Model Comparison Exercise Technical Document

United States Environmental Protection Agency

Model Comparison Exercise Technical Document

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

[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.

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[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,

[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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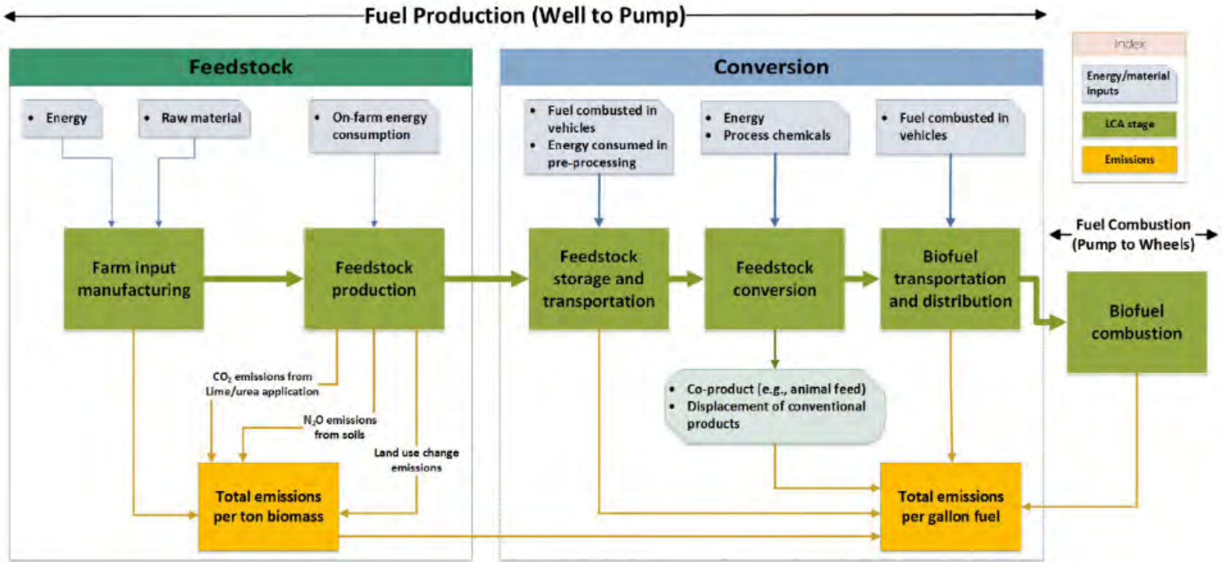
[18] NAS (2022) lists many definitions of an attributional lifecycle analysis without prescribing one particular definition. This sentence is adapted from the first sentence under the heading "Attributional Life-Cycle Assessment on page 22 of NAS (2022).
[19] NAS (2022) lists many definitions of a consequential 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.

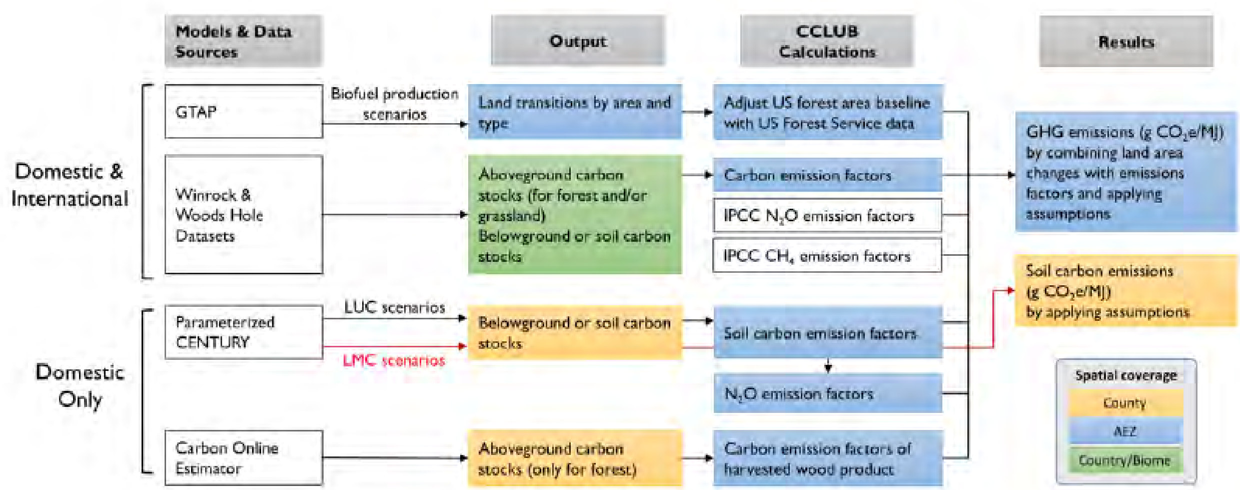
GREET is not a dynamic model as it does not make projections whereby future time periods depend on the simulation of prior time periods. However, it does include projected background data, using projections from sources such as the U.S. Energy Information Administration (EIA). GREET users can select 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

[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.

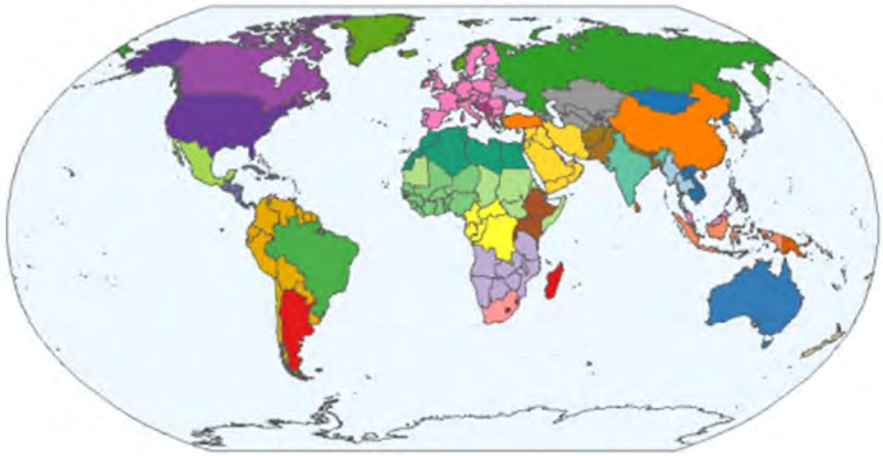
[38] ICAO. Models and Databases. https://www.icao.int/environmental-protection/pages/modelling-and-databases.aspx.

[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.

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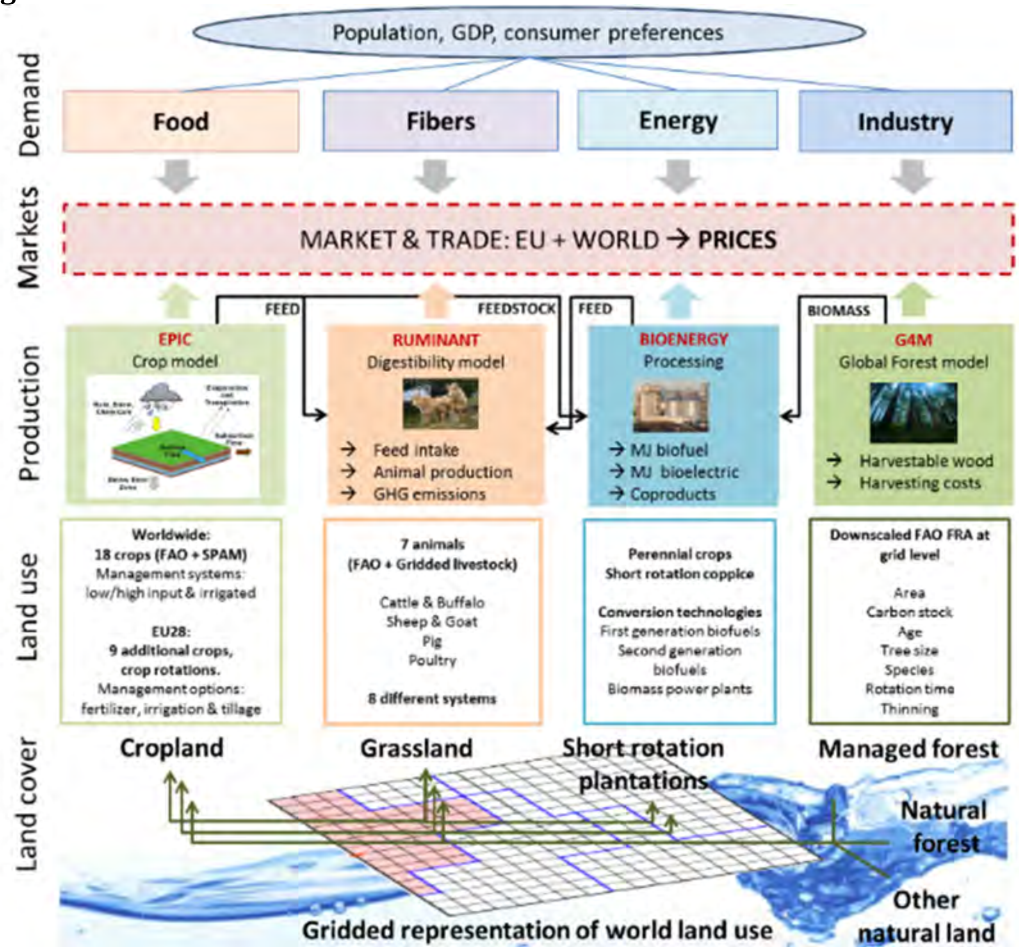
[42] IIASA. (2020). "GLOBIOM regional and country level modeling." SUPREMA GLOBIOM-MAGNET Training. December 4, 2020. https://iiasa.github.io/GLOBIOM/training_material/GLOBIOM/GLOBIOM-Topic_RegionalApplications_APalazzo_Nov2020.pdf.

[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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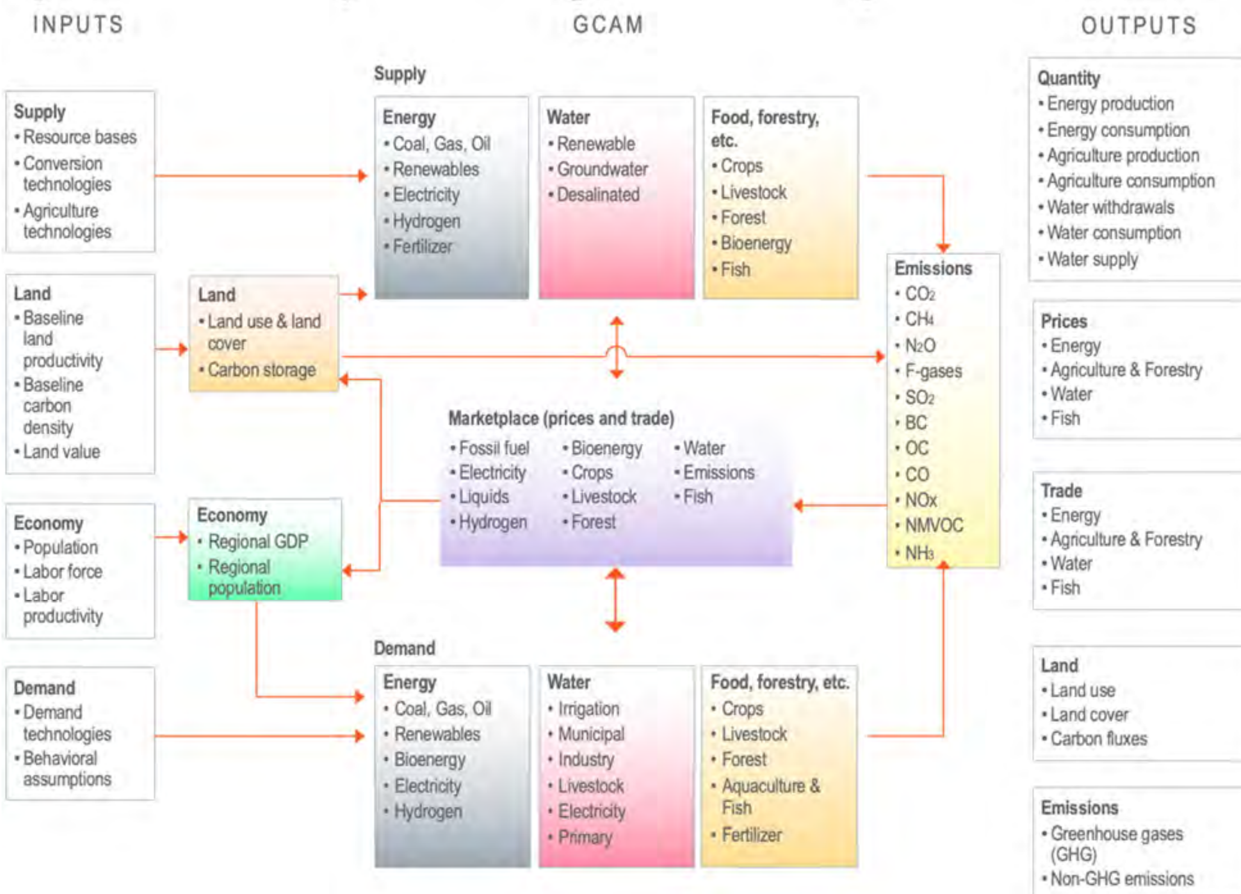
[53] For more information, see https://gcims.pnnl.gov/community.
[54] Thomson AM, Calvin KV, Smith SJ, Kyle GP, Volke A, Patel P, et al. RCP4. 5: a pathway for stabilization of radiative forcing by 2100. Clim Change 2011;109:77.
[55] Calvin K, Bond-Lamberty B, Clarke L, Edmonds J, Eom J, Hartin C, et 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

