREET framework, the overall CI for soybean oil biodiesel saw the most influence from the soybean crop yields. Energy used in growing soybean on the field was the next most important factor. Nitrogen fertilizer used to obtain higher crop yields was again the third highest parameter of importance in this sensitivity analysis. There was not a wide variation of results in this exercise, and the greatest variation was in soybean farming rather than soybean oil biodiesel production but that is due in part to a limited amount of available data on variations in biodiesel production. The relatively small variation in estimates suggests that variation in the parameters tested is not a large source of uncertainty for supply chain LCA of soybean oil biodiesel. However, there are other assumptions that have a larger influence on soybean oil biodiesel LCA estimates, as discussed in the sections that follow.

With some minor differences, we saw similarities between the most influential parameters across corn ethanol and soybean oil biodiesel in this exercise. Crop yields and nitrogen fertilizer as inputs were among the most influential factors in both scenarios and had some of the largest impacts on these results based on the data provided. However, while both sensitivities included farming practices, these did not include LUC parameters.

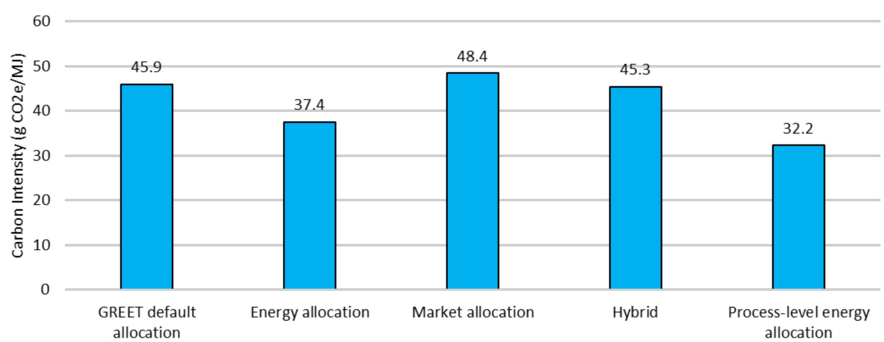
9.1.3.3 Allocation Sensitivity Analysis

Corn ethanol and soybean oil biodiesel production processes both yield biofuels as well as economically significant coproducts. Dry mill corn ethanol production for example produces distillers grains that are often used as livestock feed, and corn oil that is a vegetable oil that can be used for cooking. Both have the potential to be further processed for producing biodiesel. Similarly, soybean oil biodiesel transesterification results in coproducts such as soy meal which is high in fiber and can be used as cattle feed, and glycerin that has a range of applications across cosmetics and pharmaceuticals.

For supply chain LCA models such as GREET, these coproducts are relevant because the GHG impacts of the fuel of interest and its coproducts can be accounted for using various methods and therefore yield different GHG results depending on the allocation methods used. Allocation methods can use the economic values of the different product streams, the embedded energy content (where applicable), or physical properties such as mass. This allocation sensitivity analysis shows the variation in the CI values presented using the default input parameters and how the resulting GHG emissions can vary quite significantly depending on the LCA allocation methods selected.

For corn ethanol in GREET, Argonne uses a default displacement allocation method whereby dried distillers grains are given a coproduct credit under the assumption they will be used in place of conventional animal feeds such as corn and soybean meal. This results in the estimated default CI value of 45.9 gCO_2/MJ for corn ethanol shown in Figure 9.1.3-3, but this result can vary significantly if the allocation method used is instead based on the energy content of the ethanol and distillers grains or based on market value of the distillers grains versus the ethanol fuel (which in turn relies on constantly varying and geographically diverse market values). A hybrid method is also presented to allocate distillers grains, ethanol, and corn oil first based on the market value first, and then energy allocation is used to calculate emissions for ethanol and corn oil. The last results shown are a process-level allocation method that assigns emission burdens of individual process steps to the product that is responsible for each specific process. These last two allocation methods are further detailed in Wang et al. (2015).[246] Based on allocation method alone in this scenario, we derived a range between 32.2 – 48.4 gCO_2/MJ for corn ethanol (excluding LUC impacts).

Figure 9.1.3-3: Variations in the Carbon Intensity of Corn Ethanol Based on Various LCA Allocation Methods

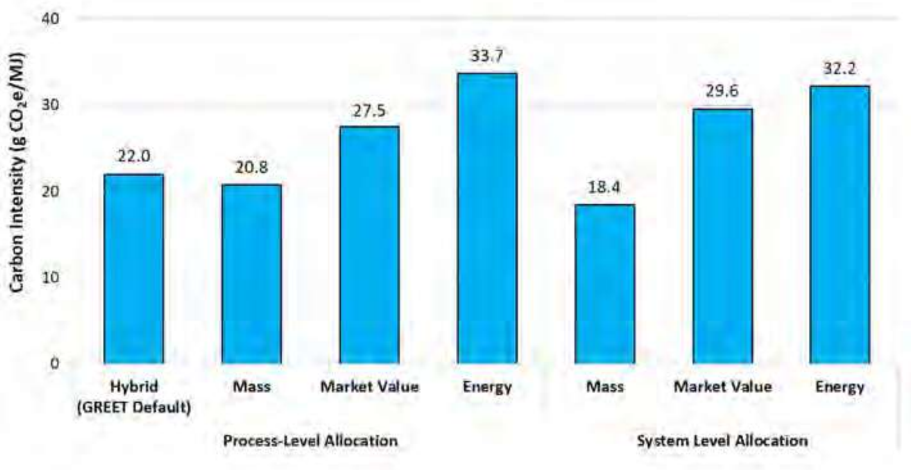


For soybean oil biodiesel, Argonne presents further delineations of LCA allocation methods used either at the *process* level (assigning the GHG impacts based on the individual steps that are involved, in this case soybean oil and soybean meal at the crushing facilities and then between biodiesel and glycerin at the biodiesel plants) or the *system* level (in this instance assigning the GHG burden across biodiesel, soy meal, and glycerin as products rather than

[246] Wang, Zhichao, Jennifer B. Dunn, Jeongwoo Han, and Michael Q. Wang. 2015. "Influence of Corn Oil Recovery on Life-Cycle Greenhouse Gas Emissions of Corn Ethanol and Corn Oil Biodiesel." Biotechnology for Biofuels 8 (1): 178. https://doi.org/10.1186/s13068-015-0350-8.

individual steps). Within each of the process- and system-level allocation methods, there are the same three methods of allocation shown for corn ethanol: mass, market value, and energy allocation. Argonne by default uses a hybrid allocation method for soybean oil biodiesel in GREET whereby mass-based allocation is used to account for the soybean meal coproduct from soybean crushing and market-based allocation is used to account for the glycerine coproduct from biodiesel production. This results in the estimated default CI value of 22.0 gCO_2/MJ for soybean oil biodiesel as shown in Figure 9.1.3-4. Based on different allocation methods alone in this scenario, we derived a range between 18.4 – 33.7 gCO_2/MJ for soybean oil biodiesel (excluding LUC impacts), exemplifying how complicated it can be to perform LCA allocation for various biofuels. This results in the estimated default CI value of 22.0 gCO_2/MJ for soybean oil biodiesel as shown in Figure 9.1.3-4. Based on different allocation methods alone in this scenario, we derived a range between 18.4 – 33.7 gCO_2/MJ for soybean oil biodiesel (excluding LUC impacts).

Figure 9.1.3-4: Variations in the Carbon Intensity of Soybean Oil Biodiesel Based on Various LCA Allocation Methods



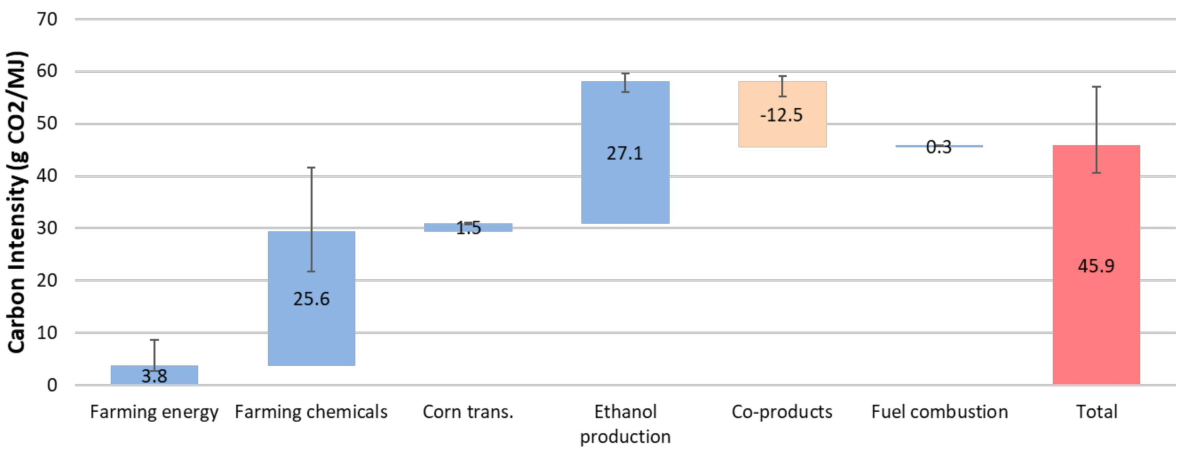
As illustrated by the figures above in this allocation sensitivity analysis section, coproduct allocation methods can have a significant impact on biofuel LCA estimates when using a supply chain LCA model such as GREET. As with the above sections, these results did not include GREET's reported LUC GHG emissions that come from CCLUB and rely on GTAP data.

9.1.3.4 Stochastic Parameter Analysis

Relying on the same parameter inputs and distributions shown in Tables 9.1.3-1 and 9.1.3-2, we also conducted a sensitivity analysis using the stochastic tool built into the GREET model. This tool allows for stochastic analyses of probable ranges of the different factors that result in the likelihood of multiple outcomes, to conduct parameter uncertainty. This stochastic tool also does not make changes to the land use change results that come from CCLUB translating GTAP data but focuses on agricultural practices, fuel production, and transportation. Therefore, the uncertainty present in LUC emissions estimates, discussed in other sections above and below, is not considered here. Because GREET operates as a static attributional LCA framework, any uncertainties in market-mediated responses to biofuel consumption in the agricultural or energy sectors is also not considered, nor are any uncertainties regarding dynamic change over time.

A probability density function (PDF) was developed for the corn ethanol pathway analyzed using the stochastic tool. GREET breaks down the corn ethanol pathway into the following steps: farming energy, farming chemicals, ethanol production, coproducts, and tailpipe fuel combustion (non-CO_2 emissions). The base values are presented along with what are known as P10 and P90 values that make up the uncertainty bars. Ninety percent of the observations in the stochastic analysis are above the P10 value, while ninety percent of observations fall below the P90 value. Figure 9.1.3-5 below shows the stochastic analysis results for corn ethanol. This stochastic analysis for corn ethanol relying on the input data provided would imply an 80 percent probability that the GREET estimate for the fuel would be between 40.7 and 57.0 gCO_2/MJ (before accounting for LUC). The greatest variation identified based on data provided came from farming chemicals used to support corn yields.

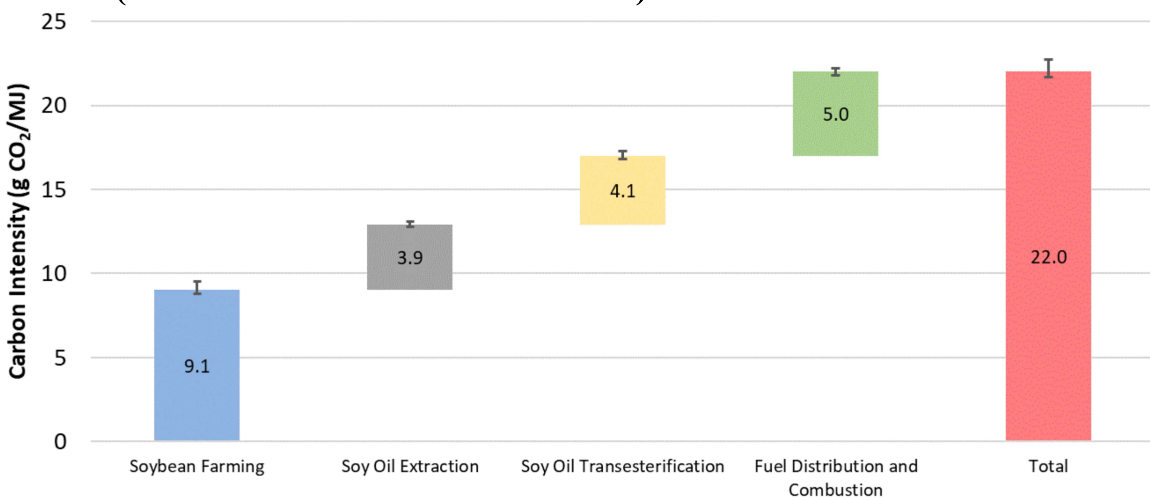
Figure 9.1.3-5: Stochastic analysis results of USA corn ethanol by lifecycle stage in GREET (whiskers indicate P10 and P90 values)



A stochastic analysis developed using GREET's stochastic tool for the soybean oil biodiesel pathway is also presented below in Figure 9.1.3-6. Categories for this pathway are broken down using the following steps: soybean farming, soy oil extraction at the biodiesel production facility, soybean oil transesterification (the process of converting the soybean oil into biodiesel), and the combined fuel distribution and tailpipe fuel combustion (non-CO_2 emissions). Again, the base values are presented along with the P10 and P90 values that make up the uncertainty bars. This stochastic analysis using the input data provided would imply an 80 percent probability that soybean oil biodiesel would have a CI between 21.5 and 22.7 gCO_2/MJ (before accounting for LUC). As with the sensitivity analysis above (Section 9.1.3.2), there was not a wide variation of results in this exercise due in part to the assumed triangular parameter values which were chosen based on the limited amount of data available to inform the distribution shapes.

This should not provide the artificial inference that there is little variation in GHGs from soybean farming and soybean oil biodiesel production but instead is an indication of potential results and an opportunity for further research. Soybean farming showed the greatest area of uncertainty, which would be likely to be even greater if the scope of these data were expanded beyond the United States. We also note that the estimates in Figure 9.1-3-6 are estimates of the average supply chain GHG emissions associated with average soybean oil biodiesel. GREET may estimate higher or lower LCA emissions for biodiesel produced from soybeans grown on a particular farm or produced at a particular biodiesel facility.

Figure 9.1.3-6: Stochastic analysis results of USA soybean oil biodiesel by lifecycle stage in GREET (whiskers indicate P10 and P90 values)



9.1.3.5 Land Use Change Sensitivity Analysis

As GREET is an attributional (or “supply chain”) LCA model that does not endogenously estimate indirect emissions such as those resulting from indirect land use change, GREET incorporates a module called the Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) to account for indirect land use change emissions.[247] CCLUB relies on a selection of land use change estimates from GTAP studies conducted between 2011–2018, and includes two corn ethanol and four soybean oil biodiesel scenarios that are described in Table 1-1 of this document. We describe the CCLUB module in greater detail in Section 2.1 of this document.

As a final parameter sensitivity analysis for GREET, we show a range of results representing variations of soil organic carbon emission factors data sets and related assumptions as options in the CCLUB module. By default, CCLUB relies on soil organic carbon emission factors from the CENTURY model developed by Colorado State University for domestic land use change calculations, and a separate dataset by Winrock International for international land use change emission calculations.[248] In our LUC sensitivity analysis, we present results using both emission factors datasets where applicable, as well as varying the soil depth considered and

[247] Kwon, Hoyoung, et al. (2021). Carbon calculator for land use change from biofuels production (CCLUB) users' manual and technical documentation, Argonne National Lab, Argonne, IL. https://greet.es.anl.gov/publication-cclub-manual-r7-2021
[248] Ibid. See details about how these emission factor datasets are developed and used in the CCLUB manual.

tillage practices. Similarly, we included results both based on assumptions about corn and soybean crop yields increasing over time or remaining static.

CCLUB includes a forest prorating factor that is meant to adjust the forest land in GTAP results to better align with the amount of accessible forest land as reported by the Cropland Data Layer (CDL), a dataset developed by USDA's National Agricultural Statistics Service.[249] Argonne accordingly applies this proration factor by region to the accessible forest land that GTAP predicts will be converted in order to satisfy land needed to meet a given biofuel shock based on a ratio of the differences between GTAP's assumed forest landcover versus what was in USDA's CDL. This results in different amounts of assumed forest land to cropland conversions and therefore LUC GHG emissions. We took the approach in this sensitivity analysis of presenting results both with and without CCLUB making this forest proration factor adjustment.