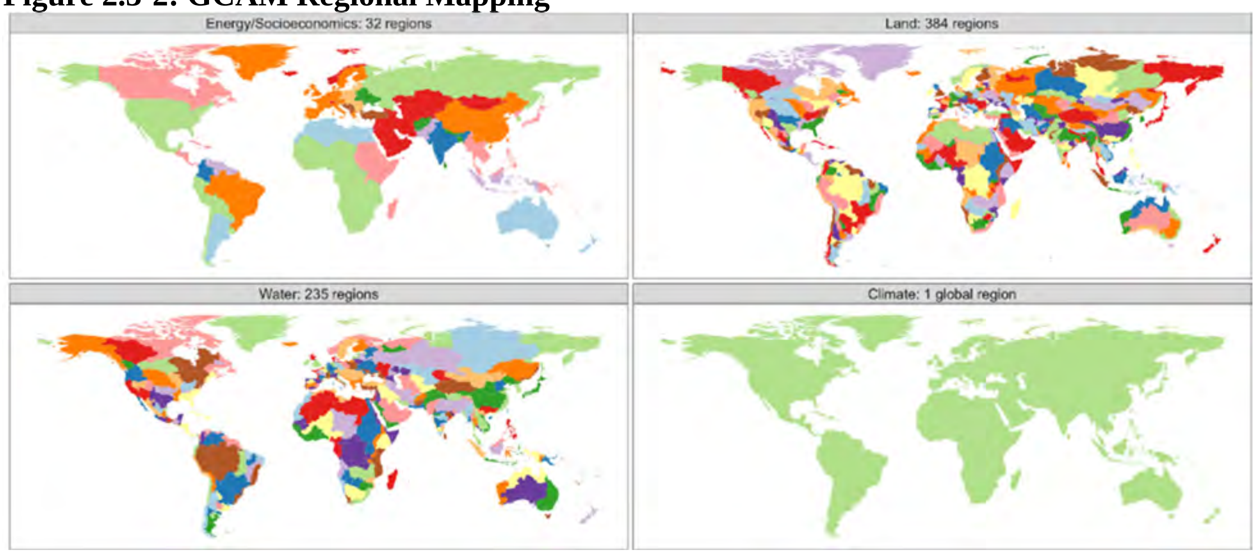
[67] More detailed information on the GCAM energy system can be found in online documentation, see http://jgcri.github.io/gcam-doc/index.html, and also in previous studies (see Clarke L, Eom J, Marten EH, Horowitz R, Kyle P, Link R, et al. Effects of long-term climate change on global building energy 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

[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.

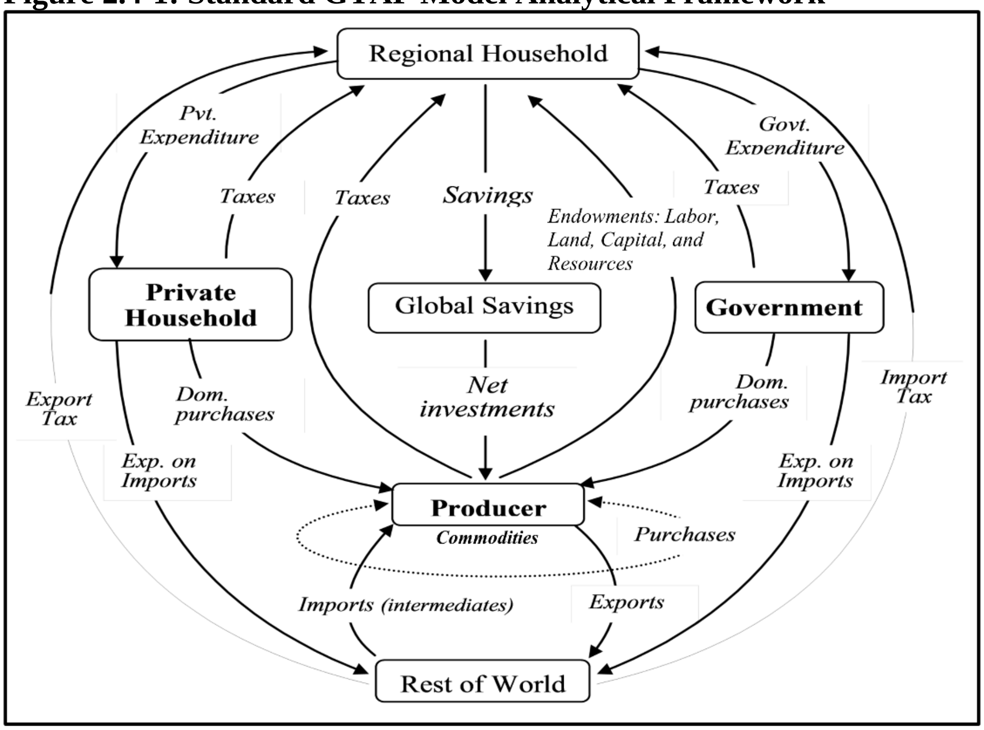
As shown in Figure 2.4-1, in each region of this model a regional household collects all the income in its region and spends it over three expenditure types: private household (representing all consumers), government, and savings, as governed by a utility function. A representative firm maximizes profits 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

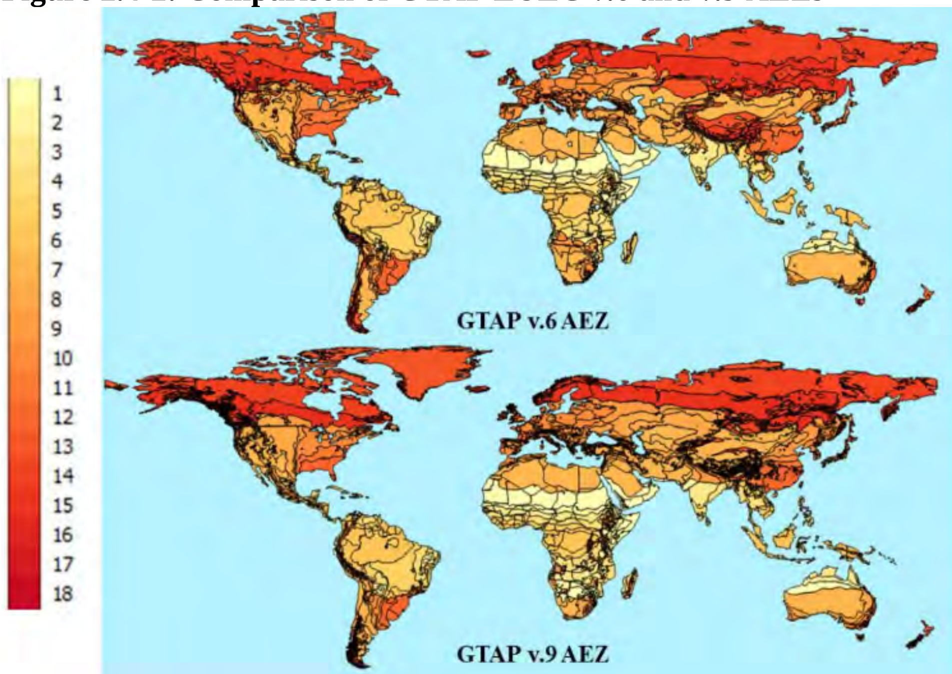
[93] Golub, A. A., et al. (2017). Global Land Use Impacts of U.S. Ethanol: Revised Analysis Using GDyn-BIO Framework. Handbook of Bioenergy Economics and Policy: Volume II: Modeling Land Use and Greenhouse Gas Implications. M. Khanna and D. Zilberman. New York, NY, Springer New York: 183-212.; Oladosu, 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.

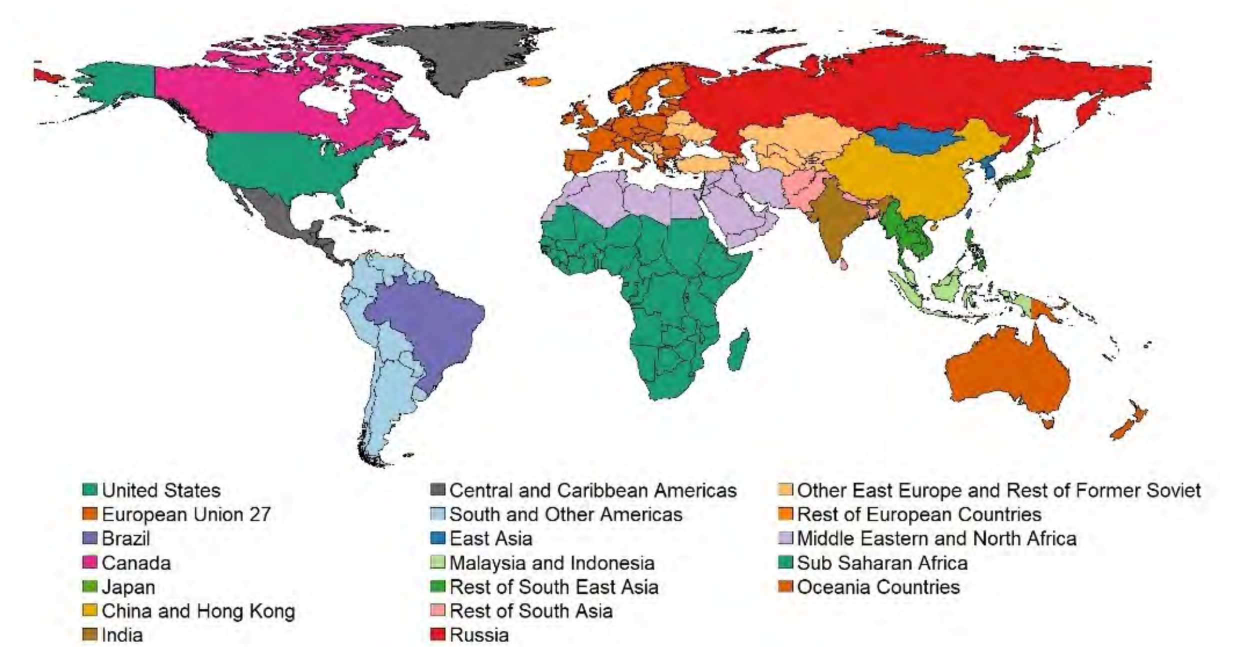
[97] Hertel, T.W., Golub, A.A., Jones, A.D., O'Hare, M., Plevin, R.J., Kammen, D.M., 2010. Effects of US maize ethanol on global land use and greenhouse gas emissions: estimating market-mediated responses. BioScience 60, 223-231. See the supporting information which says on page 27, "The current version 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

[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

[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).

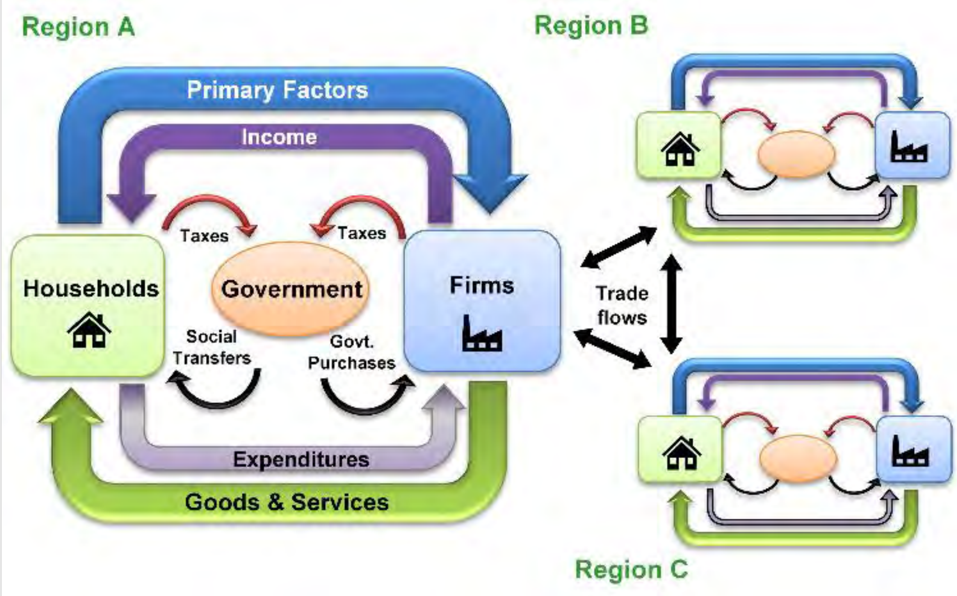
2.5 The Applied Dynamic Analysis of the Global Economy (ADAGE) Model

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.