GREET's default LUC scenario for corn ethanol is referred to as "Corn Ethanol 2011" in CCLUB and is described in Taheripour et al. (2011).[250] The scenario represents an increase in USA corn ethanol production from 2004 levels (3.41 billion gallons) to 15 billion gallons (a shock size of 11.59 billion gallons). Table 9.1.3-3 presents 20 different permutations and a range of different emissions based on changing the assumptions for how CCLUB interprets this single modeled GTAP scenario for land use change representing a corn shock. Argonne's pre-selected options in CCLUB yield an estimate of 7.4 gCO_2e/MJ of corn ethanol for induced land use change, while varying the assumptions in this sensitivity analysis yields a range between 6.5 gCO_2e/MJ to 9.7 gCO_2e/MJ when relying on CENTURY emission factors for domestic LUC emissions, with the main differences coming from variations in the corn yield and tillage practices. That estimated range expands to a high value of 16.2 gCO_2e/MJ if both the domestic and international LUC emissions are based on the 2009 Winrock emissions factor data.

[249] USDA National Agricultural Statistics Service (NASS) Cropland Data Layer (CDL) is available online at: https://croplandcros.scinet.usda.gov/

[250] Taheripour, F., et al. (2011). Global land use change due to the U.S. cellulosic biofuels program simulated with the GTAP model, Argonne National Laboratory: 47.

Table 9.1.3-3: CCLUB Sensitivity Results for "Corn Ethanol 2011" Scenario by Parameter

Select Domestic Emissions Modeling Scenario	Select International Emissions Modeling Scenario	Domestic Emissions Modeling Scenario	Soil depth considered in modeling	Harvested Wood Product (HWP) Scenario	Tillage Practice for Corn and Corn Stover Production	Forest Prorating Factor	Domestic (Data Cell)	Foreign (Data Cell)	gCO_2e/MJ
Century	Winrock	yield increase	30 cm	HEATH	No Till	Yes	109.6	432.7	6.7
Century	Winrock	yield increase	100 cm	HEATH	No Till	Yes	91.5	432.7	6.5
Century	Winrock	yield constant	30 cm	HEATH	No Till	Yes	235.6	432.7	8.3
Century	Winrock	yield constant	100 cm	HEATH	No Till	Yes	245.7	432.7	8.4
Century	Winrock	yield increase	30 cm	HEATH	No Till	No	146.3	432.7	7.2
Century	Winrock	yield increase	100 cm	HEATH	No Till	No	130.9	432.7	7.0
Century	Winrock	yield constant	30 cm	HEATH	No Till	No	274.2	432.7	8.8
Century	Winrock	yield constant	100 cm	HEATH	No Till	No	287.4	432.7	8.9
Century	Winrock	yield increase	30 cm	HEATH	US Average	Yes	157.7	432.7	7.3
Century	Winrock	yield increase	100 cm	HEATH	US Average	Yes	162.4	432.7	7.4
Century	Winrock	yield constant	30 cm	HEATH	US Average	Yes	276.7	432.7	8.8
Century	Winrock	yield constant	100 cm	HEATH	US Average	Yes	307.9	432.7	9.2
Century	Winrock	yield increase	30 cm	HEATH	US Average	No	195.3	432.7	7.8
Century	Winrock	yield increase	100 cm	HEATH	US Average	No	203.5	432.7	7.9
Century	Winrock	yield constant	30 cm	HEATH	US Average	No	316.1	432.7	9.3
Century	Winrock	yield constant	100 cm	HEATH	US Average	No	351.2	432.7	9.7
Winrock	Winrock						871.1	432.7	16.2

GREET's default LUC scenario for soybean oil biodiesel is referred to as "Soy Biodiesel CARB case 8" in CCLUB and is described in Chen et al. (2018)[251] and Taheripour et al. (2017)[252]. The scenario represents an increase in U.S. soybean oil biodiesel production by 0.812 billion gallons. Table 9.1.3-4 presents eight different permutations and a range of different emissions based on changing the assumptions for how CCLUB interprets this modeled GTAP scenario for land use change representing a soybean shock. Argonne's pre-selected options in CCLUB yield an estimate of 9.3 gCO_2e/MJ of soybean oil biodiesel for induced land use change,

[251] Chen, R., Qin, Z., Han, J., Wang, M., Taheripour, F., Tyner, W., O'Connor, D., Duffield, J., 2018. Life cycle energy and greenhouse gas emission effects of biodiesel in the United States with induced land use change impacts. Bioresource Technology 251, 249–258. https://doi.org/10.1016/j.biortech.2017.12.031

[252] Taheripour, F., Zhao, X., Tyner, W.E., 2017. The impact of considering land intensification and updated data on biofuels land use change and emissions estimates. Biotechnol Biofuels 10, 191. https://doi.org/10.1186/s13068-017-0877-y

while varying the assumptions in this sensitivity analysis yields a range between 9.0 gCO_2e/MJ to 9.6 gCO_2e/MJ when relying on CENTURY emission factors alone for domestic LUC emissions, with the variations primarily again coming from assumed soybean yield and tillage practices. That estimated range expands significantly to a high value of 21.5 gCO_2e/MJ if both the domestic and international LUC emissions are based on the 2009 Winrock emissions factor data.

Table 9.1.3-4: CCLUB Sensitivity Results for "Soy Biodiesel CARB case 8" Scenario by Parameter

Domestic Emissions Modeling Scenario	International Emissions Modeling Scenario	Harvested Wood Product (HWP) Scenario	Tillage Practice for Corn and Corn Stover Production	Forest Prorating Factor	Domestic Emissions	Foreign Emissions	gCO_2e/MJ
Century	Winrock	HEATH	No Till	Yes	24.4	1,105.7	9.0
Century	Winrock	HEATH	No Till	No	53.8	1,105.7	9.2
Century	Winrock	HEATH	US Average	Yes	68.2	1,105.7	9.3
Century	Winrock	HEATH	US Average	No	98.6	1,105.7	9.5
Winrock	Winrock				1,613.7	1,105.7	21.5

Both the corn ethanol and soybean oil biodiesel LUC sensitivity analysis results show that even relying on the same LUC results from GTAP can yield significantly different emission results based on assumption differences such as the emission factors used and other key data sets or data interpretations.

We do not present results in this section with the intention of concluding what a range of potential emissions the GREET model can be for corn ethanol and soybean oil biodiesel, as that is outside the scope of this analysis. Instead, we mean to illustrate the variation in results that come from key assumptions and where the model framework demonstrates the most variation in its estimates based on those assumptions.

Across the various sensitivities we performed for GREET, corn ethanol and soybean oil biodiesel each relied on a single LUC scenario provided by GTAP and interpreted by CCLUB. While other models showed a significant variation in LUC impacts based on differing sensitivity assumptions, the *area* of LUC was held constant for GREET. Instead, these sensitivities highlighted variability associated with other assumptions. Our parameter and stochastic sensitivities demonstrated the importance to emissions that corn and soybean yields have on results and how they vary considerably across the country (they also vary over time). Data based on industry surveys also suggested that there is still a significant range of efficiencies for energy inputs both on fields and in biofuel facilities. On LCA allocation methods, we demonstrated how impactful decisions are in emissions accounting for ethanol or biodiesel versus coproducts. Similar to what is shown in the next section (Section 9.2), the soil carbon assumptions illustrated in our GREET LUC sensitivity analysis had a relatively large impact based on the datasets used to represent LUC emissions from static GTAP scenarios. Finally, some of these same areas seem important for additional research. The uncertainty around farming chemical use for example was also seen with our GCAM sensitivities.

9.2 Soil Organic Carbon Sensitivities

Land use change emissions estimation is an important component of crop-based biofuel lifecycle analysis, as demonstrated by the results we present in Sections 6.7 and 7.7. Estimates of LUC emissions from the conversion of other land types to cropland vary to some extent based on the type of land being converted. But beyond this another important area of variability is the assumed carbon density of lands and the quantity of carbon emitted or sequestered when land transitions from one state to another. The magnitude of this carbon exchange varies based on climate, soil type, vegetation type, soil microbial activity, and numerous other factors. At the time of the March 2010 RFS rule, most model soil carbon assumptions were based on field scale sampling of soils and other estimation techniques, which were then extrapolated and applied to much larger areas of land than their empirical samples covered. A small number of global satellite-based data sets, such as the MODIS-based Winrock data we used to estimate LUC emissions from the FAPRI model, also existed, but were relatively new. Over the last decade, empirical satellite-based datasets have become more numerous and sophisticated, necessitating revisitation of this area of science.[253]

We observed in Section 9.1.1 above that the GCAM results produced for this exercise are sensitive to the assumed value of soil carbon density input parameters. For the analysis described in Section 9.1.1, we stochastically varied the soil carbon and vegetation densities assumed in GCAM, with independent distributions for each land category. The sensitivity analysis described in this section is different, as it tests the influence of using different soil carbon data sources, described below, to determine the baseline soil carbon densities.

The soil carbon assumptions of GCAM rely on a simple carbon cycle model that tracks cohorts of soil and vegetation carbon over time, starting in 1750, the first spin-up year. In previous versions of GCAM, average terminal carbon stocks (above and below ground vegetative carbon and soil carbon) for each land use type were assumed exogenously based on aggregate data, not differentiated by GCAM land use region. More recently, carbon stock data acquisition and modeling capabilities have improved, and current vegetation and soil carbon stock maps can be generated using sophisticated mathematical and statistical techniques. In an additional set of runs, we tested the impacts of different soil carbon stocks on the land use change emissions in GCAM.

The GCAM results presented in the core scenarios in Sections 5-7 use globally gridded soil carbon stock data from SoilGrids 2017[254] (30 cm depth) and vegetative carbon stock data from Spawn et al. (2020).[255] SoilGrids is based on soil profile observations from the WoSIS database that have been interpolated via random forest machine algorithms to 250 m grid cells. Because GCAM represents land at a water basin level, the model needs only one carbon stock input per

[253] For more information on carbon stock datasets see: Spawn-Lee, S., "Carbon: Where is it and how can we know?" EPA Workshop on Biofuel Greenhouse Gas Modeling, 2022. https://www.epa.gov/system/files/documents/2022-03/biofuel-ghg-model-workshop-measure-map-soil-carbon-2022-02-28.pdf

[254] Hengl, T., Mendes de Jesus, J., Heuvelink, G. B., Ruiperez Gonzalez, M., Kilibarda, M., Blagotic, A., . & Guevara, M. A. (2017). SoilGrids250m: Global gridded soil information based on machine learning. PLoS one, 12(2), e0169748.

[255] Spawn, S.A., Sullivan, C.C., Lark, T.J. et al. Harmonized global maps of above and belowground biomass carbon density in the year 2010. Sci Data 7, 112 (2020).

land type, per water basin.[256] Summary statistics (the third quartile) were calculated for every land use type in each basin to represent the steady state soil carbon stock at the beginning of environmental simulation in 1700.[257]

To test the sensitivity of GCAM results to soil carbon stock assumptions, we tested GCAM using 3 additional soil C datasets, as shown in Table 9.2-1. The Harmonized World Soils Database (HWSD) uses a "paint by number" approach to categorize carbon stocks. The map was built on several different global and regional expert-informed soil databases (SOTER, ESD, Soil Map of China, WISE), built on a 30 arc-second resolution (approximately 1 km), and reprojected with a grid scale size of 250 m. Each grid cell has estimates informed from these databases, with areas lacking data filled in using machine learning estimates. In some countries, the soil boundaries are defined polygons, with the center value assumed to be the value for the entire polygon (hence the description as a "paint by number" approach). This type of map can result in distinct boundaries at political or geological boundaries.

Table 9.2-1: Soil carbon stock datasets used for sensitivity analysis in GCAM

Dataset	Method	Depth	Resolution
Harmonized World Soils Database (HWSD)[258]	Professionally derived "Paint by Number"	30 cm	30 arc-second
Food and Agricultural Organization Global Soil Organic Carbon Map (FAO GLOSIS)[259]	Combination raster of country driven soil maps	30 cm	30 arc-second
SoilGrids 2017[260]	Random forest machine learning	30 cm	250 m
SoilGrids 2020[261]	Random forest machine learning	30 cm	250 m

The FAO GLOSIS (Global Soil Information System) map is based on data collected and reported by national institutions. The countries, under the guidance of the Intergovernmental Technical Panel on Soils and the Global Soil Partnership Secretariat, used a uniform methodology with modern soil digital mapping tools to create national maps, which were then standardized to the global area. These maps were built on a 30 arc-second resolution (approximately 1 km), and reprojected with a grid scale size of 250 m. Over 63 percent of the

[256] Further description of the land allocation module in GCAM is available at: https://jgcri.github.io/gcam-doc/land.html

[257] Since GCAM requires estimates of soil carbon from 1700, and the soil data we have represents modern day, the moirai framework utilized the Q3 (third quartile) SoilGrids data, to represent a historic baseline.

[258] Wieder, W.R., J. Boehnert, G.B. Bonan, and M. Langseth. 2014. Regridded Harmonized World Soil Database v1.2. Data set. Available on-line [http://daac.ornl.gov] from Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, Tennessee, USA. http://dx.doi.org/10.3334/ORNLDAAC/1247

[259] FAO and ITPS. 2018. Global Soil Organic Carbon Map (GSOCmap) Technical Report. Rome. 162 pp. https://www.fao.org/3/I8891EN/i8891en.pdf

[260] Hengl, T., Mendes de Jesus, J., Heuvelink, G. B., Ruiperez Gonzalez, M., Kilibarda, M., Blagotic, A., . & Guevara, M. A. (2017). SoilGrids250m: Global gridded soil information based on machine learning. PLoS one, 12(2), e0169748.

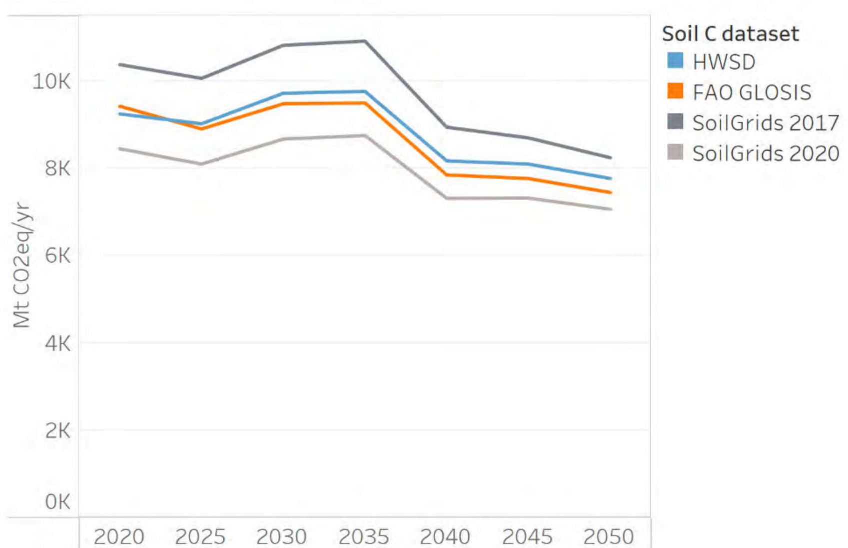
[261] Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D.: SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240, 2021.

world map is based on country submissions. Countries that did not participate were filled in using the SoilGrids 2017 map (1.9 percent of the world), and the remainder were calculated using the Global Soil Partnership Secretariat partnerships and gap filling.

SoilGrids 2020 is an update of SoilGrids 2017. The SoilGrids 2020 estimate includes more soil observations and a different set of environmental covariates than SoilGrids 2017. This created a different interpolation of the data to a 250 m grid cell level. This method is more computationally intensive than the method used for SoilGrids 2017, so the carbon stock is only available for 0-30 cm depth. One benefit of SoilGrids 2020 over SoilGrids 2017 is that the methods used to interpolate the SoilGrids 2017 map created some overestimates of SOC, especially in the far northern latitudes (60-90°N).[262] However, the soil carbon levels for the rest of the world tended to be lower than most other soil carbon mapping estimates, so both 2017 and 2020 SoilGrids maps provide different information. We include SoilGrids 2017 in our analysis because it is currently the default soil carbon dataset in GCAM v6.