[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

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[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.

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[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.

[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.

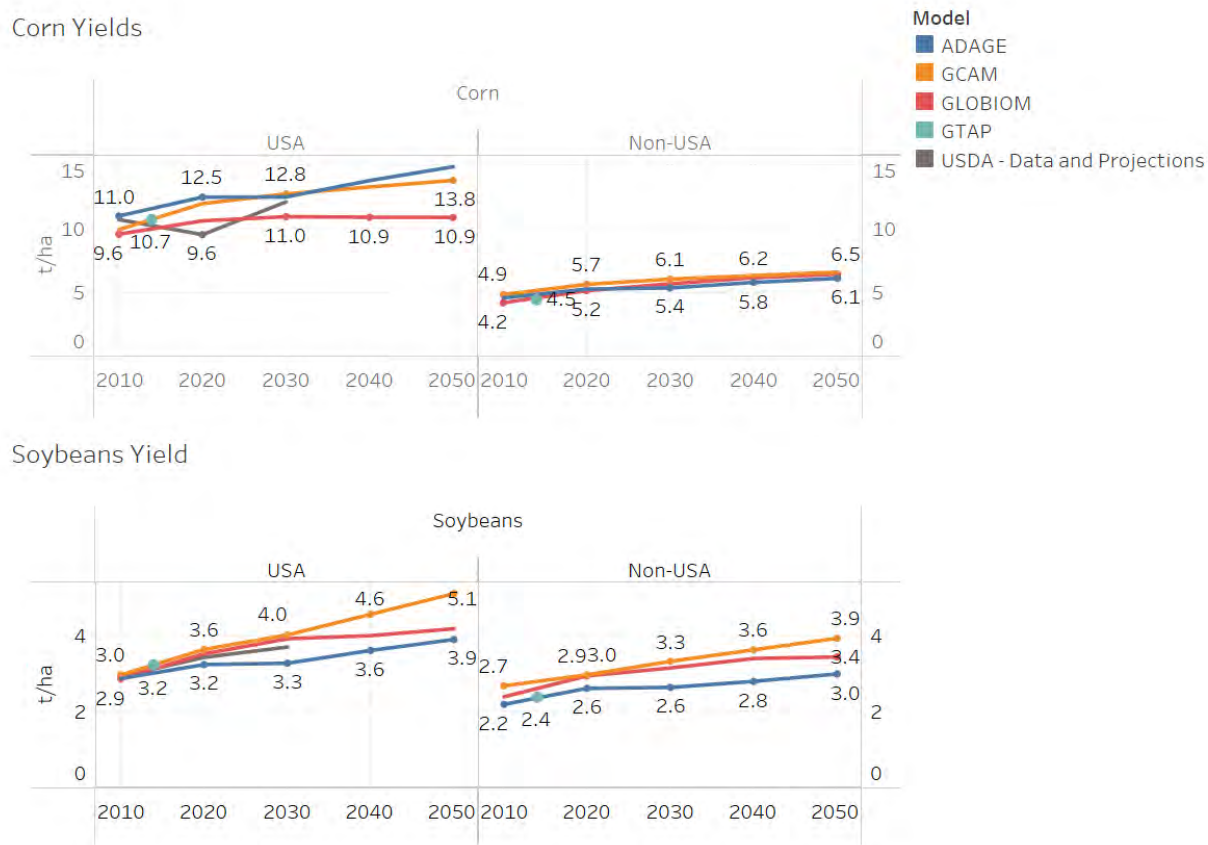
These models also have the ability to change crop yields endogenously, based on changes in prices or other factors, as does the GTAP model. In ADAGE and GTAP, a nested CES (constant elasticity of substitution) function governs the endogenous yield changes. Materials (e.g., fertilizer) or energy (e.g., 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

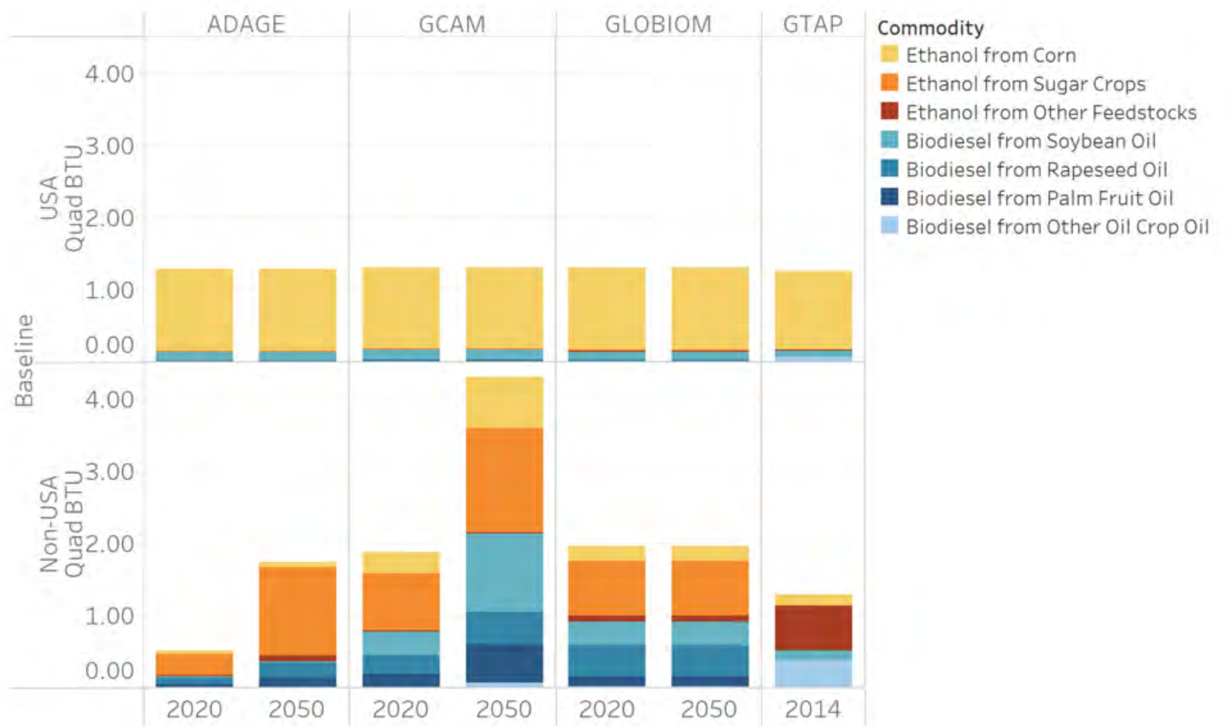
Each model was given specifications for biofuel consumption in the USA region to stay constant at specific levels in the reference case.[171] However, constraints were not placed on biofuel consumption in non-USA regions. Figure 5.4-1 shows the biofuel consumption in ADAGE, GCAM, GLOBIOM, and GTAP. The 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

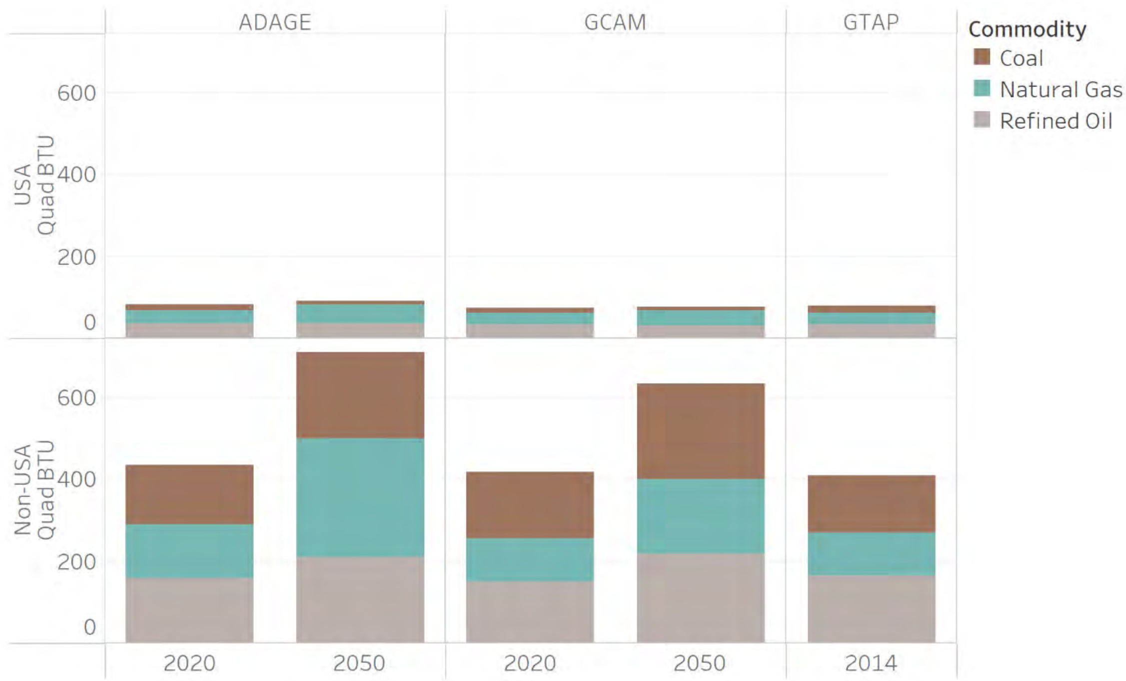


ADAGE, GCAM, and GTAP show similar fossil fuel consumption in the reference case (Figure 5.4-2).[173] Consumption of natural gas, coal, and refined oil is slightly higher in the USA region in 2020 in ADAGE than GCAM. In GTAP, the 2014 coal consumption in the USA is higher than the 2020 consumption in 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

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[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.

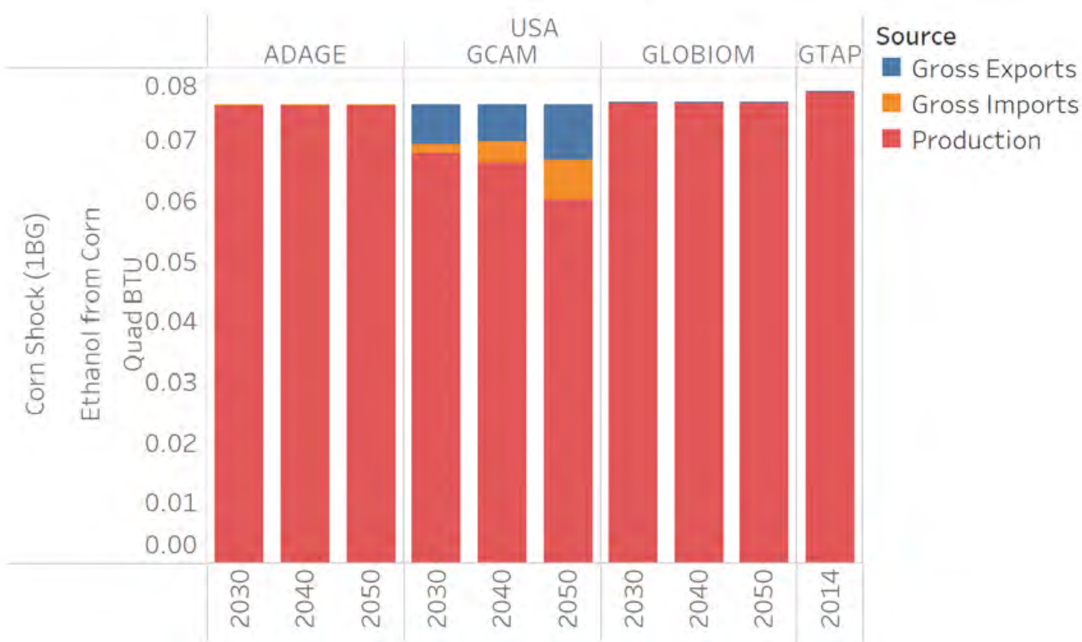
6.1 Sourcing Overview

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]