In GCAM, land use change emissions are determined by the amount of land use change, the location of land use change, and the difference in carbon stock between the starting and ending land types. GCAM does not use soil carbon stock information to determine the types and locations of land that change. Therefore, the quantity and location of land use change did not vary across the runs, and differences in emissions are entirely based on differences in soil carbon stock assumptions. Figure 9.2-1 shows the global emissions from land use change in the reference case for each set of soil carbon stock assumptions. SoilGrids 2017 produces the highest emissions and SoilGrids 2020 produces the lowest emissions.

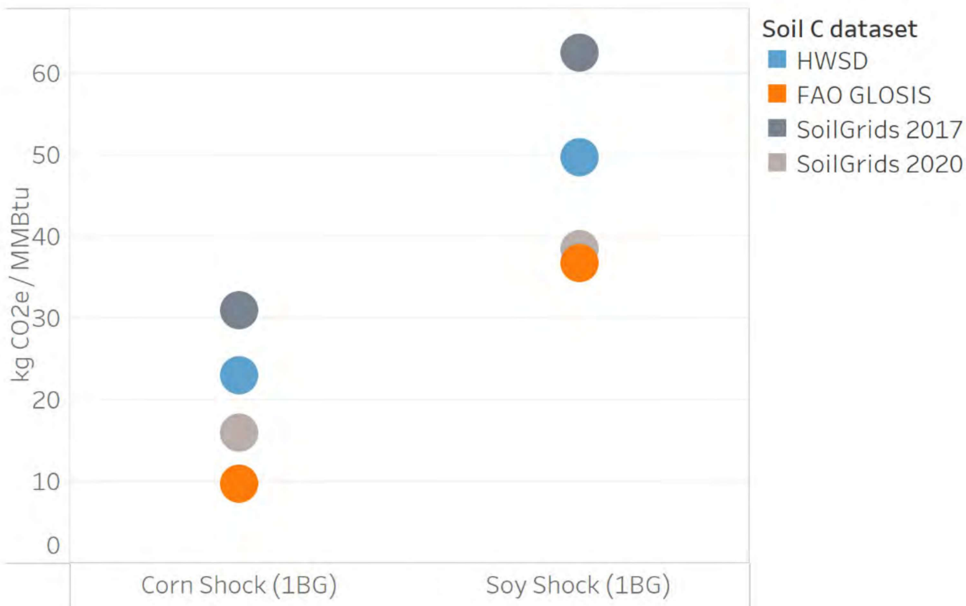
Figure 9.2-1: Global emissions from land use change in the reference case using four soil carbon datasets



[262] Tifafi, M., Guenet, B., Hatté, C. (2018), Large differences in global and regional total soil carbon stock estimates based on SoilGrids, HWSD, and NCSCD: Intercomparison and evaluation based on field data from USA, England, Wales, and France. Global Biogeochemical Cycles, 32, (1), 42-56

In Figure 9.2-2, we calculated the CI, as described in Sections 6.7 and 7.7. The CI is based on the difference between the corn ethanol or soybean oil biodiesel scenario and the reference case. The FAO GLOSIS dataset produces the lowest CI results, even though SoilGrids 2020 had the lowest LUC emissions in the reference case. This is because the corn ethanol and soybean oil biodiesel scenarios had land use change in different locations than the reference case. The CI of land use change varies greatly across the runs, from 9-31 $kgCO_2e$/MMBTU for corn ethanol and 36-63 $kgCO_2e$/MMBTU for soybean oil biodiesel. For each of the soil carbon stock assumptions, the CI from land use change is around twice as high for soybean oil biodiesel as for corn ethanol.

Figure 9.2-2: Carbon intensity from land use change emissions for the corn ethanol shock and the soybean oil biodiesel shock using a range of soil carbon datasets



We draw no conclusions here about which soil carbon data set is most appropriate to use for biofuel lifecycle analysis in GCAM or any other modeling framework. While this is a valid scientific question, it was beyond the scope and resources of this exercise. Rather, our intention is to show that the choice of soil carbon stock assumption, among commonly used datasets, can have a large impact on the modeled CI of corn ethanol and soybean oil biodiesel within a given modeling framework. Further work will be needed to explore how different soil carbon datasets impact the results of other models, and to determine which soil carbon dataset is most appropriate to use in this context.

9.3 Land Conversion Elasticity Sensitivities

In the soybean oil biodiesel results presented in Section 7, one of the major differences between the ADAGE results and the results of the other models is the emissions from land use change. We ran a set of sensitivity scenarios to determine whether changing the model parameters changes the result that a large amount of forestland is converted to cropland.

As explained in Section 2.5, the direction and magnitude of land use change in ADAGE is determined by differences in prices between land types (which are in part driven by differences in net primary production [NPP]) and fixed factor elasticities between the land types. In the results presented above, the fixed factor elasticity from pasture to cropland is the same as that from managed forest to cropland (Table 9.3-1). This means if prices of pasture and forest are equal to each other, it is equally easy to convert forest to cropland and pasture to cropland. In contrast, the fixed factor elasticity from cropland to pasture is higher than the fixed factor elasticity from cropland to managed forest, meaning that given equal prices, more cropland would convert to pasture than to managed forest. In these scenarios, because of assumptions of NPP declining for forest and rising for pasture over time in key non-USA soybean-producing regions, the price of managed forest declines while the price of pasture rises. Since the fixed factor elasticity of converting these two land types to cropland is assumed to be equal, more of the lower cost land, i.e., managed forest is converted in non-USA regions in these results.

Table 9.3-1: Fixed factor elasticity between land types in ADAGE core scenarios

Land Conversion		**From**				
		Cropland	Pastureland	Managed Forestland	Natural Forestland	Grassland
To	Cropland		0.26	0.26		
	Pastureland	0.3				0.02-0.509
	Managed Forestland	0.15			0.02-0.509	
	Natural Forestland	0.15		0.15		
	Grassland	0.15	0.15	0.15		

Note: Elasticity values for agricultural lands converting to other land types are assumed to be the same for all regions. Elasticities for natural land conversion to agricultural land vary by region and range from 0.02 to 0.509.

We conducted a sensitivity analysis on the fixed factor elasticities between land types to assess the impact of making it more difficult to convert forest to cropland than pasture to cropland. The alternative elasticity values used in this sensitivity analysis are shown in Table 9.3-2. In this sensitivity, the fixed factor elasticities from pasture/managed forest to cropland were swapped with the fixed factor elasticities from cropland to pasture/managed forest. In this scenario, the fixed factor elasticity from pasture to cropland is twice as large as the fixed factor elasticity from managed forest to cropland, making it easier to convert pasture than forest to cropland.

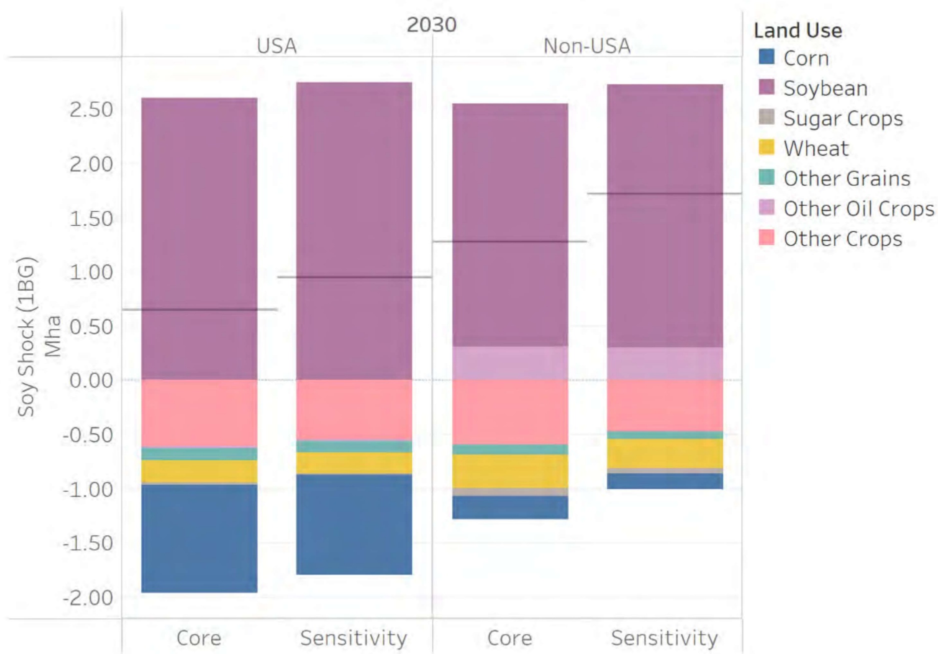
Table 9.3-2: Fixed factor elasticity between land types in ADAGE sensitivity runs

Land Conversion		From				
		Cropland	Pastureland	Managed Forestland	Natural Forestland	Grassland
To	Cropland		0.3	0.15		
	Pastureland	0.26				0.02-0.509
	Managed Forestland	0.26			0.02-0.509	
	Natural Forestland	0.15		0.15		
	Grassland	0.15	0.15	0.15		

Note: Elasticity values for agricultural lands converting to other land types are assumed to be the same for all regions. Elasticities for natural land conversion to agricultural land vary by region and range from 0.02 to 0.509.

We focus on the results of the soybean oil biodiesel scenario. As shown in Figure 9.3-1, the new runs ("Sensitivity") have more additional soybean cropland than the runs described in Section 7 ("Core"). In the sensitivity runs, the soybean yield does not increase as much as in the core runs, so more cropland is needed to produce soybeans for biodiesel. The sensitivity runs also show a greater increase in total cropland. There is less shifting of land from other crop types to soybean.

Figure 9.3-1: Difference in cropland area by crop type (million hectares) in the soybean oil biodiesel shock relative to the reference case in 2030 for the original ADAGE runs ("Core") and the fixed factor elasticity sensitivity runs ("Sensitivity")[263]



In the sensitivity runs, there is a large change in the type of land converted to cropland, relative to the core runs (Figure 9.3-2). In the USA region, managed pasture is still the primary

[263] Horizontal lines show the net change in cropland.

land type that is converted to cropland. However, in the non-USA regions, land is converted from pasture and grassland rather than forest. Even though prices and production of the land types did not change in this sensitivity, decreasing the land conversion elasticity of forest to cropland resulted in a large reduction in the amount of forest conversion.

Figure 9.3-2: Difference in land use (million hectares) in the soybean oil biodiesel shock relative to the reference case in 2030 for the original ADAGE runs ("Core") and the fixed factor elasticity sensitivity runs ("Sensitivity")

As a result of the change to the land conversion elasticity, the estimated CI from land use change decreased substantially, from 295 $kgCO_2eq/MMBTU$ to 33 $kgCO_2eq/MMBTU$ (Table 9.3-3). In the sensitivity runs, there is more total land use change, but much less emissions from land use change. This emphasizes that the type of land converted and the carbon stock of the converted land plays a major role in the emissions from land use change.

Table 9.3-1: Carbon intensity of soybean oil biodiesel and corn ethanol ($kgCO_2eq$/MMBTU) calculated using emissions reported by each ADAGE run

		Soybean oil biodiesel		Corn ethanol	
		Core	Sensitivity	Core	Sensitivity
Sector - specific emissions	Energy Sector	-28	-30	-15	-17
	Crop Production	7	8	14	14
	Livestock Sector	0.7	0.7	0.1	0.1
	Other	1	1	1	1
	Land Use Change	295	33	-1	-1
Totals	Agriculture, forestry, and land use	303	41	14	14
	Global GHG Impact	276	12	-1	-3

The corn ethanol sensitivity scenario similarly shows less corn yield increase than the core corn ethanol scenario, and more additional cropland. However, the core corn ethanol scenario results in conversion of pasture to cropland, and this does not change in the sensitivity. The estimated CI for the corn ethanol scenarios are shown in Table 9.3-3. The land use change CI in the sensitivity is similar to the core run.

These results illustrate the importance of considering land parameter assumptions in the models. We do not make conclusions here about which of these sets of results is more correct. Rather, these results show that if there are assumptions in a model that allow more forest to be converted in a biofuel scenario, then the emissions can be much higher. Future work could explore whether there are other similarly important parameters in the models. For cases where data are not available to set a parameter value (as is often the case for elasticity values), future work could involve developing methods to use historical data to inform the choice of parameter value.

9.4 Summary of Parameter Sensitivities

In this section we discussed the results of five sensitivity experiments testing the influence of parameter input values on biofuel GHG impact estimates, including stochastic analyses of GCAM, GLOBIOM, and the GREET model, a separate soil organic carbon sensitivity analysis of GCAM, and a land conversion elasticity sensitivity of the ADAGE model.

Stochastic parameter experiments with GCAM indicate the assumptions relating to soil carbon stocks, the ease of substitution between land and crop types, and the N_2O emissions intensity of agriculture are influential parameters for corn ethanol and soybean oil biodiesel GHG impact estimates. The parameter controlling substitution between the non-USA regions refined oil and biodiesel is also influential for the soybean oil biodiesel GHG estimates.

A similar stochastic experiment with GLOBIOM considering only soybean oil biodiesel GHG impact estimates finds that a different set of parameters are the most influential. For example, the GLOBIOM experiment finds biomass carbon stock assumptions to be influential, whereas these assumptions were not identified as influential by the stochastic GCAM experiment. Other parameters that registered as influential in the GLOBIOM stochastic experiment but not in the GCAM stochastic experiment include assumptions related to tropical peat soil, substitution between vegetable oils, and yield elasticities for corn and soybeans.

The land conversion elasticity sensitivity experiment with the ADAGE model finds that land use change GHG estimates for soybean oil biodiesel are highly sensitive to the assumed fixed factor elasticities for forest and pasture to cropland. These results indicate that parameter influence on biofuel GHG impact estimates is model dependent, i.e., a set of parameters that is influential in one model may not be influential in another model.

The stochastic analyses conducted with the GREET model, using a specific set of assumed parameter uncertainty distributions, suggest that supply chain LCA estimates for corn ethanol are more sensitive to parameter input values than such estimates for soybean oil biodiesel. Scenario sensitivity analyses with the GREET model indicate that corn ethanol and soybean oil biodiesel estimates are more sensitive to coproduct allocation choices and assumptions related to land conversion GHG emissions factors.

A parameter sensitivity analysis with different soil carbon datasets in GCAM indicates that the initial steady state soil carbon conditions have a relatively large influence on land use change GHG estimates. This suggests that estimates from the same model are likely to change over time as science evolves and new data sets become available.

10 Summary of Findings and Future Research

Through this model comparison exercise, we aimed to move the science forward on analyzing the lifecycle GHG impacts of the increased use of biofuel, understand model differences, and examine how those differences impact model results. As described in Section 1, this effort is consistent with recommendations from the NASEM report, "Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States," which emphasizes the importance of comparing results across multiple economic models and considering uncertainty.[264] The detailed results and insights from this model comparison exercise are explained in the sections above. This section summarizes our main findings, including areas of similarity and difference across the models considered in this exercise, and potential areas for future research.

[264] NASEM recommendation 4-2: "Current and future LCFS [low carbon fuel standard] policies should strive to reduce model uncertainties and compare results across multiple economic modeling approaches and transparently communicate uncertainties." NASEM recommendation 4-3: "LCA studies used to inform policy should explicitly consider parameter uncertainty, scenario uncertainty, and model uncertainty." National Academies of Sciences, Engineering, and Medicine 2022. Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States. Washington, DC: The National Academies Press. https://doi.org/10.17226/26402.

Some of these observations and findings are relevant only to certain models, based on their characteristics and areas of coverage. As explained throughout this document, not every model considered in this study includes all sectors of the economy or all types of interactions discussed in this section. For example, we do not discuss GREET in any of our findings related to economic interactions, nor do we discuss GREET and GLOBIOM in any of our findings related to the energy sector. Models that are not listed in the findings of each subsection in this summary do not model the features described in that subsection.

Framework Differences

Supply chain LCA models produce a fundamentally different analysis than economic models. Supply chain LCA models generate detailed and transparent fuel production emissions estimates. However, they do not evaluate all the indirect emissions associated with a change in biofuel consumption. The economic models in our comparison are broad in scope, but they lack certain supply chain details and are associated with greater variability. Their complexity makes it difficult to identify the precise reasons that estimates vary across the models.

The emissions impacts observed in this exercise do not remain static over time in frameworks with the ability to model dynamic change. The dynamic models considered in this exercise, ADAGE, GCAM, and GLOBIOM, all agree that land use, crop production, livestock markets, and energy markets would all be expected to adjust over time in response to a biofuel shock, with cascading impacts on GHG emissions. **Dynamically modeling the impacts of biofuels over time results in different model solutions for GHG emissions than what would be predicted by more simply extrapolating results in a single time step forward through post hoc estimation**. We make no conclusions about whether dynamic or static models are more appropriate for different applications, but it is important to address the fact that they arrive at different conclusions and to robustly consider the time period used for biofuel LCA modeling.[265]

Land Use Change and Emissions

Land use change and associated emissions magnitudes vary across the range of scenarios presented in this exercise. Results between models show differences in the types of land which transfer into cropland status between the reference and biofuel shock scenarios. Our Monte Carlo and land conversion elasticity parameter sensitivity analyses show that these estimates can also vary within individual models, depending on the parameter assumptions used. There are several important factors in explaining these differences in LUC estimates among and within models. Models use different economic equations, mathematical decision frameworks,[266] and assumptions to estimate which types of land to convert, in what quantities, and in which regions. The quantities and location of LUC intersect with the global commodity market dynamics discussed above. Differences in mathematical representations of LUC may lead to model results which convert primarily one type of land or, conversely, results which spread the LUC impact

[265] It is also important to consider the model reference case assumptions, including model projections into the future. The parameter sensitivity analyses discussed in Section 9 suggest several concrete examples, such as the projection of future crop yields, which critically influence model results.
[266] For example, ADAGE and GTAP use a CES structure, GCAM uses logit nests, and GLOBIOM uses a global gridded system.

across multiple land types. Neither of these strategies necessarily leads to higher or lower LUC emissions relative to the other. For example, the ADAGE modeling results demonstrate that concentrating LUC to one type of conversion may lead to relatively larger LUC emissions estimates (as shown in the soybean oil biodiesel results) or relatively smaller LUC emissions estimates (as shown in the corn ethanol results). Within models, our sensitivity analyses demonstrate that input parameter assumptions, such as those described in Sections 9.1.1 and 9.3, may alter economic decisions and thus affect which land types are selected for conversion. This model comparison and the associated sensitivity analyses have indicated that assumptions about the ease of land substitution, especially from carbon-rich lands, remain a critical area of uncertainty in biofuel LCA modeling. Future modeling efforts should robustly quantify this uncertainty using either the types of methods described in this exercise or other rigorous methods. **This exercise highlights that inclusion of land use change emissions is critical for biofuel lifecycle analysis and that frameworks must have the ability to robustly quantify uncertainty in land use change and LUC emissions**.

Further, spatial resolution in the land sector varies substantially across models and this affects the scale at which economic land conversion decisions are made. This major area of difference among models is critically tied to the scope of each model and the associated computational burdens of land use modeling. It is unlikely that the CGE models, which must necessarily resolve equations for more economic sectors, can achieve the spatial resolution present in PE models and IAMs. However, the uncertainties created by coarser spatial resolution may be quantifiable through targeted uncertainty analysis. Uncertainty also still exists at the resolution represented by PE models and IAMs given that these LUC results are necessarily estimates of the sum of economic decisions made by multiple actors. We conclude that **there is no one correct level of spatial resolution for biofuel LCA modeling. Sensitivity and uncertainty analysis will be critical at all scales.**

The economic models included in this exercise also restrict land conversion to varying degrees, and the differences in assumptions across models are especially large for the most carbon-rich arable lands (i.e., natural forests and grasslands). However, these assumptions are also uniformly exogenous and previous literature has demonstrated that, to at least some extent, they can be aligned across modeling frameworks. Future research could explore this space and test whether LUC estimates across models become more similar when similar categories and quantities of lands are available for conversion to cropland.

Additionally, the models use different assumptions about the carbon stocks of the different land types, resulting in different emissions from land use change. A sensitivity analysis using GCAM shows that when different soil carbon stock assumptions are used, there are large differences in the resulting land use change emissions, even though the type and amount of land converted is the same in each run. The stochastic parameter sensitivities conducted with GCAM, GLOBIOM, and GREET also demonstrate that assumptions about soil carbon exchange from LUC may substantially impact emissions results. **Addressing variability and uncertainty in soil carbon content globally and regionally will be critical to future biofuel LCA efforts.** A potential area for future research is to align carbon stock assumptions across multiple models to better understand the relative impacts of land use change amount/type and carbon stocks on land use change emissions.

Energy Market Impacts

The models that include energy market impacts (ADAGE, GCAM, and GTAP) all estimate significant indirect effects on fossil and/or bio-based energy consumption in the USA and non-USA regions in both the corn ethanol and soybean oil biodiesel shocks. The results from these models are in broad agreement that global displacement of refined oil[267] consumption due to the increase in biofuel consumption is estimated to generate net global energy emissions savings. However, the amount of refined oil displaced globally was not equal to the increase in biofuel consumption on an energy basis (i.e., a 1:1 displacement). This finding has broad relevance to biofuel LCA because modeling efforts using frameworks which do not include an energy sector generally assume 1:1 displacement by default. All three models in this study with energy sectors show smaller global refined oil savings than would be expected from a 1:1 displacement. There are some directional differences regarding the impact in the USA region. The ADAGE and GTAP results show less domestic refined oil displacement than would be expected from a 1:1 displacement, while the GCAM results show more domestic refined oil displacement than would be expected from a 1:1 displacement. However, the larger driver of the global result is refined oil and biofuel consumption in the non-USA regions. Non-USA refined oil consumption increases in the results from each of these models as a result of the shock. In ADAGE and GCAM, there are significant changes in non-USA biofuel production and consumption as well. In the ADAGE soybean oil biodiesel scenario, the non-USA regions collectively produce more biodiesel and consume less of it, exporting that fuel to the USA region instead. This reduced biodiesel consumption increases demand for fossil fuels. The increased production is associated with agricultural sector emissions. The GCAM results show impacts on non-USA biofuel production and consumption as well, particularly sugar crop ethanol in the corn ethanol scenario, and soybean oil biodiesel in the soybean oil biodiesel scenario. These results also show substantial changes in biofuel trade to and from the USA region in response to the shocks. The results across all three models collectively indicate that **the assumption of 1:1 displacement of refined oil for biofuel may be insufficient to capture the energy sector impacts of biofuels; consequential modeling of the energy sector is an appropriate methodology for capturing these impacts**.

This insight illustrates the importance of including indirect energy market impacts in a modeling framework. The ADAGE, GCAM, and GTAP results consistently indicate that the assumption of a 1:1 refined oil displacement may be an overestimate of global fossil fuel emissions savings. This becomes a crucial issue for biofuel lifecycle analysis, firstly, because smaller fossil fuel emissions savings increase the estimated emissions intensity of the biofuel being modeled and, secondly, because increased non-USA production of biofuels is associated with emissions as well. However, further sensitivities would be needed to better understand the driving factors behind the differences in the fossil fuel displacement across the models.

Global Trade

Global trade plays an important role in modeled emissions results from both the land and energy sectors of these frameworks. Model results from the economic models considered in this

[267] In these models, refined oil is an aggregation of all refined petroleum products, including gasoline and diesel.

exercise consistently demonstrate that biofuel shocks can impact agricultural commodity trade and energy trade in important ways. These include impacts on trade in refined oil and biofuels, soybean meal and DDG feed products, and vegetable oils, among others. These changes in terms of trade lead to differences in the energy emissions savings estimated by the models as well as differences in the quantity of non-USA land use change estimated by the models. There is general agreement among the economic models that these trade-driven impacts will occur to some degree. However, despite the uniform agreement on the importance of trade-driven impacts across the economic models included in this exercise, these models show different degrees of trade responsiveness, which leads to results of differing magnitudes. **Model trade structure and assumed flexibility critically influence the modeled emissions results.**

Commodity Substitutability

A second key factor, intertwined with trade, is commodity substitutability. Results in this exercise from ADAGE, GCAM, GLOBIOM, and GTAP align in estimating commodity substitution as a significant part of their scenario solution. As our sourcing analyses in Sections 6.1 and 7.1 above demonstrate, the degree to which this substitution occurs varies across models. However, results from all of the models support two overarching findings: first, that estimates of indirect GHG impacts are sensitive to whether and how substitution interactions are considered and, second, that uncertainty in the ease of commodity substitution at different price points must be considered. Key interactions include the substitutability of: biofuels for fossil fuels, one biofuel for another, DDG and soybean meal for other feed products, and soybean oil for other vegetable oils. Our modeling exercise has demonstrated that **these commodity substitutability relationships critically impact overall GHG emissions results from biofuel LCA modeling**. We summarize these critical impacts further below.

Crop and Coproduct Consumption by End Use

The results of the corn ethanol and soybean oil biodiesel scenarios also show significant effects on end uses of biofuel feedstocks and coproducts across ADAGE, GCAM, GLOBIOM and GTAP, most notably effects on corn, DDG, and soybean meal animal feed use and soybean oil food use. In the corn ethanol scenario, the model results consistently show a decrease in corn consumption for feed use and an increase in DDG consumption. However, the model results differ crucially in their estimates regarding the location of DDG consumption (i.e., USA vs non-USA regions) as well as the degree of displacement of other types of feed. Similarly, in the soybean oil biodiesel scenario, the model results show an increase in soybean meal[268] production and use for feed. The models all estimate this influx of soybean meal will lead to a global increase in feed use on a mass basis. However, the models differ regarding the location of soybean meal production and the degree of displacement of other types of feed. Increased use of DDG or soybean meal for feed can result in lower land use change emissions if these coproducts displace crops for feed use. On the other hand, increased use of DDG or soybean meal for feed can result in higher livestock sector emissions if their use causes an increase in total feed use, rather than replacing other types of feed. Exploring the emissions impact of DDG and soybean meal consumption location on overall GHG results is a potential area of future research, and one which is closely related to further research into model commodity trade behavior more generally.

[268] In ADAGE, the soybean meal is included in the aggregated "other oil seed meal" category.

It is clear however that **explicit modeling of the global livestock sector, including global feed markets, is an important capability for estimating the emissions associated with an increase in biofuel consumption**. Modeling efforts which do not include these economic dynamics exclude both critical drivers of overall GHG emissions and critical sources of uncertainty in GHG modeling results.

In the soybean oil biodiesel scenario, the models differ in the amount of food displacement. ADAGE results do not show any impact on food consumption. On the other hand, GCAM, GLOBIOM, and GTAP results all show a decrease in the amount of soybean oil used for food. In the GTAP results, a very small amount of the soybean oil is replaced by other oils; these results also show an overall reduction in crops consumed for food. GTAP results also show a decrease in soybean oil used for other uses (e.g., processing into other products) that is not replaced by other oils. In the GCAM and GLOBIOM results, there is also a decrease in soybean oil for food use. However, a major difference between these results and the GTAP results is that the GCAM and GLOBIOM results show much greater replacement of soybean oil in the food market with palm oil, rapeseed oil, and/or other crop oil, whereas the GTAP results show very little replacement of soybean oil with other oils. The degree of substitution varies between GCAM and GLOBIOM, with GLOBIOM results showing a net decrease in consumption of crops for food, and GCAM results showing a nearly net zero change in consumption of crops for food. Substitution of soybean oil with other oil types could result in a reduction of land use change emissions from soybean production because less new soybean oil production is needed for the biofuel shock. However, substitution of soybean oil with other vegetable oils could also result in increased emissions from land use change.[269] The effect of the number of vegetable oil substitutes in a model on the lifecycle results, and the degree of substitution among feed commodities and food commodities, particularly in the non-USA regions, is a potential area for future study. **Inclusion of explicit global vegetable oil competition is critical to biofuel lifecycle analysis results because this competition affects the quantity and location of estimated LUC emissions impacts**.

Feedstock Production

Both intensification and extensification of corn and soybean feedstock production occur across ADAGE, GCAM, GLOBIOM, and GTAP results in response to changing commodity prices. In each of these models, extensification, including crop shifting, contributes to more of the biofuel sourcing than intensification. All four models estimate yield increases of corn in the corn ethanol scenario and soybeans in the soybean oil biodiesel scenario, but these increases are small relative to the reference case yields. One factor could be that our volume shocks are not large enough to induce much change in corn and soybean prices; indeed, the feedstock crop price changes in these scenario results appear fairly small across models. In our soybean oil biofuel volume sensitivity scenario, the models appear fairly stable in this area with respect to the size of the shock, suggesting that shock size might not have significant influence on model yield response. However, further research using a wider range of shock sizes and reference case assumptions could test this hypothesis more rigorously than we have been able to in this exercise.

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[269] For example, land use change to produce palm oil could result in increased emissions, particularly if the land converted is peat land.

We can observe generally that the models considered in this exercise do not see yield improvements as a primary strategy for supplying additional biofuel feedstock, given our scenario assumptions. Rather, feedstock crop extensification, including crop shifting, appears to be relied upon more than intensification to increase the net supply of biofuel feedstock for biofuel production across the economic modeling results presented in this exercise. This finding appears to be robust across a wide range of uncertainty analyses. However, that is not to say crop yield assumptions do not affect the results. Indeed, our parametric sensitivities do suggest that crop productivity assumptions may be influential, though other parameters appear to be more influential. Further research could better define this influence. **The ability to endogenously consider tradeoffs between intensification and extensification is an important capability for estimating the emissions associated with an increase in biofuel consumption.**

Soybean oil biodiesel and corn ethanol results vary

The models included in this study show greater diversity in feedstock sourcing strategies for soybean oil biodiesel than they do for corn ethanol, and this wider range of options leads to greater variability in the GHG results. There are several important reasons for this greater diversity of strategies, which were explored throughout this document. For example, compared to the corn ethanol results, there is less agreement among the models about where in the world soybean oil biodiesel production would change in response to a change in USA region soybean oil biodiesel consumption. Because of these differences in sourcing strategy, the model results differ regarding the amount and location of soybean oil production, vegetable oil and biodiesel trade, and land use change impacts of the shock.

Much of the new production of corn and corn ethanol in the corn ethanol shock results is estimated to occur in the USA region. Conversely, in at least some of the modeling results, much of the new production of soybeans, soybean oil and soybean oil biodiesel in the soybean oil biodiesel shock results is estimated to occur outside the USA region. Partly for this reason, the corn ethanol shock affects overall global trade, commodity production, and land use decisions to a lesser extent than the soybean oil biodiesel shock. Across the suite of results from the MCE, the USA imports more soybean oil biodiesel than corn ethanol. To the extent the increase in USA consumption of soybean oil biodiesel increases non-USA soybean oil biodiesel exports, some of the models choose to substitute this lost non-USA consumption of soybean oil biodiesel with greater use of palm oil biodiesel or fossil fuels. To the extent that new biofuel feedstock crops must be produced in these modeled scenarios to help satisfy demand for biofuels, each unit of soybean oil biodiesel feedstock supplied in this way requires more land than does an equivalent unit of corn ethanol feedstock supplied. This is because there is a lower yield per acre of soybeans, and, implicitly, of soybean oil, compared to corn. Along with land use, soybean oil biodiesel production also has much greater potential impacts on livestock production per unit of fuel produced than does corn ethanol production. Soybean meal produced per gallon of soybean oil biodiesel is greater than the amount of DDG produced per gallon of corn ethanol, which, all else equal, can lead to a greater expansion of livestock production in the soybean oil biodiesel scenario. These possibilities are realized to greater and lesser extents across the models and across sensitivity analyses. **Models included in the MCE produced a wider range of LCA GHG estimates for soybean oil biodiesel than corn ethanol**. This wider range of estimates is related to the greater diversity of feedstock sourcing strategies and the greater sensitivity of the biodiesel estimates to the variability and uncertainty present in the parameter assumptions discussed above.

Sensitivity Analysis

Alternative volume scenarios examine whether and how the assumed magnitude of the volume shock of USA biofuel consumption impacts GHG emissions and other model output values. In one scenario, where the soybean oil biodiesel volume is reduced to 500 MG, the ADAGE, GCAM, and GTAP results do not differ substantially from the 1 BG scenario when they are considered on a per billion gallon basis. GLOBIOM results do show some differences, such as GHG emissions impacts per billion gallons, between the 1 BG and the 500 MG soybean oil biodiesel shocks. In a combined scenario, in which corn ethanol and soybean oil biodiesel were simultaneously increased by 1 BG each, the results generally equal the sum of impacts observed in the individual 1 BG corn ethanol and soybean oil biodiesel core scenarios for ADAGE, GCAM, and GTAP. GLOBIOM results for the combined scenarios show more differences in the estimated output values, including GHG emissions, compared to the sum of the individual scenarios. These results indicate that, within the range of volumes considered, shock size does not lead to substantially different impacts on the modeled agriculture system and estimated GHG emissions in most of the frameworks we have tested.