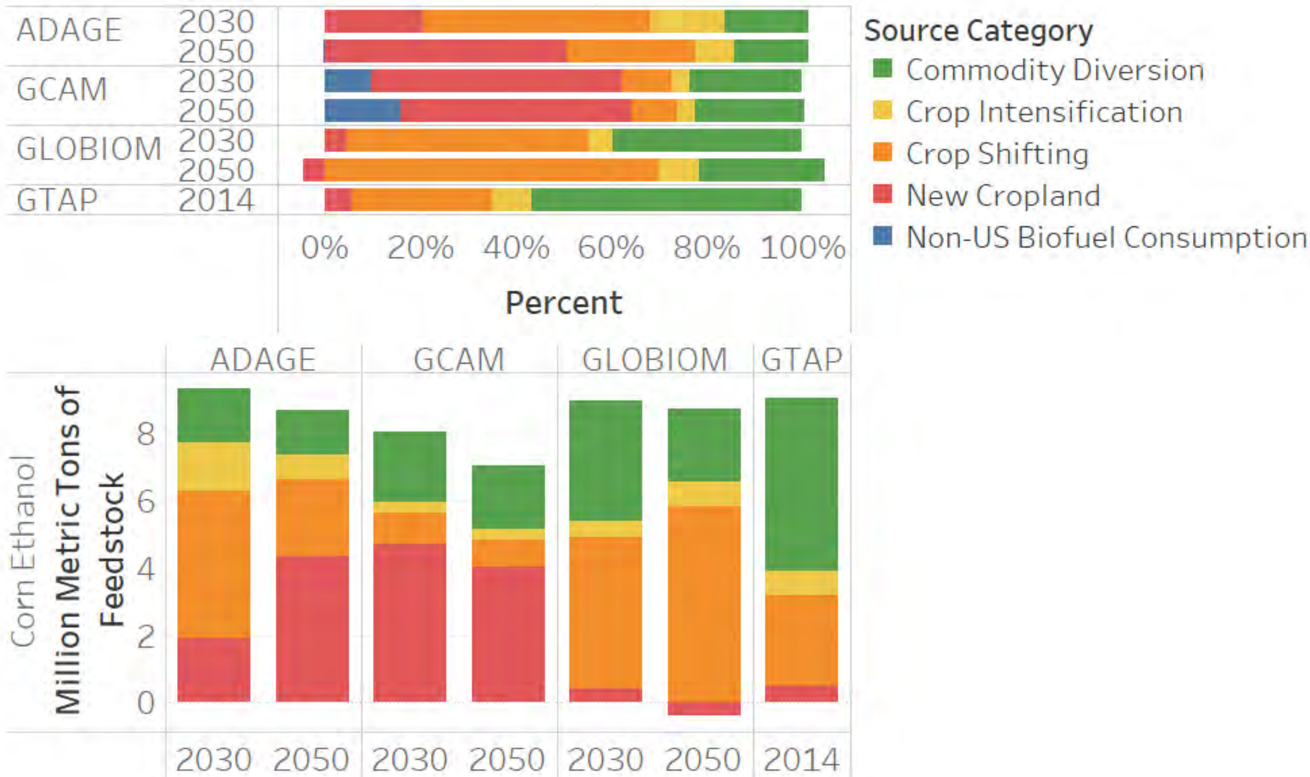
ADAGE, GCAM, GLOBIOM, and GTAP meet the corn ethanol shock through different amounts of corn diversion from other uses, crop intensification, crop shifting to corn, and new cropland (Figure 6.1-2). Based on the assumed conversion factor of corn to corn ethanol (Section 4), if all of the shock were met 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.

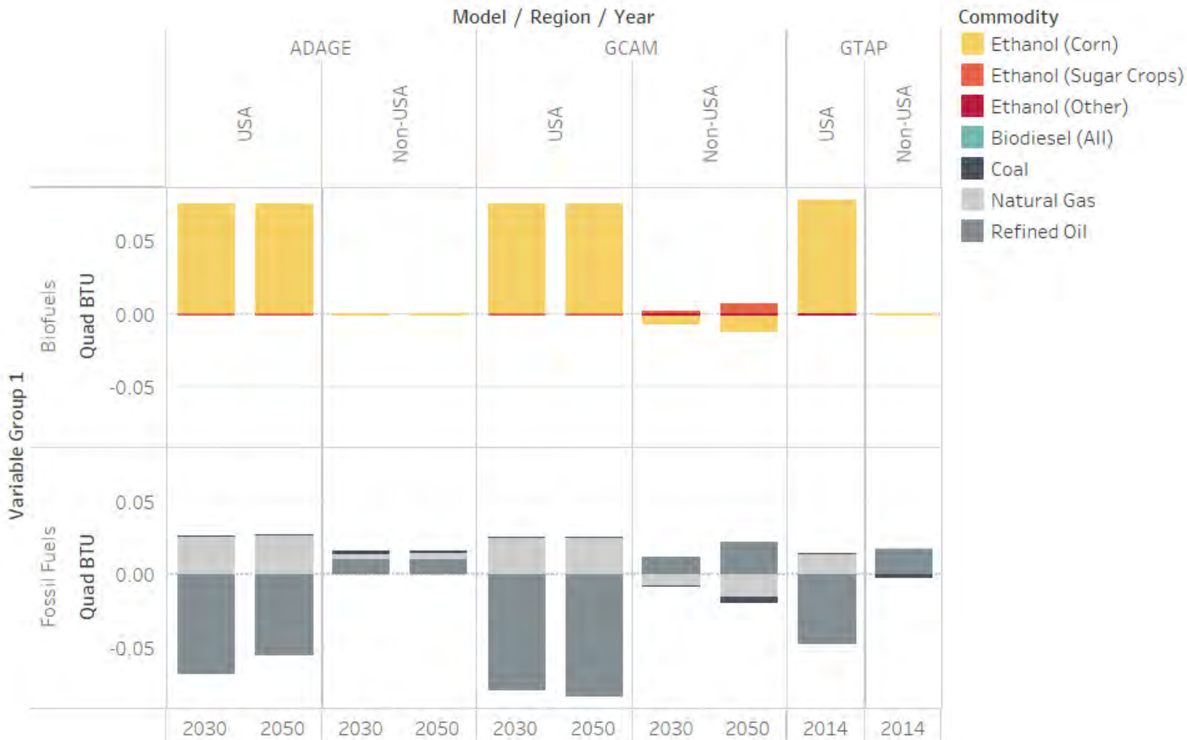
energy inputs required to grow, transport, and process additional feedstock. Correspondingly, a reduction in the extraction and refining of petroleum would result in decreased demand for the energy sources required in those processes. Finally, all of the above effects on demand for energy sources will 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.

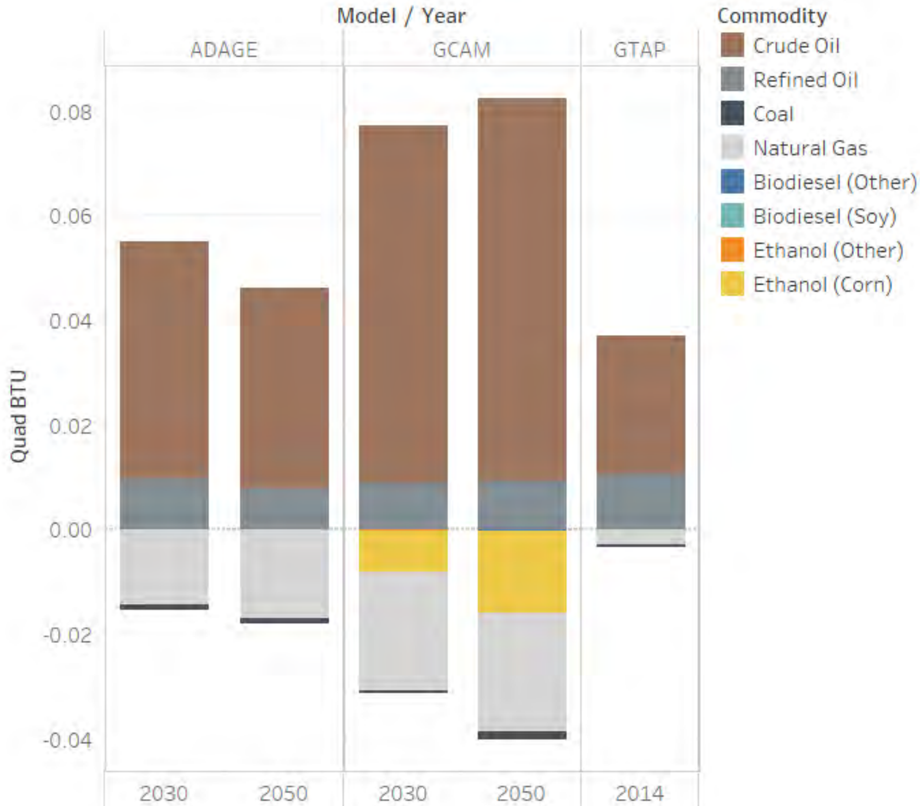
[180] I.e., the cumulative changes in energy consumption expressed as a percentage of the cumulative change in US corn ethanol consumption over the duration of the modeled period.
[181] In these models, refined oil is an aggregation of all refined petroleum products, including gasoline and diesel.

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]

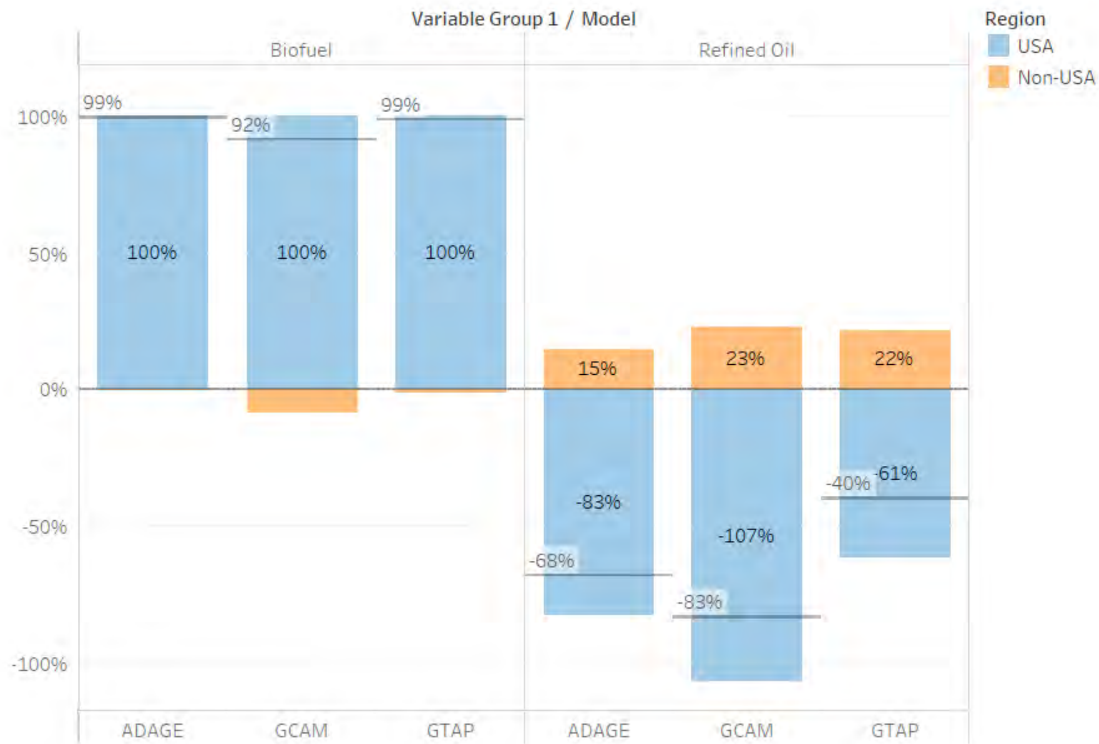


Figure 6.2-3 illustrates these cumulative relative effects within the USA region and non-USA regions for both biofuels and refined oil. The left pane depicts the effect of the corn ethanol shock on total biofuel consumption within the USA region (blue) and non-USA region (orange). As discussed in Section 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.

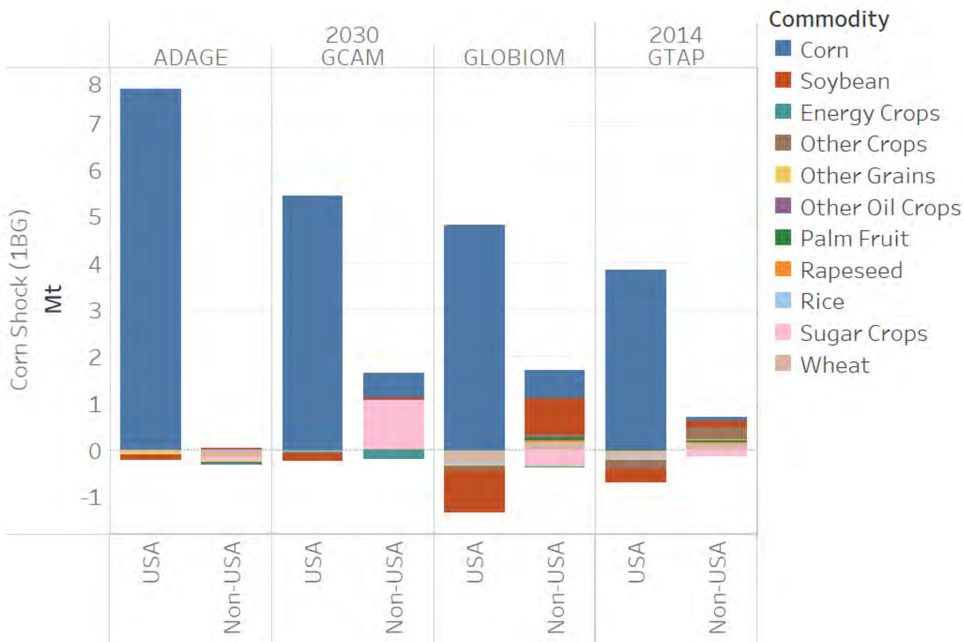
As seen in the figure, there is greater than perfect displacement of refined oil in the USA region in the GCAM results (107 percent). This displacement exceeds 100 percent primarily because GCAM projects that the corn ethanol shock will increase the average price of fuel in the USA region's gasoline 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.