Finally, stochastic sensitivity analysis identifies which parameter assumptions are particularly important for a particular model and scenario. Monte Carlo simulations with GCAM indicate that assumptions relating to soil carbon stocks and the ease of substitution among land types and crop types have a relatively large influence on the corn ethanol and soybean oil biodiesel results. The parameter controlling substitution between non-USA regions refined oil and biodiesel is also influential for the soybean oil biodiesel GHG estimates. A similar analysis with GLOBIOM finds that biophysical parameters, including those governing the expansion response of palm cultivation into peatland and governing the emissions associated with such expansion, are influential on soybean oil biodiesel GHG estimates. Stochastic analysis with GREET indicates that parameter assumptions have less influence on the supply chain LCA estimates for corn ethanol and soybean oil biodiesel when using an attributional LCA model. However, the sensitivity analysis with GREET shows more uncertainty associated with coproduct allocation choices and for assumptions related to induced land use change GHG emissions. Considered alongside the other results of this exercise, **these parameter sensitivity analyses indicate that substantial uncertainty in the emissions associated with corn ethanol and soybean oil biodiesel remains, both within and across models, and that additional research on economic model parameters remains a high priority**. These sensitivity analyses can help us allocate limited research resources by highlighting which types of parameters are most influential. Additional parametric sensitivity analysis could help us further pinpoint specific parameters for additional research and analysis.

Conclusions

In sum, we draw some important general conclusions from this model comparison exercise. First, ADAGE, GCAM, GLOBIOM and GTAP estimate that substantial indirect effects would be induced by the corn ethanol and, especially, soybean oil biodiesel shocks that we ran for this exercise. These indirect effects are important drivers in the modeled emissions associated with these fuels, which highlights the importance of considering indirect effects in LCA.[270]

Second, we find substantial uncertainty regarding the overall greenhouse gas intensity of the two biofuels examined in this exercise, corn ethanol and soybean oil biodiesel. Based on this model comparison exercise, it is evident that variation in estimates remains high across models, and within individual models when parameter uncertainty is considered. Although models have advanced and new data has become available since EPA modeled the lifecycle GHG emissions associated with corn ethanol and soybean oil biodiesel for the March 2010 RFS2 rule, there is still a large degree of variation and uncertainty in lifecycle GHG estimates that consider significant indirect emissions. The analyses we have conducted for this exercise highlight the value of sensitivity analysis as a way of understanding which parameters and assumptions influence the model results. Furthermore, given that uncertainty remains high for this type of analysis, it is critical to perform robust uncertainty analysis and provide information about the range of potential effects and risks of greater biofuel consumption. It is also important to compare model results and parameters to historic observation.

To summarize, we find that the following model characteristics are critical for evaluating the GHG impacts, including direct and indirect emissions, associated with a change in biofuel consumption:

1. **Supply chain LCA models produce a fundamentally different analysis than economic models.** Supply chain LCA models evaluate the GHG emissions emanating from a particular supply chain, whereas economic models evaluate the GHG impacts of a *change* in biofuel consumption. Supply chain LCA models generate detailed and transparent fuel production emissions estimates. However, they do not evaluate all of the indirect emissions associated with a change in biofuel consumption. The economic models in our comparison are broad in scope, but they lack certain supply chain details.
2. **Land use change emissions are a major contributor to the overall emissions.** ADAGE, GCAM, GLOBIOM, and GTAP all include land use change and land use change emissions. GREET includes a static estimate of land use change emissions using previous GTAP results with a different shock size and a 2004 baseline. Estimates of land use change vary significantly. Drivers of variation in these estimates include differences in assumptions related to trade, the substitutability of food and feed products, and land conversion, as well as structural differences in how models represent land categories.
3. **This exercise showed that when impacts of biofuel consumption on global energy markets are considered, GHG emissions estimates are significantly altered**. The

[270] This finding also supports NASEM recommendation 2-2: "When a decision-maker wishes to understand the consequences of a proposed decision or action on net GHG emissions, CLCA [consequential lifecycle analysis] is appropriate. Modelers should provide transparency, justification, and sensitivity/robustness analysis for modeling choices for the scenarios modeled with and without the proposed decision or action." National Academies of Sciences, Engineering, and Medicine 2022. Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States. Washington, DC: The National Academies Press. https://doi.org/10.17226/26402.

models that include energy sector results (ADAGE, GCAM, and GTAP) all estimate that displacement of refined oil for biofuel is less than 1:1, reducing the GHG emission reductions associated with the biofuels modeled. This indicates that economic modeling of the energy sector may be required to avoid overestimating the emissions reductions from fossil fuel consumption.

4. **Model trade structure and assumed flexibility influence the modeled emissions results.** There is general agreement among the economic models that these trade-driven impacts will occur to some degree. However, these models show different degrees of trade responsiveness, which impacts trade flows at differing magnitudes across model results.
5. Certain commodity consumption dynamics appear to substantially influence GHG emissions results. DDG and soybean meal's impact on the livestock and feed sectors can affect the estimated GHG emissions associated with biofuels. **Explicit modeling of the global livestock sector, including global feed markets, is an important capability for estimating the emissions associated with an increase in biofuel consumption.**
6. **The degree to which other vegetable oils replace soybean oil diverted to fuel production from other markets can impact GHG emissions associated with soybean oil biodiesel.** Results in this exercise from economic models (ADAGE, GCAM, GLOBIOM, and GTAP) align in estimating commodity substitution as a significant part of their scenario solution. Inclusion of explicit global vegetable oil competition is critical to biofuel lifecycle analysis results because this competition affects the quantity and location of estimated LUC emissions impacts.
7. **The ability to endogenously consider tradeoffs between intensification and extensification is an important capability for estimating the emissions associated with an increase in biofuel consumption.** Both intensification and extensification of corn and soybean feedstock production occur across ADAGE, GCAM, GLOBIOM, and GTAP results in response to changing commodity prices. The degree of crop yield intensification influences the amount of extensification needed to produce new feedstock for biofuels. ADAGE, GCAM, GLOBIOM, and GTAP can all model increased crop yields in response to crop prices. GLOBIOM and GTAP also explicitly consider multi-cropping.
8. **Models included in the MCE produced a wider range of LCA GHG estimates for soybean oil biodiesel than corn ethanol**. The models show much greater diversity in feedstock sourcing strategies for soybean oil biodiesel than they do for corn ethanol, and this wider range of options contributes to greater variability in the GHG results. There are several important reasons for this greater diversity of strategies which were discussed throughout this document.
9. **This exercise demonstrated that a wide range of results can be obtained by varying parameter values, highlighting the importance of sensitivity and uncertainty analysis.** Stochastic uncertainty analysis can currently be performed with GCAM, GLOBIOM, and GREET, and Monte Carlo analysis can be performed with GCAM and GLOBIOM. Other types of sensitivity analysis, such as varying individual parameters, can be performed with ADAGE and GTAP as well. Sensitivity analysis, which considers

uncertainty within a given model, can help identify which parameters influence model results. However, pinpointing the direct causes of why one estimate differs from another would require additional research.

Next Steps

A primary goal of this modeling exercise is to help advance the science related to understanding how different modeling tools can be used to assess the GHG impacts of biofuels. We understand that there is significant interest amongst stakeholders in a separate but related topic: namely, how to determine which models, methods, and data are best suited for evaluating the GHG impact of biofuels. Some stakeholders have suggested that EPA should include criteria for such evaluative purposes as part of this MCE.

This MCE intentionally does not directly address that subject, nor does it include proposed criteria. We have in this document instead focused on improving our understanding of the current state of science for biofuel GHG modeling, including, but not limited to, how the different models vary, how those variations affect results, and which parameters are critical to model results. We have not developed a set of criteria against which different models can be assessed, though we recognize that the development and use of such criteria could be critical in helping to inform future policy decisions. EPA notes that the criteria used to assess different models could vary greatly depending on the context in which lifecycle GHG modeling is being used. For example, the criteria could differ if the context was a holistic program-wide regulatory analysis as opposed to an assessment of individual fuel pathways. Criteria might also differ based on the extent to which fuel volumes from a given individual biofuel pathway appear likely to have impacts on the broader energy or agricultural sectors. To the extent EPA goes on to develop criteria against which we evaluate different models, this model comparison exercise provides critical information which will help EPA's work.

The preceding sections of this document note areas for further research, and we are interested in hearing stakeholder input on those suggestions. EPA is also interested in feedback and evaluation from outside researchers and organizations on this model comparison exercise. We plan to directly engage with stakeholders to collect input, consider our outstanding research needs in this area, and identify those lines of inquiry most critical to future decisions.

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Biofuels Induced Land Use Change Emissions: The Role of Implemented Land Use Emission Factors

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Abstract: Biofuels' induced land-use change (ILUC) emissions have been widely studied over the past 15 years. Many studies have addressed uncertainties associated with these estimates. These studies have broadly examined uncertainties associated with the choice of economic models, their assumptions and parameters, and a few bio-physical variables. However, uncertainties in land-use emission factors that represent the soil and vegetation carbon contents of various land types across the world and are used to estimate carbon fluxes due to land conversions are mostly overlooked. This paper calls attention to this important omission. It highlights some important sources of uncertainty in land-use emissions factors, explores the range in these factors from established data sources, and compares the influence of their variability on ILUC emissions for several sustainable aviation fuel (SAF) pathways. The estimated land-use changes for each pathway are taken from a well-known computable general equilibrium model, GTAP-BIO. Two well-known carbon calculator models (CCLUB and AEZ-EF) that represent two different sets of emissions factors are used to convert the GTAP-BIO estimated land-use changes to ILUC emissions. The results show that the calculated ILUC emissions obtained from these carbon calculators for each examined SAF pathway are largely different, even for the same amortization time horizon. For example, the ILUC emissions values obtained from the AEZ-EF and CCLUB models for producing jet fuel from corn ethanol for a 25-year amortization period are 24.9 gCO_2e/MJ and 15.96 gCO_2e/MJ, respectively. This represents a 60% difference between the results of these two carbon calculators for the same set of land-use changes. The results show larger differences for other pathways as well.

Keywords: biofuels; ILUC; emission factors; uncertainties

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1. Introduction

Since the late 2000s, many papers have estimated greenhouse gas (GHG) emissions of biofuels' induced land-use change (ILUC). To accomplish this task, as described by the Committee on Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States [1], the examined studies for the calculation of ILUC emissions followed a similar approach consisting of two sequential phases: (i) using an economic model to project regional land-use changes for the biofuel under study, and (ii) implementing a set of land-use emission factors (LUEFs) combined with some supporting assumptions to convert the projected land-use changes to GHG emissions. In general, the LUEFs estimate the soil and vegetation carbon content of land and are used to quantify emissions from different types of land conversions.

The existing literature has frequently noted that the estimated ILUC emissions values are uncertain [1–8]. The variations in modeling approach and structure, modeling assumptions and data, and implemented economic parameters are identified as the main sources of uncertainties in ILUC emissions values. However, only a few papers have studied uncertainties in LUEFs and their associated assumptions. Plevin et al. [6] conducted a sensitivity assessment combining the GTAP-BIO model with an agro-ecological zone emission factor (AEZ-EF) model [9,10] and concluded that the estimated ILUC emissions values are more sensitive to the changes in economic parameters than the changes in LUEFs. However, by using only one source for LUEFs, the authors' sensitivity assessment did not account for variability in background data or modeling assumptions behind the LUEFs. Leland et al. [7] performed a similar sensitivity assessment focusing on the impacts of four selected AEZ-EF input parameters on ILUC emission. In a related perspective, Taheripour and Tyner [4] examined the influence of different sets of LUEFs in combination with the estimated land-use changes for various biofuel pathways obtained from the GTAP-BIO model and concluded that the estimated ILUC emissions value of each pathway vary significantly with changes in the implemented LUEFs obtained from alternative sources.

In another study, Chen et al. [8] compared the estimated land-use changes for several biodiesel pathways obtained from the GTAP-BIO model using two different set of emission factors, including the Carbon Calculator for Land-Use and Land Management Change from Biofuels Production (CCLUB) [11] and AEZ-EF models. The authors showed that the ILUC emissions value of each pathway vary significantly with the implemented LUEFs used in these emission accounting models. In particular, they showed that the selected LUEFs for marginal cropland could largely alter the estimated ILUC emissions values. The findings of these studies demonstrate that the role of LUEFs in assessing ILUC emissions values is an important gap in land-use change research that has not been adequately evaluated.

This paper aims to fill this knowledge gap with two different but related research activities. The first evaluates the available sources of information on vegetation and soil carbon datasets that have been used in developing LUEFs to understand their similarities and differences across various land types and ecological conditions. The second applies the two emission accounting models mentioned above (AEZ-EF and CCLUB) to estimated land-use changes obtained from an advanced version of the GTAP-BIO model for eight Sustainable Aviation Fuel (SAF) pathways to examine the sensitivity of the ILUC emissions values to the changes in the LUEFs embedded in these accounting models. The eight selected SAF pathways represent those pathways that could be deployed in the US. These research activities significantly contribute to the debates on uncertainties in ILUC emissions values by highlighting how differences in the data source and LUEF modeling approach affect ILUC emissions values.

The article is organized as follows. The Materials and Methods section explains how ILUC emissions have been calculated and introduces the data sources that are often used to estimate LUEFs and their components. This section also outlines the main features of the GTAP-BIO model, which is frequently applied to estimate ILUC emissions. The section ends with a presentation of methods used in the present study to calculate ILUC emissions for a set of eight biofuel aviation pathways with two different set of LUEFs to highlight the importance of uncertainties in these factors. The results section includes a presentation of the wide ranges of LUEFs obtained from different datasets, a review of the causes of differences between LUEF datasets, and highlights the influence of these differences on a case study of ILUC emissions for the eight aviation biofuel pathways. We conclude the article with a short discussion emphasizing the importance of uncertainties in LUEFs and the ways that this line of uncertainty should be addressed by future research.

2. Materials and Methods

2.1. Common Approach in Calcualting ILUC Emissions

As noted in the Introduction, two sets of data are required to calculate ILUC emissions from a biofuel pathway: (i) estimated land-use changes due to an increase in consumption/production of the selected biofuel, and (ii) a set of LUEFs for the relevant land-use transitions. In general, regardless of differences across modeling practices, the following stylized formula has been implemented to calculate an ILUC emissions value for a given pathway (Zhao et al. [12]):

$$ILUC = \frac{\sum_{i,k,r} \Delta L_{i,k,r} \times LUEF_{i,k,r}}{T \times E} \quad (1)$$

In this formula, the index i represents the list of all types of land transitions (e.g., forest to cropland, forest to pasture, etc.), the index k shows spatial resolution (which could represent the national level, agro-ecological level, grid cell, or any other geographical resolution) within each country, and the index r indicates countries. The variables ΔL, $LUEF$, T, and E are land conversions in hectares, land-use emission factors measured in gCO_2e per hectare, amortization time horizon in years, and annual energy produced by the pathway under study measured in megajoules (MJ), respectively. Therefore, an ILUC emissions value estimates emissions in gCO_2e/MJ.

Hence, one needs to determine ΔL, $LUEF$, T, and E in calculating ILUC emissions values. The last two variables of this list are usually predetermined by the accounting system and fuel type, respectively. However, the first two variables are unknown and must be estimated, simulated, or measured. A sizeable expansion in production or consumption of a biofuel pathway that uses agricultural feedstocks (e.g., corn, soybeans, or perennial grasses) could induce land-use changes directly or indirectly at the local, national, and international levels (Hertel et al. [13]. The size, location, and type of land-use changes (i.e., $\Delta L_{i,k,r}$) could vary based on the characteristics of the pathway under consideration and on many economic and biophysical variables. Unfortunately, land-use changes are not directly observable or measurable. Economic models have been used to estimate land-use changes. In this paper, we use the results of a well-known computable general equilibrium (CGE) model, GTAP-BIO, which has been widely used in this field of research to assess land-use changes for various biofuel pathways.

2.2. Components and Sources of LUEFs

In calculating ILUC emissions values, one needs to determine the variable $LUEF_{i,k,r}$ for the i, k, and r indices, which is not a trivial task. In principle, this variable should capture all types of carbon fluxes associated with each type of land conversion. These fluxes are driven by changes in biological and mineral carbon pools, including soil organic carbon, carbon stock in above- and belowground live biomass, and dead organic matter and litter. Additionally, some carbon accounting frameworks include forgone carbon sequestration, emissions due to biomass burning through land clearing, and non-CO_2 emissions associated with the land use, land-use change, and forestry (LULUCF). Because of differences in background data and the included categories of emissions, alternative data sources provide widely varying estimates of $LUEF_{i,k,r}$ for the same land-use transition and location.

Several foundational data sources in this field include the Harmonized World Soil Database (HWSD) [14], IPCC [15,16], Winrock [17], and Woods Hole [18] datasets of carbon in soil and vegetation. Terrestrial-biogeochemical models such as Century [19,20], Daycent [21], TEM [22], and ISAM [23] have also been widely used to estimate the core components of *LUEFs*. Additional sources for critical background data on terrestrial carbon pools and associated GHG emissions during land-use transitions include individual studies such as Gibbs et al. [24], Saatchi et al. [25], and Batjes [26].

In addition to the required data on soil and vegetation carbon stocks, depending on the case under study, one may need additional information or use certain assumptions to mix and match $\Delta L_{i,k,r}$ and $LUEF_{i,k,r}$ variables. One may follow different approaches and assumptions to facilitate this process, which can cause significant variations in the resulting ILUC emissions values. The following three examples represent different approaches that the AEZ-EF and CCLUB models use to match the GTAP-BIO estimated land-use changes with their emission factors. Example 1: The GTAP-BIO model projects conversion of "cropland pasture" (a category of marginal land) to crop production due to biofuel shocks. In an ad hoc manner, the AEZ-EF model assumes that the soil carbon content for this type of land in each AEZ region is half of that of pasture land. On the other hand, the CCLUB model relies on a terrestrial-biogeochemical model (Century) to evaluate carbon content for this type of land by AEZ. Example 2: The AEZ-EF uses some assumptions and extends the original GTAP-BIO land conversions beyond the land conversions that this CGE model provides to match the land conversions with its emissions factors. For instance, the AEZ-EF model includes emission factors for converting forest or pasture to sugarcane. The GTAP-BIO model does not determine these land conversions. However, the AEZ-EF model uses some assumptions and determines these land conversions. The CCLUB model only uses the original GTAP-BIO land conversions. Example 3: The AEZ-EF uses some assumptions and assigns a portion of converted forest to cropland as forest on peat land, while the CCLUB uses more recent data with a different assumed portion of converted forest to cropland as forest on peat land.

Because the results of the GTAP-BIO model are used in this paper, we use two emissions accounting models that have been developed and used to convert the results of this model to ILUC emissions values. These two models are the AEZ-EF and CCLUB. The AEZ-EF model relies on IPCC, FAO, HWSD, and several other data sources to convert the GTAP-BIO results to ILUC emissions. This model follows the IPCC approach of using the differences in the biomass and soil organic carbon (SOC) pools between land-cover types as the emissions (or sequestration) values from land conversion.

In contrast, CCLUB provides users with Century simulated GHG emissions changes in US domestic land conversions to cropland and the option of using either the Winrock or Woods Hole data sources for international land conversions to simulate biomass and SOC changes between land-use categories over a period of time. As mentioned earlier, using the Century model, the CCLUB model also provides some assessments for the emission factors associated with the land category of "cropland pasture". In conclusion, the AEZ-EF and CCLUB models use different sources of data on carbon pools and follow different assumptions to convert the results of the GTAP-BIO model to ILUC emissions, especially for US domestic land conversions.

To highlight uncertainties and variations in the data on $LUEF_{i,k,r}$, we first review four existing sets of emission factors for converting forest to cropland and pasture to cropland: AEZ-EF, TEM, Winrock, and Woods Hole. These datasets have been used in calculating ILUC values for various US biofuel pathways over the past 15 years, but are limited by their reliance on outdated data in assessing emission factors. For example, the AEZ-EF model uses the 2006 IPCC guidelines for national greenhouse gas inventories instead of the new guidelines published in 2019. To highlight the potential impacts of using outdated data, we compare changes in the reference values for SOC stocks obtained from the IPCC 2006 and 2019 guidelines.

Finally, we calculate ILUC emissions values for eight aviation biofuel pathways that can be produced in the US by using the estimated land-use changes provided by the GTAP-BIO model and CCLUB carbon accounting model and compare the results with the corresponding values that have been calculated by the Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA) of the International Civil Aviation Organization (ICAO) [12] using the AEZ-EF model. The eight selected SAF pathways are introduced in the next section. In this paper, we calculate ILUC emissions values for the selected pathways using the AEZ-EF and CCLUB models to highlight their differences.

2.3. *A Short Review of GTAP-BIO Model and Implemented ΔL for the Examined SAF Pathways*

As mentioned above, the AEZ-EF and CCLUB emission calculators were designed to use the estimated land conversions (ΔL) obtained from the GTAP-BIO model. Hence, in this paper, we use the estimated land-use changes obtained from this CGE model which has been widely used in assessing ILUC emissions values due to biofuel production and policy.

This global CGE model is an advanced version of the standard GTAP model originally developed by Hertel [27]. This global macro model represents consumers and producers and simulates their behaviors in consuming and producing goods and services to determine their demands and supplies, respectively. It also includes government consumption, international trade, and investment. The standard GTAP model traces the production, consumption, and trade of all goods and services produced across the world by country. However, the standard model and its database do not represent biofuels and their by-products explicitly. The GTAP-BIO model and its database remedy this deficiency and explicitly represent supplies and uses of alternative types of biofuels that are commercially produced around the world [13,28–32]. These biofuels include ethanol produced from grains (e.g., corn and wheat) and sugar crops (e.g., sugarcane and sugar beet) and biodiesel produced from soy oil, rapeseed oil, palm oil, and other types of vegetable oils. Note that using oilseeds for biodiesel production generates oilseed meal and converting grains to ethanol generates distiller's dried grains with solubles (DDGS). These by-products play an important role when assessing the system-wide land-use effects of a biofuel pathway.

In addition, the GTAP-BIO model represents land uses by the agricultural and forestry sectors and traces their changes due to changes in demands for foods and biofuels. The agricultural sectors in this model include crop producers (rice, wheat, coarse grains, soybeans, rapeseed, palm oil, other oilseeds, sugar crops, and other crops) and livestock producers (dairy farms, ruminants, and non-ruminants). The GTAP-BIO model divides the accessible land across three land-cover categories: forest, pasture/grassland, and cropland. It then allocates pasture land across livestock activities and cropland across crop producers. The model takes into account multiple cropping (producing more than one crop per year on the same cropland), allows the return of unused cropland to crop production if needed, and takes into account yield improvement due to higher crop profitability.

An advanced version of GTAP-BIO has been developed to assess potential land-use changes for pioneering biofuels that are not yet produced at the commercial level. In addition to traditional crops, this model also has the capability to simulate the production of dedicated energy crops such as miscanthus, switchgrass, and poplar. Zhao et al. [12] have used this advanced version of the GTAP-BIO model to estimate land-use changes for a wide range of SAF pathways that can be produced across the world. This study applies the estimated land-use changes provided by Zhao et al. [12] for eight SAF pathways that can be produced in the US. These pathways are: (i) jet fuel produced from soy oil using the hydro-processed ester and fatty acid technology (soy oil HEFA); (ii) jet fuel produced from corn using the iso-butanol alcohol technology (corn ATJ); (iii) jet fuel produced from corn ethanol (corn ETJ); (iv) jet fuel produced from miscanthus using the Fischer–Tropsch technology (miscanthus FTJ); (v) jet fuel produced from switchgrass using the Fischer–Tropsch technology (switchgrass FTJ); (vi) jet fuel produced from poplar using the Fischer–Tropsch technology (poplar FTJ); (vii) jet fuel produced from miscanthus using the iso-butanol alcohol technology (miscanthus ATJ); and (viii) jet fuel produced from switchgrass using the iso-butanol alcohol technology (miscanthus ATJ). The technical details regarding these pathways are provided in the CORSIA Supporting Document [33]. More details about the estimated land-use changes for these pathways are provided in Zhao et al. [12]. The estimated land-use changes for the selected SAF pathways were obtained for the given expansions in their fuel supplies as reported in Table 1.

As shown in Table 1, in addition to jet fuel, some SAF pathways produce a conventional biofuel co-product as well. The co-product biofuels could be ethanol or biodiesel that can be used in road transportation. The biofuel co-products of the HEFA and ETJ technologies are biodiesel and diesel/gasoline, respectively. The ATJ technology produces no co-product biofuel. The total energy output for each pathway (including jet fuel and conventional biofuel) is shown in petajoules and also in billion gallons of gasoline equivalent (BGGE) in Table 1. The variable E presented in the denominator of Equation (1) represents the total energy output of each pathway after conversion to megajoules.

Table 1. Assumed expansions in supplies of the selected SAF pathways.

Pathways	Increases in Fuel Supplies in Petajoules			Increases in Fuel Supplies in Bllion Gallons of Gasolin Equivalent		
	Jet Fuel	Biofuel Co-product	Total	Jet Fuel	Biofuel Co-product	Total
Soy oil HEFA	57.1	171.3	228.4	0.47	1.4	1.86
Corn ATJ	103.8	0	103.8	0.85	0	0.85
Corn ETJ	103.8	32.2	136	0.85	0.26	1.11
Miscanthus FTJ	69.2	207.7	276.9	0.57	1.7	2.26
Switchgrass FTJ	69.2	207.7	276.9	0.57	1.7	2.26
Poplar FTJ	69.2	207.7	276.9	0.57	1.7	2.26
Miscanthus ATJ	69.2	0	69.2	0.57	0	0.57
Switchgrass ATJ	69.2	0	69.2	0.57	0	0.57

Source: Table 64 of CORSIA Supporting Document [33]. HEFA, ATJ, ETJ, and FTJ stand for producing jet fuel using hydro-processed ester and fatty acid; iso-butanol alcohol; ethanol to jet fuel; and Fischer–Tropsch technologies, respectively.

3. Results

3.1. Uncertainty in Emission Factors

The results show that the existing data sources provide different assessments of emission factors for a given land type conversion (pasture to cropland or forest to cropland) in a geographical region. Figure 1 provides comparisons across the existing data sources on emission factors for converting forest and pasture to cropland across the world. The data sources are the AEZ-EF, TEM, Winrock, and Woods Hole datasets. This figure shows the following:

- Regardless of region or data source, the emission factors of converting forest land to cropland are higher than the emission factors of converting pasture to cropland;
- Regardless of the data source for a given land type, the emission factors vary significantly across regions. This is because the vegetation cover and soil characteristics vary significantly across regions;
- For a given region and land type, alternative sources provide significantly different emission factors. This item highlights uncertainties in *LUEFs* across data sources; and
- The observed variation among the alternative sources of *LUEFs* for a given country or region is caused by many factors, including differences in model assumptions, system boundaries, primary carbon stock data sources, and categorization of ecosystems and land uses, among others. Major research efforts are needed to identify, prioritize, and validate these factors to better assess the true scope and uncertainty of ILUC emissions.

To better assess this line of uncertainty, we examined the differences between these emission factor sources by calculating the ratios of TEM/AEZ-EF, Woods Hole/AEZ-EF, and Winrock/AEZ-EF for each type of land conversion (pasture to cropland and forest to cropland) in each region. As shown in Figure 2, the ratios for both forest and pasture are highly variable across regions. This figure shows the following:

- There is a large disparity among emission factors for the pasture land to cropland transition, which often vary by a factor of three or more between the smallest and largest estimates;
- The TEM emissions factors for pasture land to cropland in Brazil, East Asia, Malaysia, and Indonesia, and the rest of South Asia are much larger than those EFs from other sources.
- The Woods Hole emission factors for pasture land to cropland in China, India, the rest of South Asia, Russia, and some European regions are much larger than those emissions factors from other sources;

- The forest land to cropland transition emissions factors from TEM and Woods Hole models are larger than those from other models;
- In each region, the disparity among the alternative sources of emission factors for forest land is also considerable, but lower than the disparity for pasture land.

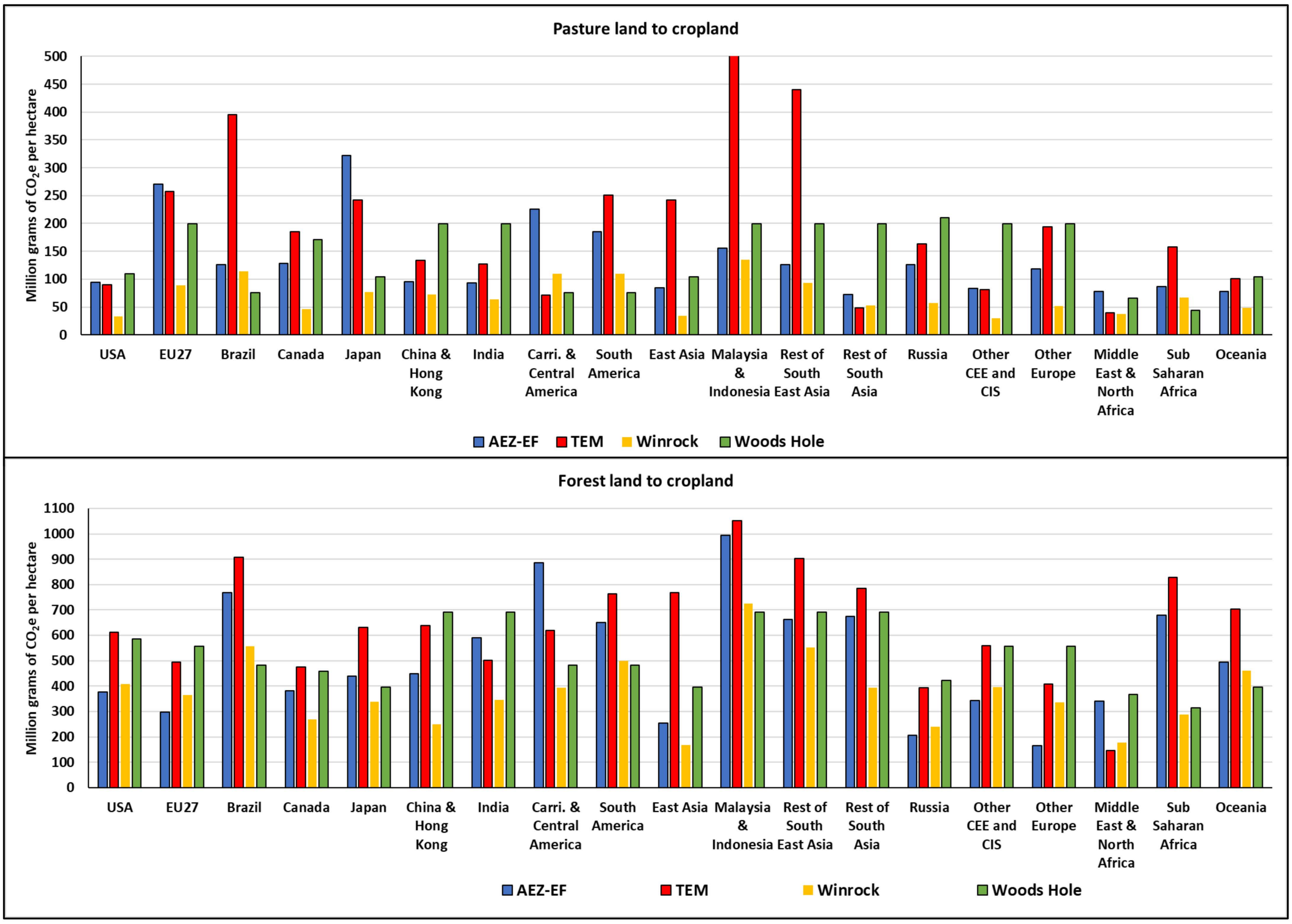

Figure 1. Emission factors for converting forest and pasture to cropland by region across different data sources. The AEZ-EF emission factors represent weighted averages across AEZs of each region using pasture and forest areas. The Winrock emission factors are taken from the CCLUB tables. Other emission factors are obtained from Taheripour and Tyner [4]. The CEE and CIS regions represent Central and Eastern Europe and the Commonwealth of Independent States, respectively.

These results suggest that differences across alternative sources of emission factors, in many cases, are extremely large. This indicates that using alternative emission factors could lead to major uncertainties in assessing ILUC emissions values. Each of these datasets represents various data items, components, and assumptions. They represent different assessments for soil organic carbon and carbon stock in above- and belowground live biomass. Their assessments for dead organic matter and litter carbon pools are different. For example, in addition to the carbon content of forest live biomass, emission factors may include carbon stored in dead organic matter consists of litter and dead wood. Quantification of these carbon sources is highly uncertain and varies across data sources. The existing data sources also follow different assumptions in calculating forgone carbon sequestration. Forgone sequestration refers to the carbon that would have been captured by soils or plants that are lost due to land-use changes. Alternative sources that provide emission factors use different data sources and follow different approaches and assumptions to assess forgone sequestration. This leads to significant variations in emissions factors. The existing emission factors may also follow different approaches in calculating biomass burning through land clearing and non-CO_2 emissions associated with LULUCF. Biomass burning may accrue in land-clearing activities induced by expansions in demand for cropland. The share of biomass burning in land-clearing activities varies across regions. In addition, various approaches could be followed in assessing the CO_2 and non-CO_2 emissions due to biomass burning. These factors jointly make the emissions induced by biomass burning very uncertain.