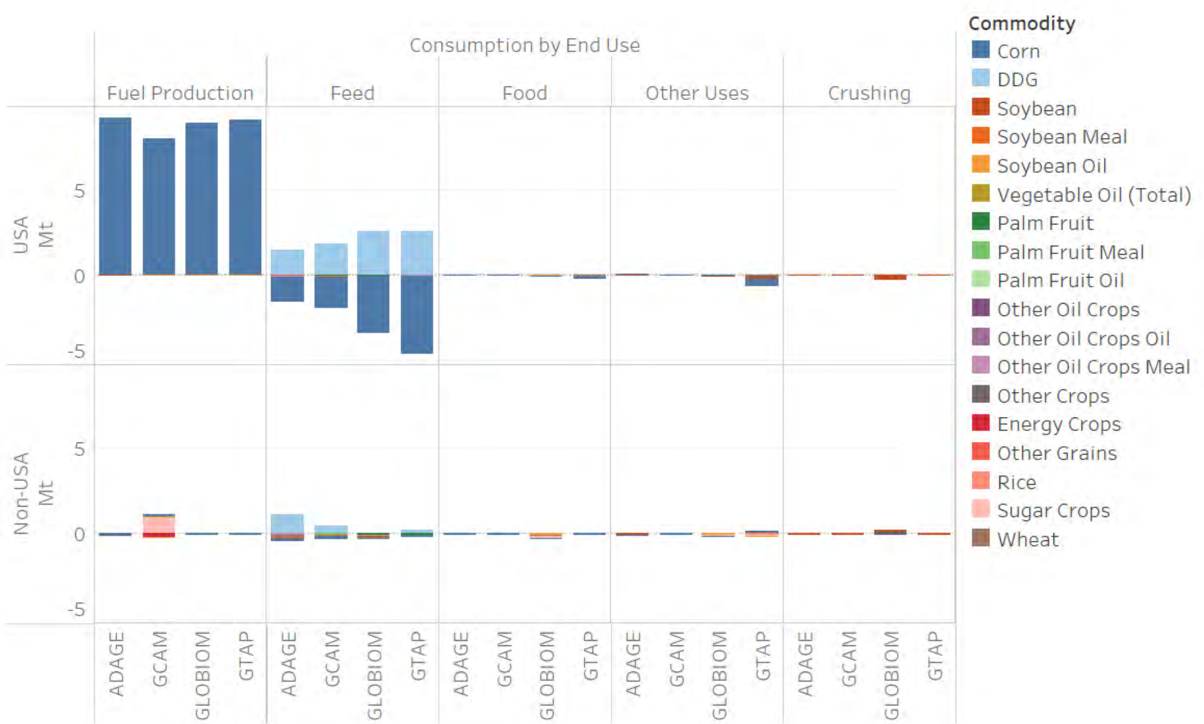
DDG is a coproduct of corn ethanol production used almost exclusively for animal feed. In these model results, the additional DDG produced from the additional corn ethanol production is used for feed to replace the corn (that is, the DDG “backfills” for the corn diverted from feed use to fuel use). Historically, 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

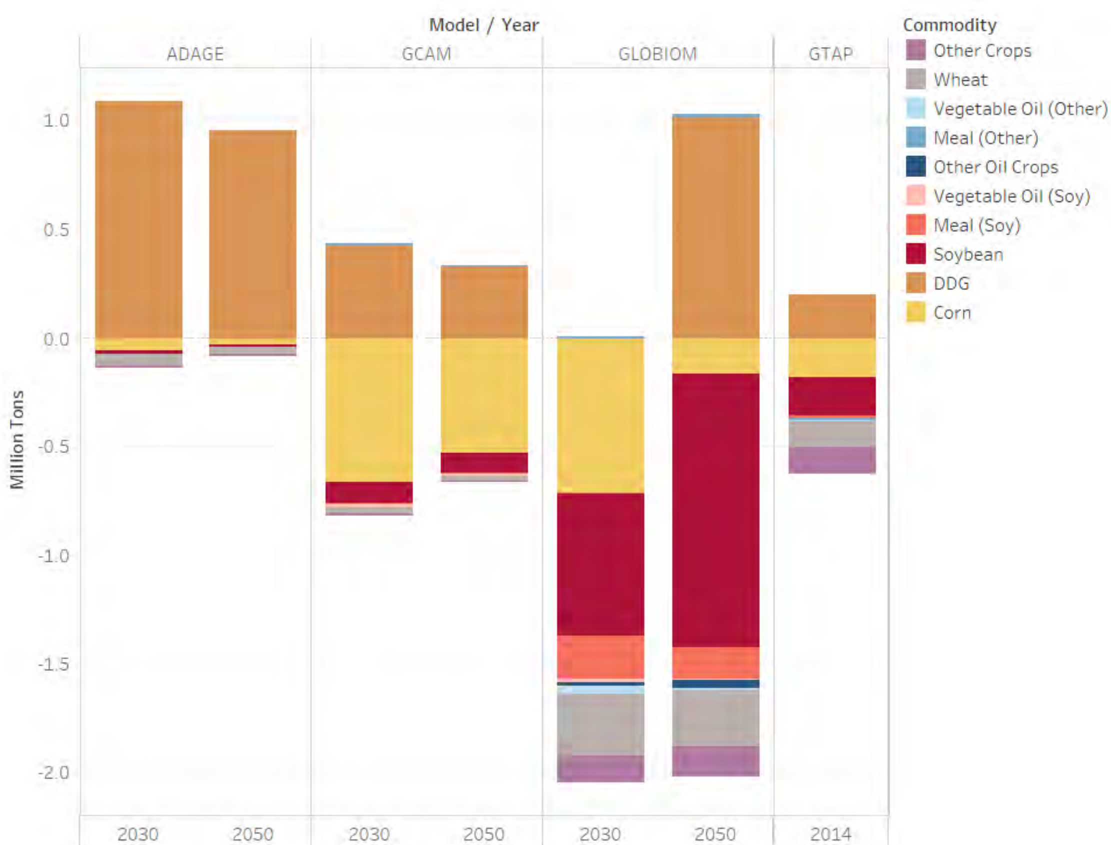
As discussed in Section 3.1.6, the structural representations of trade vary across the four economic models considered in this exercise (ADAGE, GCAM, GLOBIOM, GTAP). Because trade is more elastic by default in some model trade structures than others, one would expect the

[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)

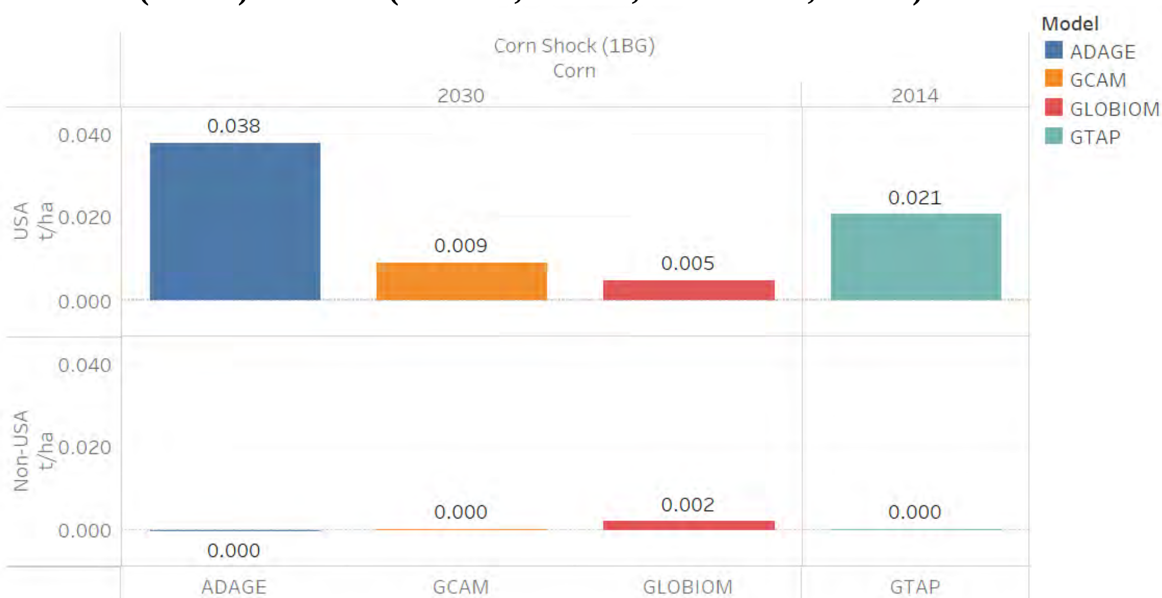
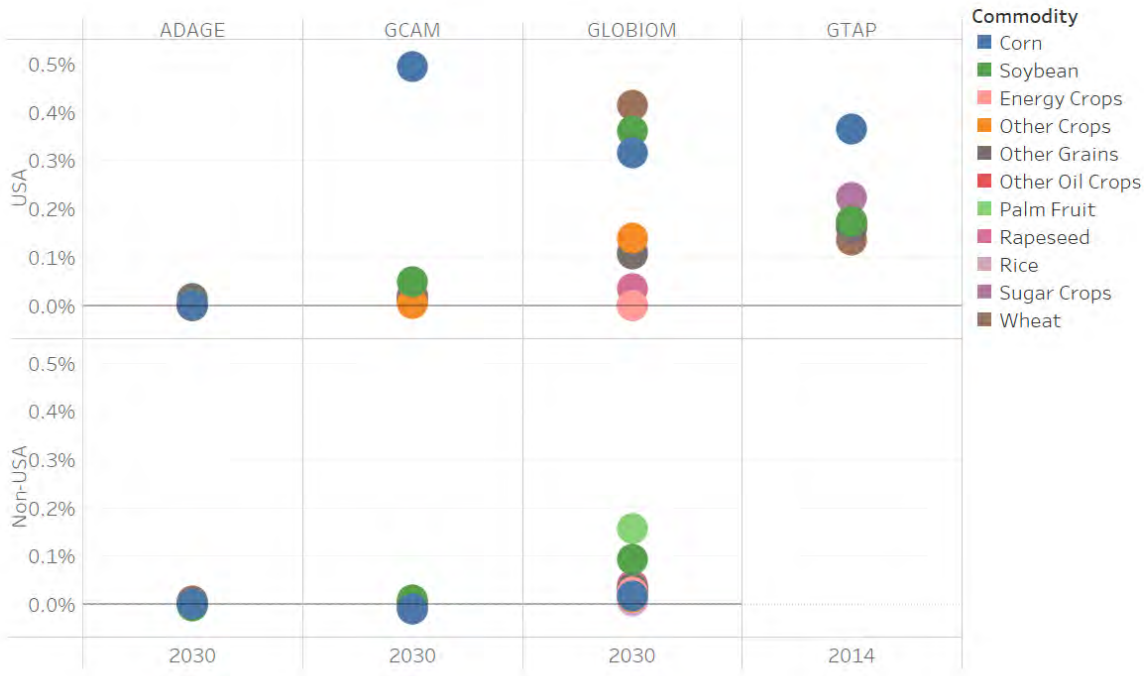