With the observed variations in the presented emission factors, it should be very clear that these factors are major sources of uncertainties. Understanding this line of uncertainty could help to provide better estimates for ILUC emissions values for alternative biofuel pathways.

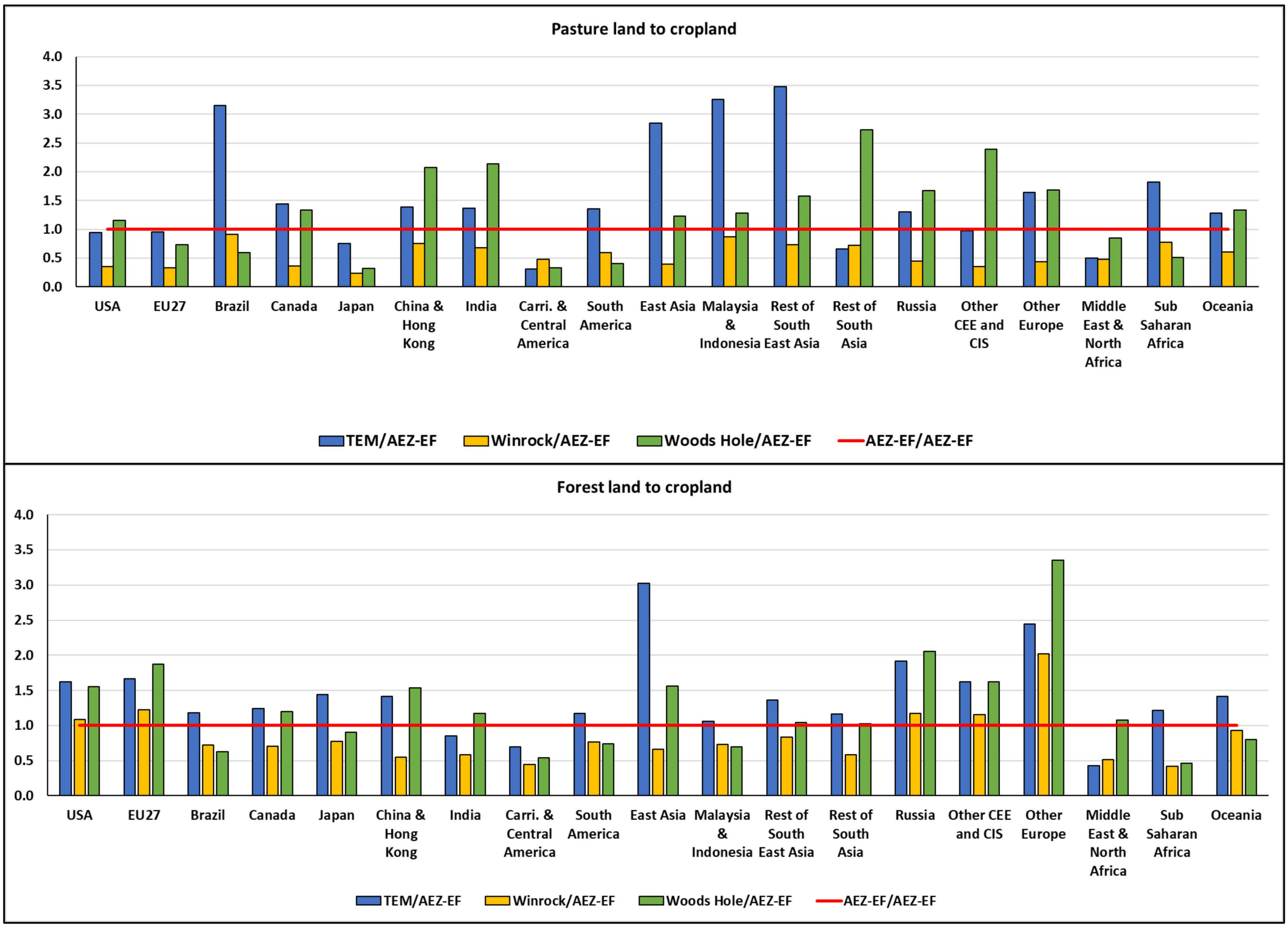

Figure 2. Ratios of emission factors of TEM/AEZ-EF, Winrock/AEZ-EF, Woods Hole/AEZ-EF, and AEZ-EF/AEZ-EF for converting pasture and forest to cropland by region. The AEZ-EF emission factors represent weighted averages across AEZs of each region using pasture and forest areas. The Winrock emission factors are taken from the CCLUB tables. Other emission factors are obtained from Taheripour and Tyner [4]. The CEE and CIS regions represent Central and Eastern Europe and the Commonwealth of Independent States, respectively.

3.2. Emission Factors Containing Outdated Data

As mentioned before, emission factors represent various data items, components, and assumptions. Many of these data items have not been updated over time, while the existing literature has provided their new updates. As an example, the AEZ-EF model following Edwards et al. [34] assumes that 33% of an increase in palm plantation is converted from forest on peatland in Malaysia and Indonesia. However, as noted by Zhao et al. [12], more recent data provided by Austin et al. [35] suggest lower rates of palm on peatland.

The AEZ-EF model relies on an outdated version of HWSD data and follows the IPCC 2006 guidelines to estimate SOC for each region-AEZ. The HWSD dataset has been revised over time. However, the AEZ-EF emission factors have not been updated accordingly. The first version of this dataset (V1.1) was released in 2009. The AEZ-EF model was built using this version. The latest version of this dataset was released in 2023. Updating the AEZ-EF data sources to represent the new version of HWSD data could affect the estimates of ILUC emissions.

As another example and as explained above, the AEZ-EF model relies on the IPCC 2006 guidelines to determine its emission factors. However, the IPCC revises its datasets and guidelines over time. These revisions suggest that soil and vegetation carbon content data sources are uncertain and subject to reassessments over time. To highlight this fact, consider Figure 3, which shows percent differences in the IPCC default reference values for soil organic carbon stocks (SOC_{REF}) for mineral soil presented in the 2019 and 2006 guidelines for various soil types and climate regions. This figure indicates that in most cases, the default SOC_{REF} values declined in the new IPCC guideline. This suggests that the AEZ-EF model that uses the 2006 IPCC guidelines in determining SOC values needs to adopt the newer 2019 IPCC guidelines to provide ILUC emissions based on the most recent available information. Note that the SOC values are not the only data items of the AEZ-EF model that should change due to revisions in the IPCC guidelines. Other important data items and assumptions that need revisions according to the newer IPCC guidelines are global warming potentials, litter data, soil stock change factors, and forest combustion factors.

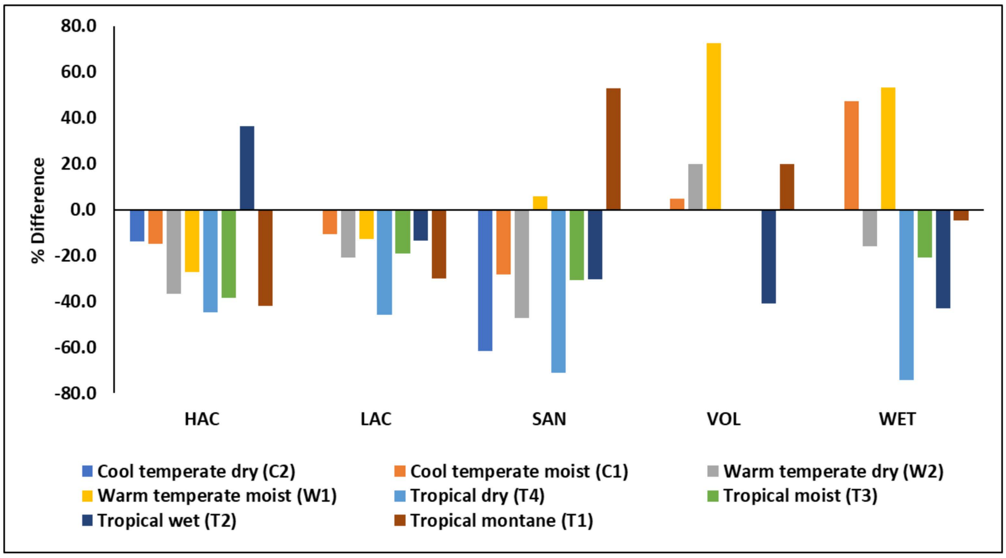

Figure 3. Percent differences in reference values for soil organic carbon stocks (SOC_{REF}) between the 2019 and 2006 IPCC national accounting guidance for various soil types and climate regions. Here, HAC, LAC, SAN, VOL, and WET stand for high activity clay soils, low activity clay soils, sandy soils, volcanic soils, and wetland soils, respectively. Percent differences are [(SOC_{REF} of 2019_SOC_{REF} of 2006)/SOC_{REF} of 2006] $\times$ 100.

3.3. ILUC Emissions for Selected SAF Pathways

The calculated ILUC emission values for the selected eight US SAF pathways differ substantially when assessed using the AEZ-EF versus CCLUB carbon accounting models (Table 2). For the soy oil HEFA, corn ATJ, and corn ETJ pathways, the CCLUB model provides lower ILUC emission values than AEZ-EF. In these cases, the difference is primarily driven by a more detailed parameterization of the "cropland pasture" land category in CCLUB compared to AEZ-EF. Based on extensive research characterizing cropland pasture, CCLUB accounts for accumulation of SOC upon conversion to cropland through Century simulations. In contrast, the AEZ-EF model assumes on an ad hoc basis that the conversion of cropland pasture to crop production releases carbon with a soil carbon content of half of that for pasture land.

Table 2. Estimated ILUC emissions values for US SAF pathways using different emissions accounting models for a 25-year amortization time horizon (gCO_2e/MJ).

Pathways	ILUC Obtained from the AEZ-EF Model				ILUC Obtained from CCLUB Model	Difference: AEZ-EF–CCLUB
	Soil Organic Carbon	Biomass Carbon	Others **	AEZ-EF Total		
Soy oil HEFA	5	1.6	13.4	20	15.0	5.0
Corn ATJ	8.4	−0.3	14.4	22.5	14.4	8.1
Corn ETJ	9.4	−0.3	15.8	24.9	15.6	9.3
Miscanthus FTJ	−33.6	−17.8	14.1	−37.3	−12.8	−24.5
Switchgrass FTJ	−17.3	−11.8	20.9	−8.2	1.0	−9.2
Poplar FTJ	−7.8	−19.5	17.7	−9.6	7.0	−16.6
Miscanthus ATJ	−51	−25.3	17.8	−58.5	−26.1	−32.3
Switchgrass ATJ	−28.7	−18.5	28.3	−18.9	−14.1	−4.7

Source: Zhao et al. [12]. HEFA, ATJ, ETJ, and FTJ stand for producing jet fuel using hydro-processed ester and fatty acid; iso-butanol alcohol; ethanol to jet fuel; and Fischer–Tropsch technologies, respectively. ** Others include natural vegetation, foregone sequestration, and peat land oxidation.

The results applying the AEZ-EF emissions factors suggest substantially lower ILUC emissions for dedicated energy crops than those calculated using the CCLUB model. For these biofuel pathways, the AEZ-EF assigns improvements in SOC per hectare of converted cropland to the dedicated energy crops. However, CCLUB only considers improvements in the SOC of cropland pasture. The implications of these differences are highlighted in Table 2. The calculated SOC values indicate that the AEF-EF model assesses large negative changes in SOC on land conversion to dedicated bioenergy crops. A match between the approaches followed by these models in assessing SOC gains could lead to lower differences between their results for the pathways that use dedicated energy crops as feedstock. As presented in Table 2, those pathways that use dedicated energy crops provide major carbon savings due to the accumulation of biomass carbon in the production processes of these energy crops as well.

As mentioned above, Table 2 shows ILUC emissions values for a 25-year amortization time horizon, the assumption in the ICAO CORSIA program. However, the US biofuel policies consider a 30-year amortization time horizon. Table 3 provides the ILUC values for the examined pathways for 25-year and 30-year amortization time horizons.

Table 3. Estimated ILUC emissions values for various SAF pathways using different emissions accounting models for 25- and 30-year amortization time periods (gCO_2e/MJ).

Pathways	Amortization Time Horizon			
	25 Years		30 Years	
	AEZ-EF	CCLUB	AEZ-EF	CCLUB
Soy oil HEFA	20.0	15.0	16.6	12.5
Corn ATJ	22.5	14.4	18.7	12.0
Corn ETJ	24.9	15.6	20.8	13.0
Miscanthus FTJ	−37.3	−12.8	−31.1	−10.7

Table 3. *Cont.*

Pathways	Amortization Time Horizon			
	25 Years		30 Years	
	AEZ-EF	CCLUB	AEZ-EF	CCLUB
Switchgrass FTJ	−8.2	1.0	−6.8	0.9
Poplar FTJ	−9.6	7.0	−8.0	5.9
Miscanthus ATJ iBuOH	−58.5	−26.1	−48.7	−21.8
Switchgrass ATJ iBuOH	−18.9	−14.1	−15.7	−11.8
Grain ATJ	22.5	14.4	18.7	12.0
Grain ETJ	24.9	15.6	20.8	13.0

HEFA, ATJ, ETJ, and FTJ stand for producing jet fuel using hydro-processed ester and fatty acid; iso-butanol alcohol; ethanol to jet fuel; and Fischer–Tropsch technologies, respectively.

As shown in Table 3, a 30-year amortization time horizon leads to lower ILUC emissions values for all pathways and for both the AEF-EF and CCLUB models.

3.4. Land-Use Emission Factors Used in Other Economic Models

Uncertainties associated with emission factors are not limited to the emission factors that are used to convert the GTAP-BIO estimated land-use changes to ILUC emissions. Other economic models that have been used to assess ILUC emissions are subject to the same uncertainties. Here, we briefly introduce the emission factors of three other economic models.

The economic projection and policy analysis (EPPA) model [36] which has been used to assess land-use changes and their associated emissions uses a set of emissions factors that were obtained from the TEM model [37,38]. These emissions factors are different from those emission factors that are reported and used by Taheripour et al. [4] using the same terrestrial model. This model estimates land-use emission factors by calculating the net ecosystem productivity, the carbon emissions due to the conversion of natural land to agricultural use, and carbon emissions because of the decomposition of forestry and agricultural products [39]. The calculations of these components are subject to various types of uncertainties regarding the implemented data and model parameters.

The global biosphere management model (GLOBIOM) [40] is another model which has been used to evaluate ILUC emissions for various biofuel pathways [33]. This model uses IPCC guidelines and data, a version of the HWSD dataset, and its own equations to calculates carbon fluxes from land-use changes. While details regarding the emission factors of this model are not available, one could expect that the emission factors of this model are also subject to uncertainties, as GLOBIOM also uses the same data sources and approaches that are used by other models.

The global change analysis model (GCAM) has also used to assess ILUC emissions. According to Kyle et al. [41], this model uses a set of predetermined emission factors. These emission factors divide the carbon pools into vegetation and soil carbon, similar to the AEZ-EF model approach. However, the vegetation carbon pool used in GCAM disregards litter and dead vegetation. This model relies on various publications to assess the soil and carbon content of land by region and AEZ. These data sources are subject to uncertainties, similar to the data sources that are used in the AEZ-EF and CCLUB models. Van de Ven et al. [42] have reported the GCAM model emission factors by land type and AEZ.

4. Discussion

This paper highlights that many studies have addressed uncertainties in ILUC emissions stemming from the choice of economic models and their assumptions and parameters, while uncertainties in LUEFs that represent soil and vegetation carbon contents of various land types across the world and are used to estimate carbon fluxes due to land conversions are mostly overlooked. We call attention to this major omission, demonstrating that common sources of LUEFs vary substantially for the same land type, geographical region, and vegetation cover. Some of this variation is due to differences in background in model system boundaries, assumptions, and data sources. The existing LUEFs not only use different sources of data to measure the soil and vegetation carbon of the global land cover, they follow different approaches in determining carbon fluxes due to changes in dead organic matter, litter carbon pools, forgone carbon sequestration, and emissions due to biomass burning that occur in land-clearing activities. LUEFs estimates often rely on outdated data sources, which could also lead to inaccurate ILUC emissions. By highlighting the differences in the calculated ILUC values from a variety of aviation biofuel pathways using two common LUEFs datasets, this study emphasizes that the choice of LUEFs dataset, and thus the variation in model systems and data sources, substantially affects ILUC values for biofuels. To reduce these uncertainties and provide more accurate ILUC emissions from biofuels, more advanced research activities are required to improve estimates in the soil and vegetation carbon of land-cover types across geographies, validate the data sources that underpin existing LUEFs, and develop a set of standard procedures for the application of biological carbon estimates and modeling systems to the field of ILUC.

As recommended by the Committee on Current Methods for Life Cycle Analyses of Low-Carbon Transportation Fuels in the United States [1], with up-to-date data sources, additional research should be conducted to improve and validate LUEFs. These improvement and validation efforts are needed to better estimate the change in GHG emissions by displacing fossil fuels with biofuels. This will help to guide policies and programs that support expansions in biofuels to ensure savings in GHG in transportation sectors by biofuels. Key policies and programs (e.g., the US Renewable Fuel Standard, the California Low Carbon Fuel Standard, and the ICAO-CORSIA program) rely on life cycle analyses and estimations of ILUC emissions to calculate the GHG emission intensities of biofuels. With new research activities that improve and validate the LUEFs, we could enhance effectiveness of the public policies in reducing GHG emissions. Without developing these crucial new studies, public policy may have unintended consequences of supporting fuel options that may have high-ILUC GHG emissions.

5. Conclusions

This study shows that while the existing literature has extensively discussed uncertainties in modeling land-use changes due to biofuels, no major effort has been made to evaluate uncertainties in land-use emission factors. Our study indicates that variations in the available data sources that provide land-use emission factors are substantially large. Hence, moving from one set of land-use emission factors to another significantly affects the estimated ILUC emissions values for a given set of estimated land-use changes for a given pathway. To highlight and confirm this important point, we explained components of several available emissions factors, data sources, and assumptions that have been used to develop those emissions factors and show that the AEZ-EF and CCLUB models, which represent two sets of different land-use emission factors, provide different assessments for ILUC emissions values. Finally, we discussed that uncertainties in emissions factors are not limited to the emissions factors used in the AEZ-EF and CCLUB models that have been frequently used to assess ILUC values in combination with the GTAP-BIO model land-use change projections. The ILUC emissions calculated by other economic models such as EPPA, CGAM, and GLOBIOM are also subject to uncertainties in land-use emission factors as well.

The varied selection of primary data sources, system boundaries, and other modeling assumptions make it very challenging to identify the root causes of the observed variations across models for emission factors for a given country/region. Major research efforts are needed to determine the sources of these variations, assess the accuracy of these models, and validate the resulting emissions factors. To reconcile large differences in emission quantification due to biofuel uses, we call for using advanced satellite and remote-sensing technology to refine emission factor quantifications and field sampling studies to verify the model estimates for large-scale quantification of emissions due to biofuel production.

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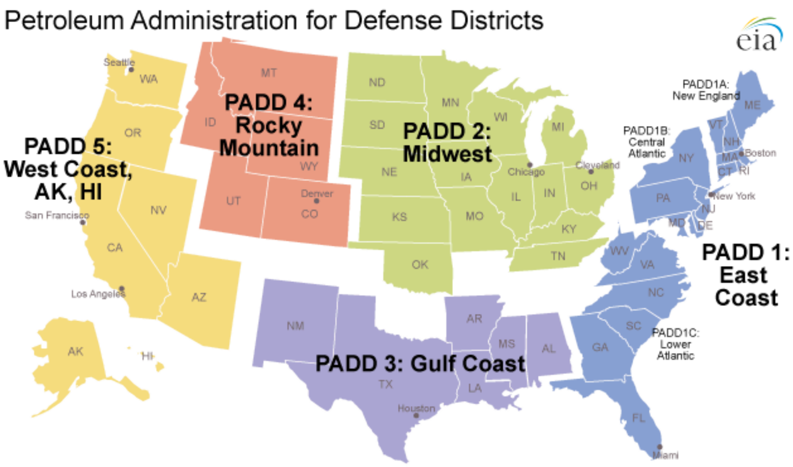
NMED EXHIBIT 139-E

Today in Energy

February 7, 2012

PADD regions enable regional analysis of petroleum product supply and movements



Source: U.S. Energy Information Administration.

The Petroleum Administration for Defense Districts (PADDs) are geographic aggregations of the 50 States and the District of Columbia into five districts: PADD 1 is the East Coast, PADD 2 the Midwest, PADD 3 the Gulf Coast, PADD 4 the Rocky Mountain Region, and PADD 5 the West Coast. Due to its large population, PADD 1 is further divided into sub-PADDs, with PADD 1A as New England, PADD 1B the Central Atlantic States, and PADD 1C comprising the Lower Atlantic States. There are two additional PADDs (PADDs VI and VII) that encompass U.S. Territories (these are not pictured on the map). The PADDs help users of EIA's petroleum data assess regional petroleum product supplies.

During World War II the Petroleum Administration for War, established by an Executive order in 1942, used these five districts to ration gasoline. Although the Administration was abolished after the war in 1946, Congress passed the Defense Production Act of 1950, which created the Petroleum Administration for Defense and used the same five districts, only now called the Petroleum Administration for Defense Districts.

The PADDs also allow data users to analyze patterns of crude oil and petroleum product movements throughout the nation. During 2010 (the latest full year for which published data are available), the bulk of petroleum product pipeline movements took place among PADDs 1, 2, and 3 (see table below). More than half of the total U.S. inter-PADD product pipeline movements were from PADD 3 (an area with significant refining capacity) to PADD 1 (a major population center). By contrast, PADDs 4 and 5 show very small volumes entering and leaving by pipeline, with nothing leaving PADD 5.

For crude oil, nearly three-quarters of the inter-PADD pipeline movements in 2010 were movements from PADD 3 to PADD 2 (see table below). These volumes include crude oil produced in the Gulf of Mexico and imports to the Gulf Coast region that move inland to refineries in PADD 2. The volume of crude oil moving by pipeline from PADD 3 to PADD 2 has steadily declined in recent years, as pipeline receipts of Canadian oil sands crude oil and increased production from North Dakota's Bakken formation have bolstered PADD 2 crude oil supplies. This increase in PADD 2 crude supplies has reduced their need for crude oil supplies from the Gulf Coast. The vast majority of the inter-PADD crude oil pipeline movements occur among PADDs 2, 3, and 4, with very little crude oil pipeline activity into or out of PADDs 1 and 5. Such crude oil and petroleum product movement patterns would be hard to discern without the availability of PADD-level data.

Petroleum Product Inter-PADD Pipeline Movements, 2010
million barrels

	SHIPPING PADD					
PADD	From 1	From 2	From 3	From 4	From 5	Total receipts
To 1	--	17	886	0	0	903
To 2	111	--	278	58	0	447
To 3	0	121	--	69	0	190
To 4	0	28	10	--	0	38
To 5	0	0	54	12	--	66
Total shipments	111	166	1228	139	0	1644

Source: U.S. Energy Information Administration, Petroleum Supply Monthly.
Download CSV Data

Crude Oil Inter-PADD Pipeline Movements, 2010
million barrels

	SHIPPING PADD					
PADD	From 1	From 2	From 3	From 4	From 5	Total receipts
To 1	--	2	6	0	0	8
To 2	0	--	440	65	0	505
To 3	5	50	--	2	0	57
To 4	0	22	0	--	0	22
To 5	0	0	0	12	--	12
Total shipments	5	74	446	79	0	604

Source: U.S. Energy Information Administration, Petroleum Supply Monthly.
Download CSV Data

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Petroleum & Other Liquids

Crude Oil Production

Period-Unit: Annual-Thousand Barrels

Graph Clear

Production	2019	2020	2021	2022	2023	2024	View History
U.S.	4,494,885	4,149,016	4,128,623	4,381,539	4,724,335	4,843,858	1859-2024
PADD 1	25,594	26,513	26,060	21,872	24,270	19,191	1981-2024
Florida	1,937	1,488	1,490	1,210	1,022	878	1981-2024
New York	277	238	266	266	251	206	1981-2024
Pennsylvania	6,117	5,298	6,334	5,195	4,832	4,450	1981-2024
Virginia	6	5	5	7	6	5	1981-2024
West Virginia	17,256	19,484	17,964	15,194	18,159	13,651	1981-2024
PADD 2	816,640	676,665	618,654	606,626	664,374	664,158	1981-2024
Illinois	8,241	7,148	7,056	6,924	6,890	6,971	1981-2024
Indiana	1,579	1,323	1,521	1,711	1,532	1,628	1981-2024
Kansas	33,193	28,258	27,905	28,003	27,698	26,829	1981-2024
Kentucky	2,505	2,265	2,464	2,252	1,876	2,040	1981-2024
Michigan	5,227	4,187	4,683	4,795	4,902	4,546	1981-2024
Missouri	85	62	60	69	63	57	1981-2024
Nebraska	1,866	1,673	1,592	1,706	1,543	1,287	1981-2024

North Dakota	☐	517,672	433,555	405,180	386,273	431,752	437,008	1981-2024
Ohio	☐	27,965	24,149	19,092	22,459	30,339	36,593	1981-2024
Oklahoma	☐	216,929	172,868	147,943	151,300	156,691	146,167	1981-2024
South Dakota	☐	1,166	1,024	1,017	961	923	868	1981-2024
Tennessee	☐	211	151	141	173	165	165	1981-2024
PADD 3	☐	2,967,196	2,822,048	2,889,354	3,149,996	3,409,394	3,521,674	1981-2024
Alabama	☐	4,859	4,295	4,291	3,821	3,591	3,357	1981-2024
Arkansas	☐	4,825	4,138	4,207	4,442	4,452	4,066	1981-2024
Louisiana	☐	45,815	36,401	34,284	36,484	34,216	30,359	1981-2024
Mississippi	☐	16,878	14,166	13,434	12,667	12,576	12,135	1981-2024
New Mexico	☐	336,999	377,811	463,501	590,105	672,271	740,402	1981-2024
Texas	☐	1,864,989	1,775,173	1,746,470	1,870,578	2,001,888	2,077,133	1981-2024
Federal Offshore (PADD 3)	☐	692,831	610,064	623,167	631,900	680,400	654,223	1981-2024
PADD 4	☐	354,345	310,595	293,541	317,372	344,404	370,826	1981-2024
Colorado	☐	192,233	171,513	153,526	160,314	166,905	170,289	1981-2024
Idaho	☐	22	1	26	42	36	19	2007-2024
Montana	☐	22,998	19,083	18,968	20,591	22,650	26,655	1981-2024
Utah	☐	36,933	31,001	35,771	45,773	58,074	67,106	1981-2024
Wyoming	☐	102,160	88,997	85,250	90,651	96,740	106,757	1981-2024
PADD 5	☐	331,111	313,195	301,015	285,673	281,893	268,008	1981-2024
Alaska	☐	170,037	163,880	159,650	159,627	155,475	154,174	1981-2024
South Alaska	☐	5,211	4,419	3,462	3,443	3,123	3,053	1981-2024
North Slope	☐	164,826	159,461	156,188	156,185	152,351	151,121	1981-2024

Arizona	☐	7	5	6	6	7	6	1981-2024
California	☐	156,350	144,521	137,144	123,120	123,186	109,828	1981-2024
Nevada	☐	268	221	223	238	207	177	1981-2024
Federal Offshore (PADD 5)	☐	4,449	4,569	3,992	2,682	3,019	3,823	1981-2024

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- = No Data Reported; **--** = Not Applicable; **NA** = Not Available; **W** = Withheld to avoid disclosure of individual company data.

Notes: Year-to-date totals include revised monthly production estimates by state published in Petroleum Navigator. Crude oil production quantities are estimated by state and summed to the PADD and the U.S. level. State production estimates reported by EIA are normally different from data reported by state agencies. For example, production estimates for Texas reported on table 26 are different from production reported by the Railroad Commission of Texas. See EIA Today In Energy article released on July 10, 2015 for an explanation of differences in production data for Texas. Totals may not equal sum of components due to independent rounding. See Definitions, Sources, and Notes link above for more information on this table.

Release Date: 10/31/2025

Next Release Date: 8/31/2026

NMED EXHIBIT 139-Fb

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Petroleum & Other Liquids

PAD District Imports by Country of Origin

Product: Crude Oil **Period/Unit:** Annual-Thousand Barrels
Import Area: Gulf Coast (PADD 3)

Show Data By:
Product Import Area Country Graph Clear

	2019	2020	2021	2022	2023	2024	View History
All Countries	720,650	666,250	567,285	597,650	624,747	603,058	1981-2024
Persian Gulf	127,832	132,525	75,701	102,668	70,601	68,709	1993-2024
OPEC*	176,839	133,475	81,208	103,617	117,121	147,233	1993-2024
Algeria						9	1993-2024
Congo (Brazzaville)							1993-2017
Equatorial Guinea	1,326						1995-2019
Gabon						785	1993-2024
Iran			2,033	507	1,729		2021-2023
Iraq	62,254	18,178	8,397	19,994	4,826	1,492	1995-2024
Kuwait	7,654	4,133	5,941	6,716	6,496	7,002	1993-2024
Libya			1,276				2004-2021
Nigeria	6,999		2,858			557	1993-2024
Saudi Arabia	57,924	110,214	59,330	75,451	57,550	60,215	1993-2024
United Arab Emirates							1993-2017

Venezuela	28,904				46,520	77,173	1993-2024
Non OPEC*	543,811	532,775	486,077	494,033	507,626	455,825	1993-2024
Angola	1,939	950	1,373	949		7,125	1993-2024
Argentina	4,305	1,896					1993-2020
Australia							1993-2018
Azerbaijan							1995-2018
Bahamas		1,007					2020-2020
Barbados							2018-2018
Belarus							2006-2006
Belize	211						2006-2019
Benin							1995-2002
Bolivia							1995-2018
Brazil	24,925	15,117	7,293	3,982	11,534	8,550	1995-2024
Brunei							1995-2002
Cameroon	1,339	622	648		617	649	1995-2024
Canada	188,209	191,557	194,765	214,870	195,730	192,444	1993-2024
Chad	1,901						2004-2019
Chile							1995-2002
China							1995-2006
Colombia	76,463	71,019	45,881	58,435	53,087	57,155	1993-2024
Congo (Kinshasa)							1993-2011
Denmark							1995-2016
Ecuador	9,839	6,133	1,455			710	1993-2024

Egypt		1,625						1993-2019
Estonia								1995-2002
Germany								2004-2004
Ghana							4	2013-2024
Guatemala		2,498	1,401	1,124	868	560	836	1995-2024
Guinea								1995-2003
Guyana			5,927	2,987	3,037	1,505	11,491	2020-2024
Indonesia								1993-2009
Italy			346					2018-2020
Ivory Coast								1995-2018
Kazakhstan								2004-2011
Kyrgyzstan								1995-2002
Malaysia								1995-2009
Mauritania								2007-2017
Mexico		203,480	218,423	188,406	194,883	228,550	151,652	1993-2024
Netherlands		486				383		2004-2023
Netherlands Antilles								2004-2004
Norway		629		798			1,834	1993-2024
Oman								1995-2016
Papua New Guinea								1995-2002
Peru			339		259			1995-2022
Qatar								1995-2011
Russia		11,747	6,369	20,941				1995-2021

Senegal						995	2024-2024
Singapore							1995-2006
South Africa							2006-2009
South Sudan	41						2019-2019
Spain							1995-2002
Syria							1993-2011
Thailand							1993-2002
Trinidad and Tobago	13,702	8,611	11,421	9,076	7,443	12,143	1993-2024
Tunisia							2006-2008
United Kingdom	12,250	4,008	10,358	8,623	8,217	10,237	1993-2024
Vietnam							1995-2012
Virgin Islands (U.S.)							1995-2002
Yemen							1993-2005

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- = No Data Reported; **--** = Not Applicable; **NA** = Not Available; **W** = Withheld to avoid disclosure of individual company data.

Notes: Crude oil and unfinished oils are reported by the PAD District in which they are processed; all other products are reported by the PAD District of entry. Crude oil includes imports for storage in the Strategic Petroleum Reserve. Totals may not equal sum of components due to independent rounding. See Definitions, Sources, and Notes link above for more information on this table.