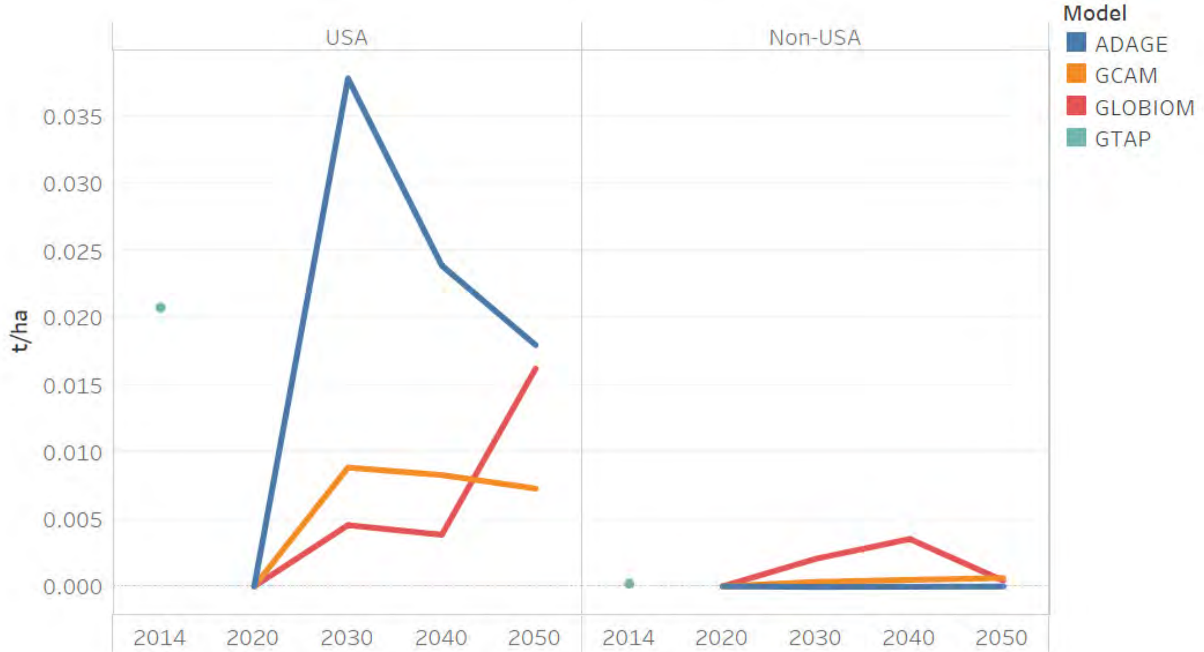
Figure 6.5-2: Percent difference in commodity prices in the corn ethanol shock relative to the reference case[185]



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.

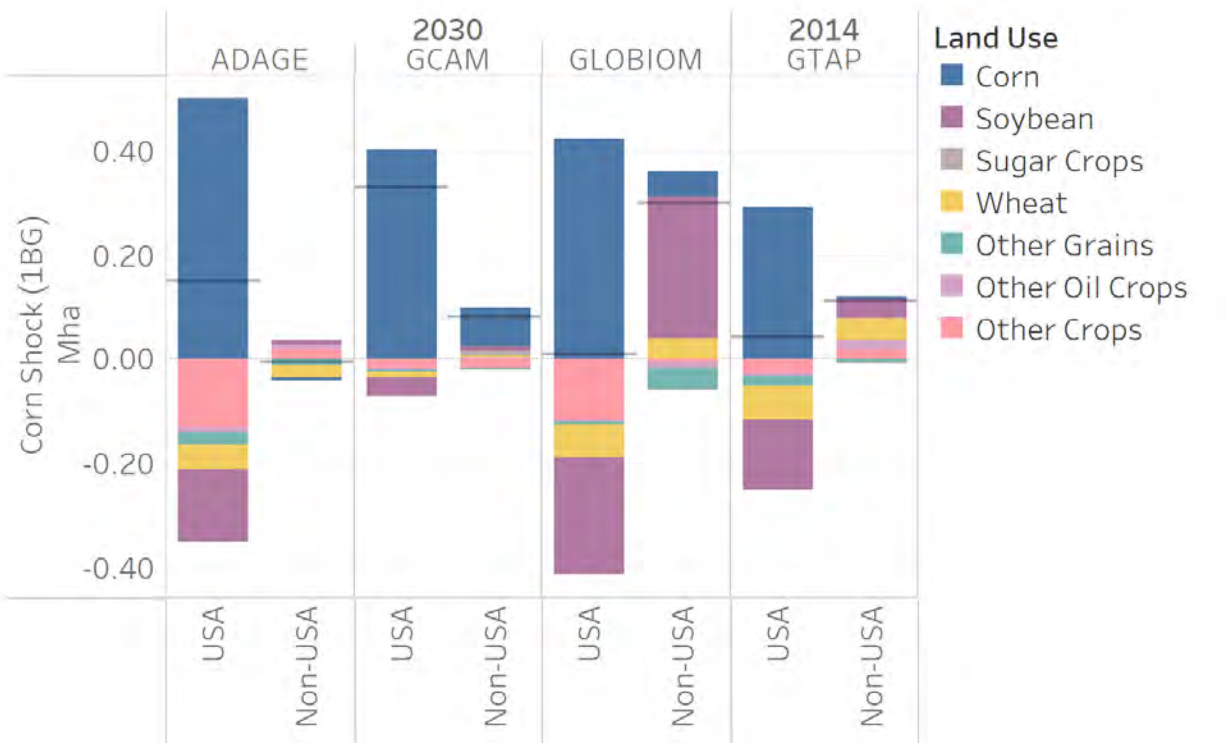
From this exercise however, we cannot draw any firm conclusions from this yield comparison regarding whether one method is superior to the others. All four of the models seem to behave reasonably in these yield results. Sensitivity analysis may reveal the degree to which GHG emissions results change 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.

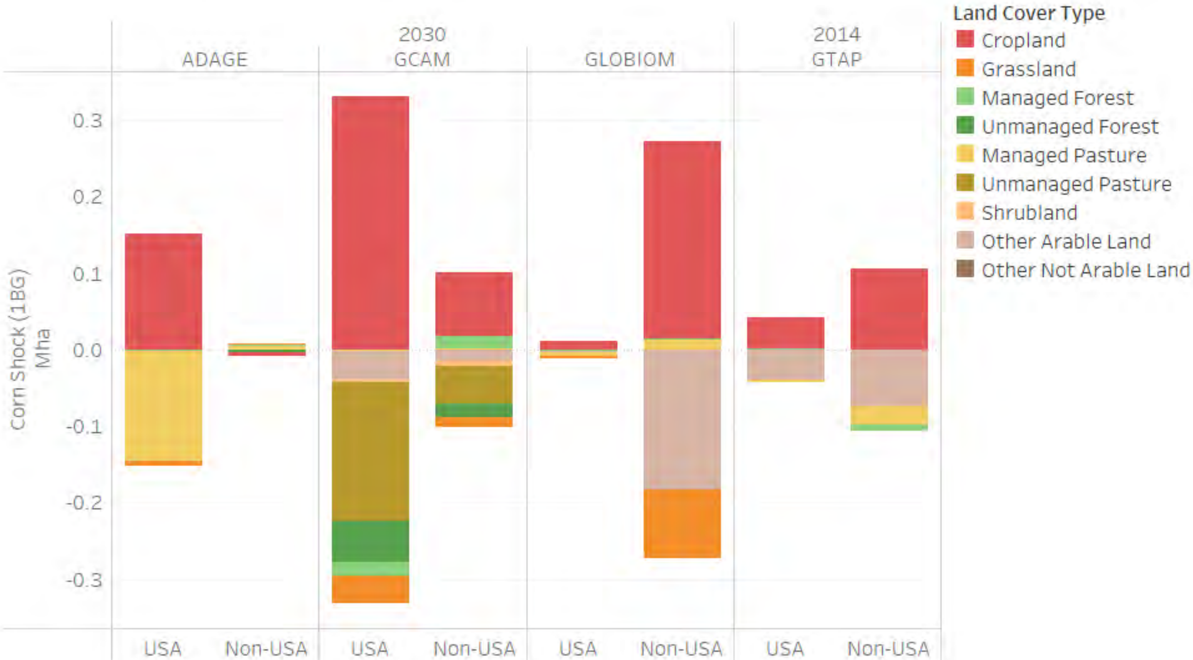
The GCAM results for the corn ethanol shock show decreasing cover for a mix of land types in both USA and non-USA regions, with the largest shift in land use estimated to come from unmanaged pasture. The change in USA land use is approximately three times greater than the non-USA change in use. In the 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.

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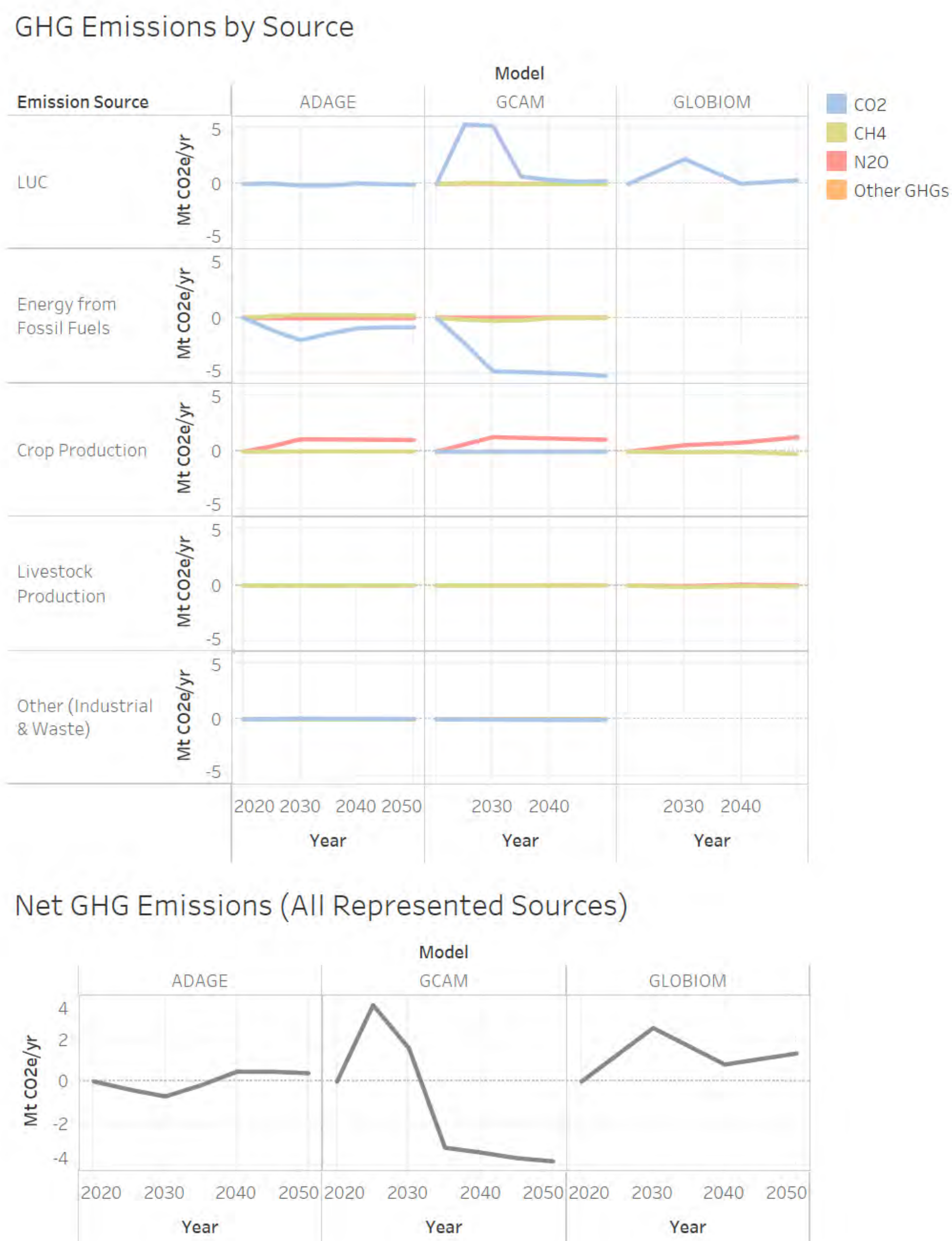
[188] In Figure 6.6-2 and 7.6-2, "Cropland" area in GTAP represents land cultivated for row crops (calculated as the change in harvested area minus the change in multicropping), while cropland pasture, and other unused cropland have been reassigned to "Other Arable Land." This differs from Figure 5.2-1, 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_2eq/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.

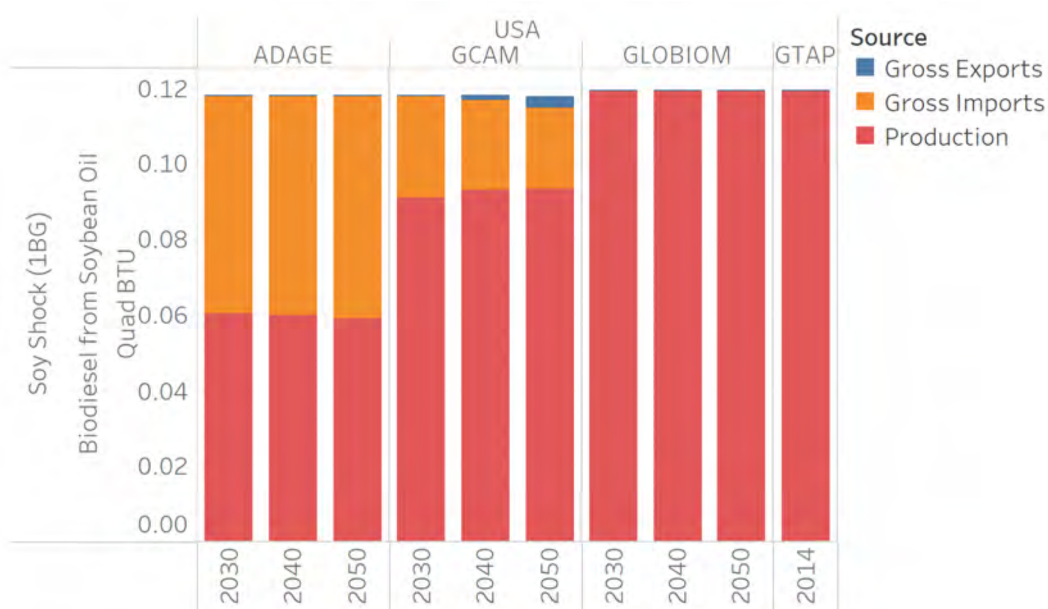
The majority of these comparisons include ADAGE, GCAM, GLOBIOM, and GTAP. Only the comparison of GHG emissions includes GREET. GREET is a supply chain LCA model that does not represent changes in agricultural and economic markets between reference and modeled scenarios, as the other models in this comparison 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]



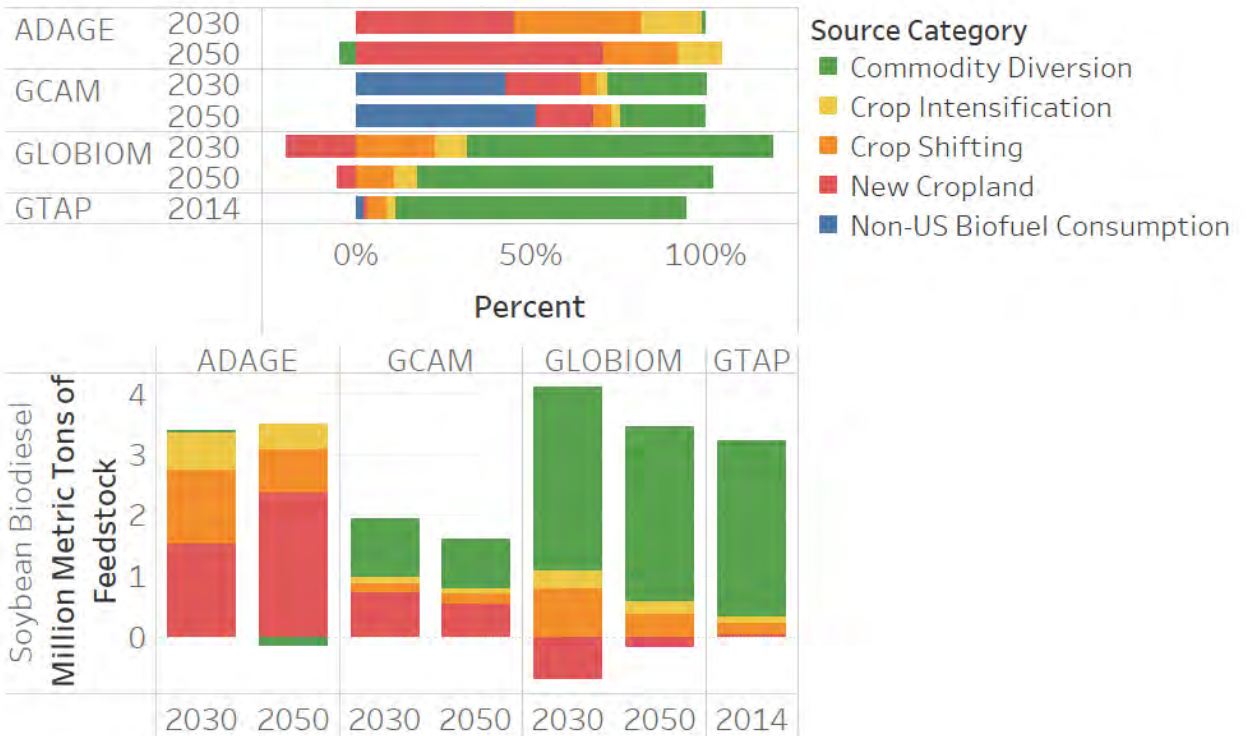
[196] Red shows the contribution increased soybean oil biodiesel production in the USA region; orange shows the contribution from increased soybean oil biodiesel gross imports to the USA region; blue shows the contribution from reduced soybean oil biodiesel gross exports from the USA region.

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

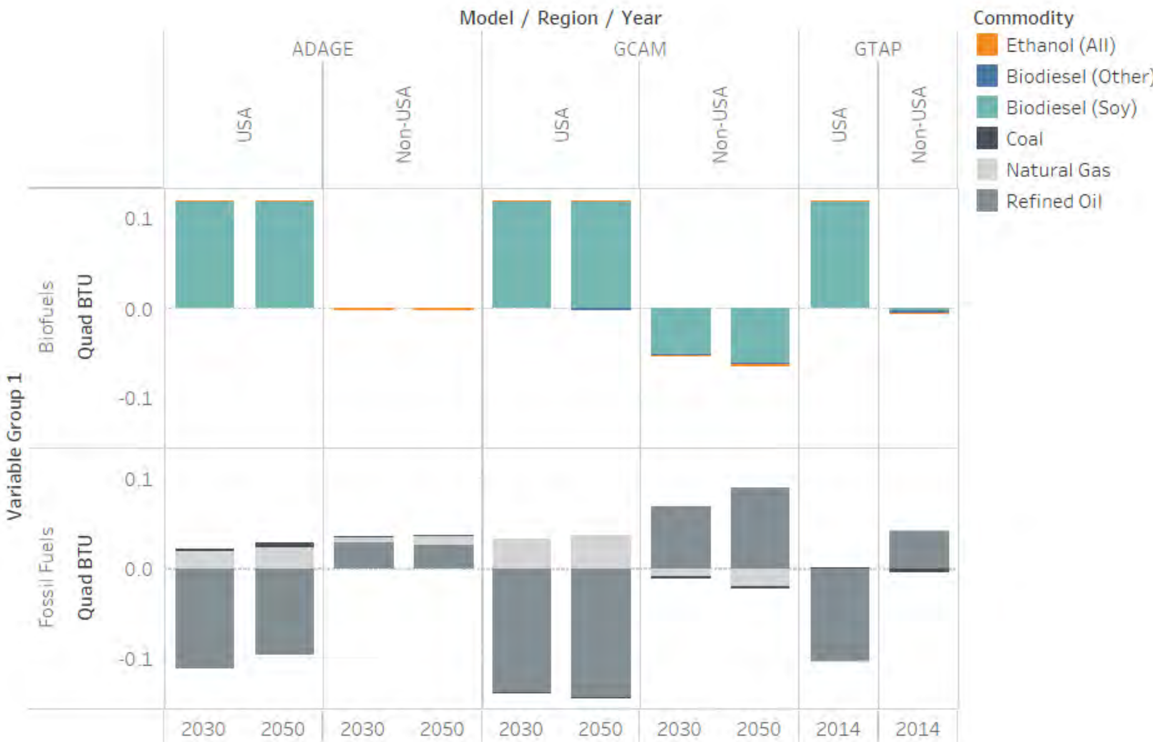
The energy market mechanisms at play in the corn ethanol shock generally hold for soybean oil biodiesel as well, though the magnitude and some of the detailed effects differ. We refer to Section 6.2 above for a discussion of those principles. As noted in that section, of the models considered under this 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)

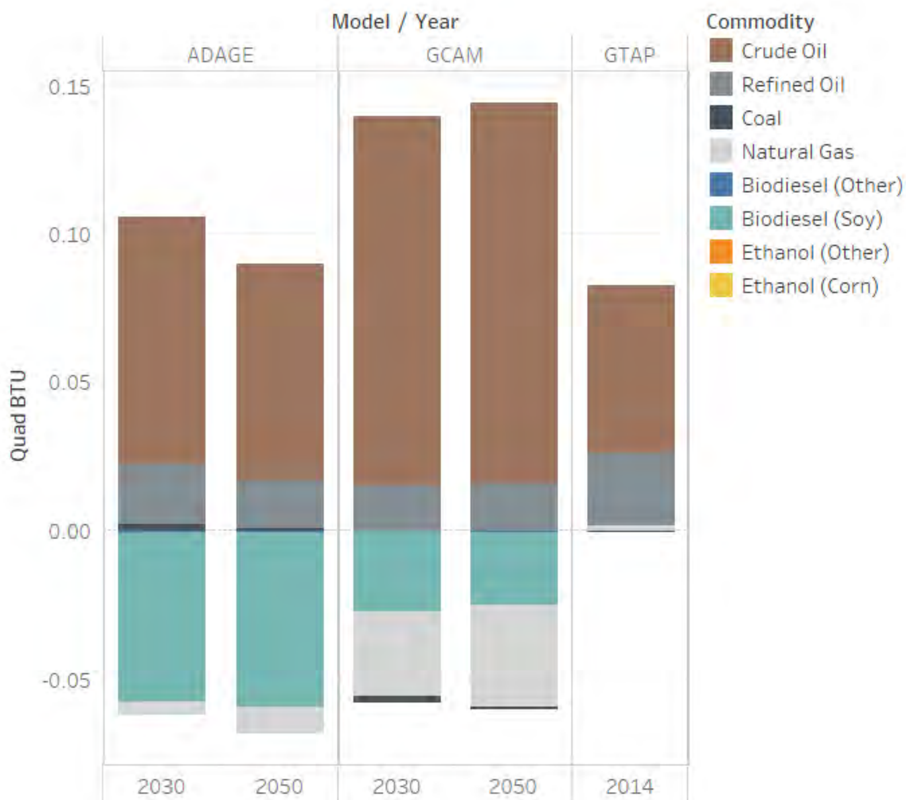


Trade in energy commodities plays a significant role in meeting the soybean oil biodiesel shock in results from several of the models considered (see Figures 7.1-1 and 7.2-1). In ADAGE and GCAM results, a substantial portion of the shock is met through greater net USA imports of soybean oil biodiesel (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.

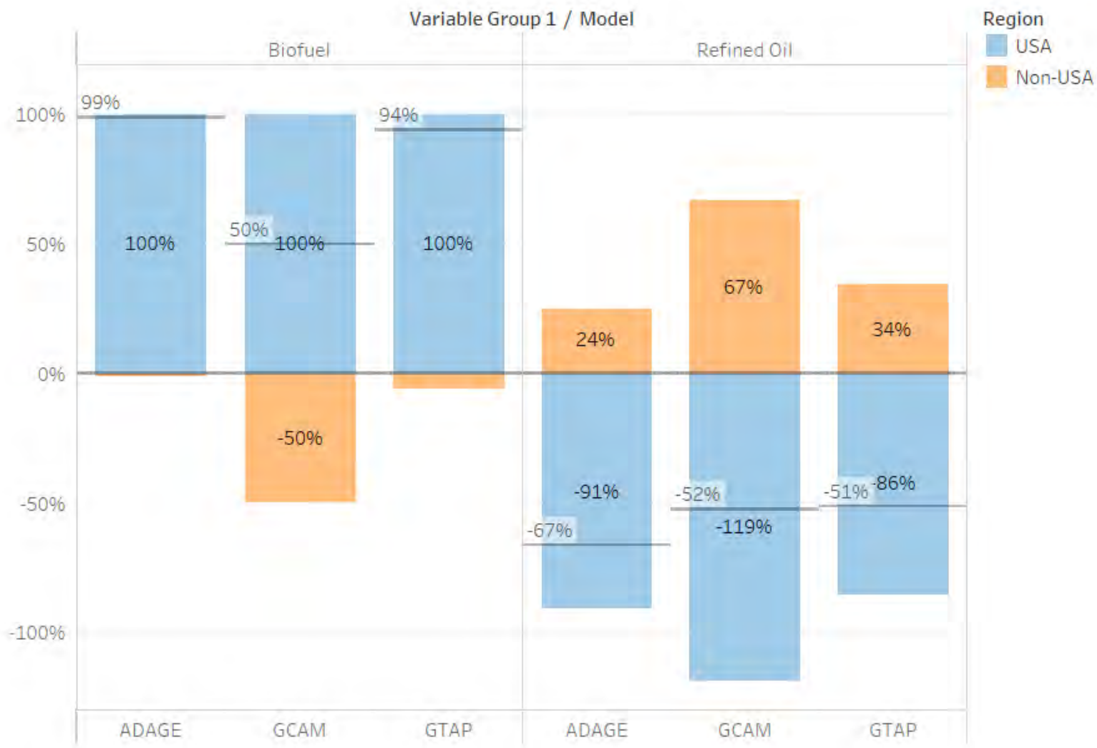
These two backfilling strategies are employed to different extents in ADAGE and GCAM results. In the GCAM results, multiple regions increase exports of soybean oil biodiesel to meet the increased demand in the USA region, but do not show commensurate increases in domestic biodiesel production. This results 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.

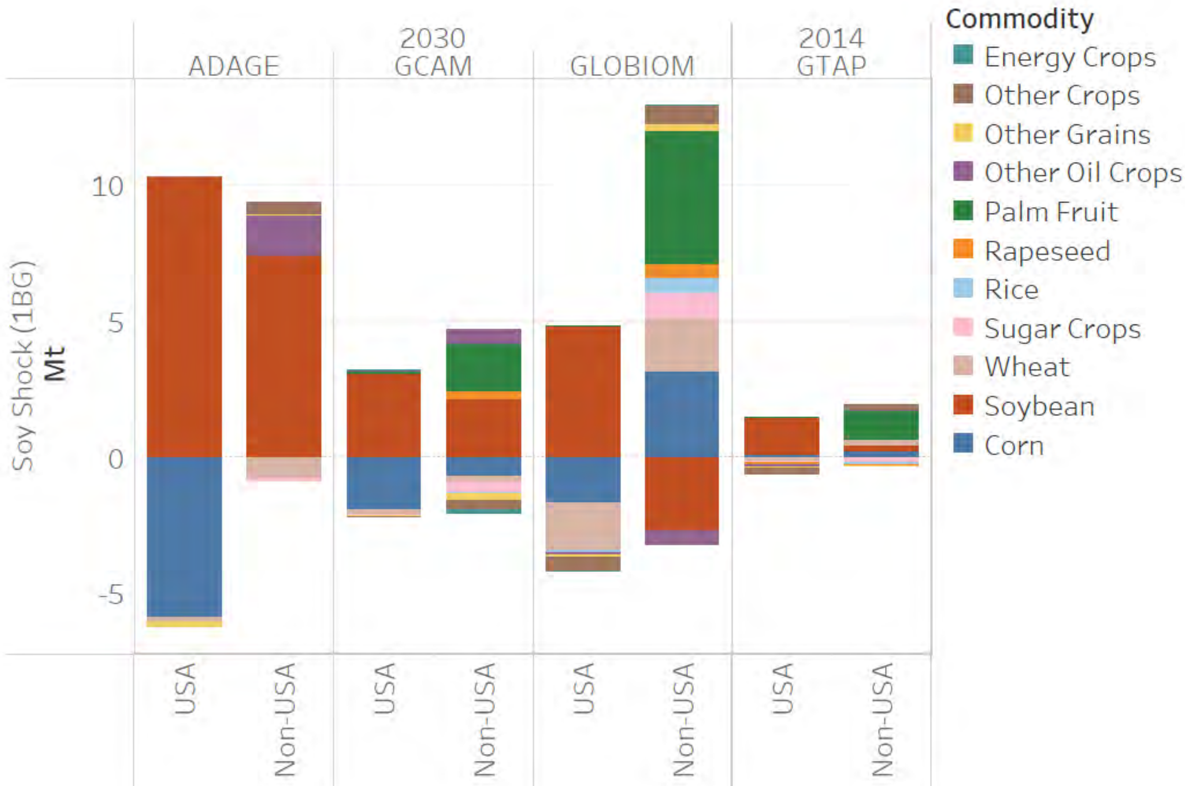
In the non-USA region, the model results show an increase in the production of oil crops. The ADAGE results show an increase in “other oil crop” production.[201] In the GTAP, GCAM, and GLOBIOM results, the increased oil crop production is primarily palm fruit. The GCAM results show decreased corn production 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.

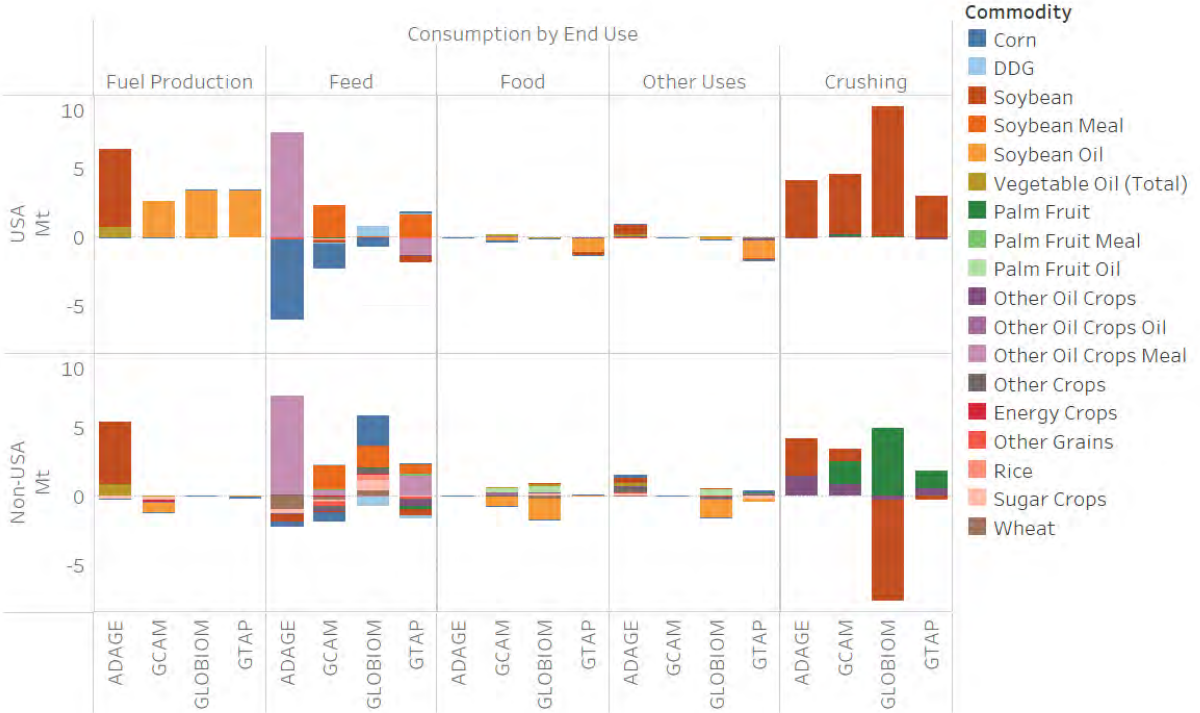
Non-USA regions show different impacts than the USA region. In the non-USA regions, the ADAGE results show an increase in soybean consumption for crushing, an increase in vegetable oil and soybean consumption for fuel production, an increase in soybean consumption for other uses (seed), and feed displacement 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

[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.

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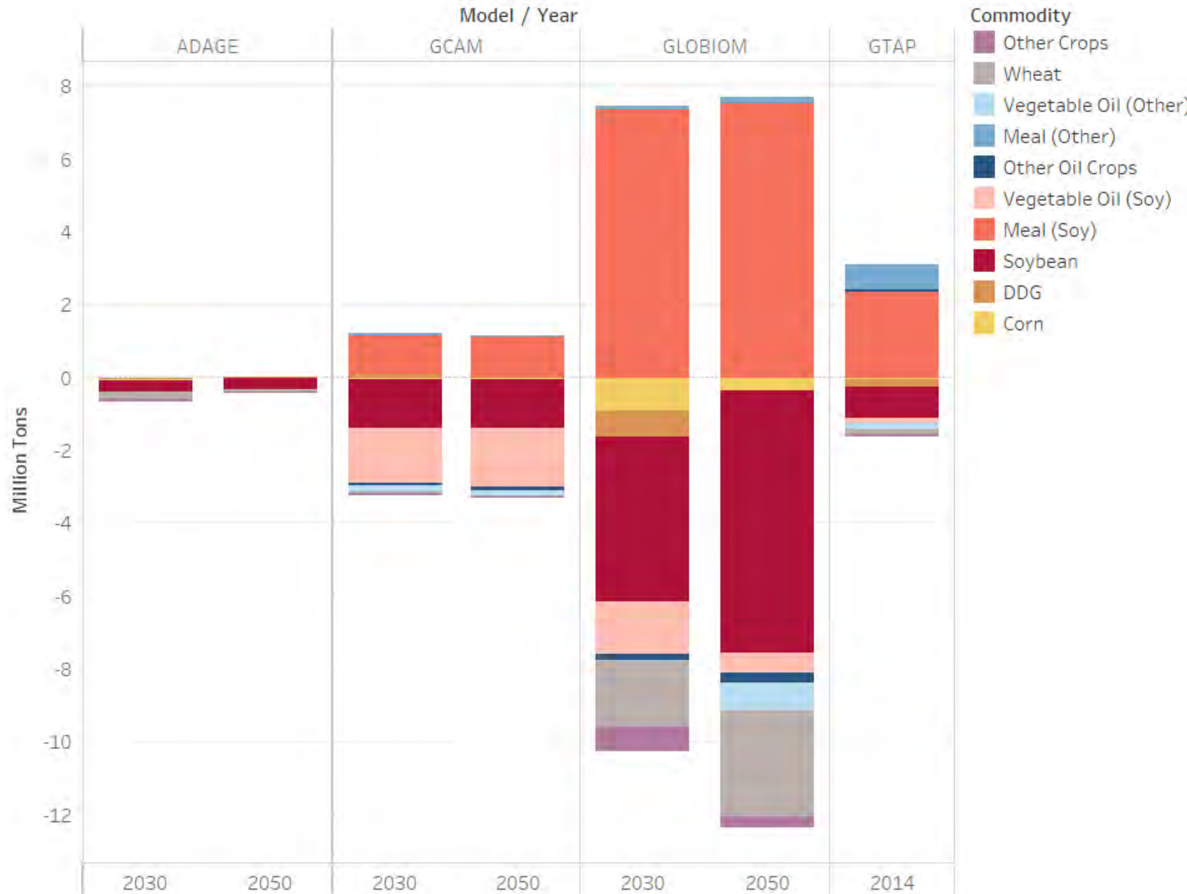
[206] Results are shown in million metric tons of each feedstock. Because soybeans contain 19 percent oil, 10 million metric tons of soybeans is equivalent to 1.9 million metric tons of soybean oil. ADAGE does not explicitly track soybean oil or soybean meal, and those are included in "Other Oil Crops 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

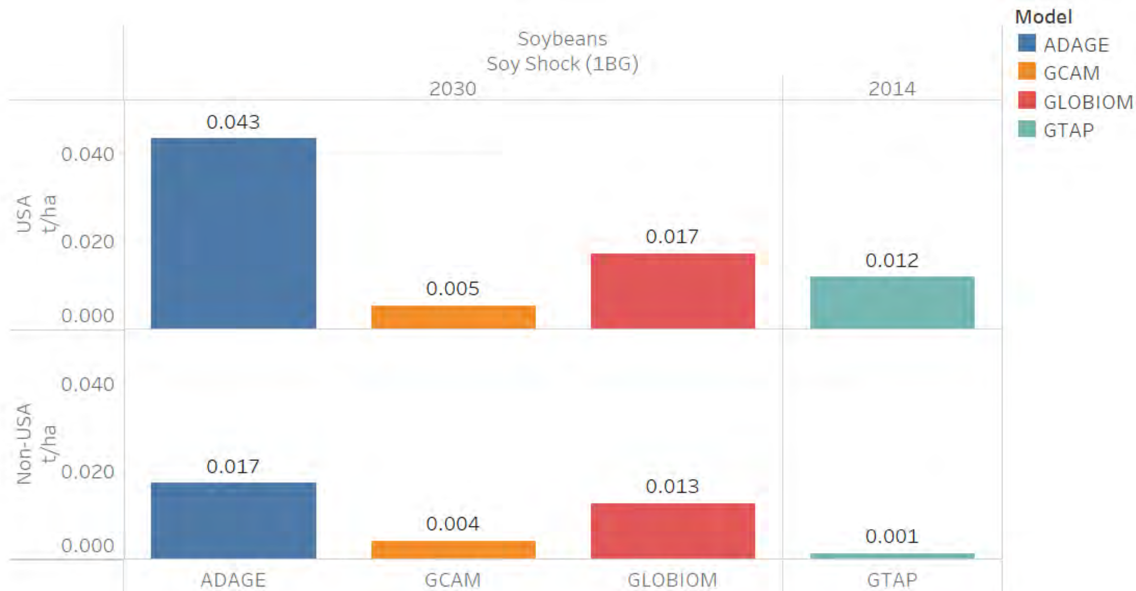
As was observed in Section 6.5 above regarding corn crop yield modeling results, the four economic models included in this comparison exercise all have the ability to increase crop yields in response to changes in crop price. However, while these models share some similar theoretical underpinnings regarding 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.

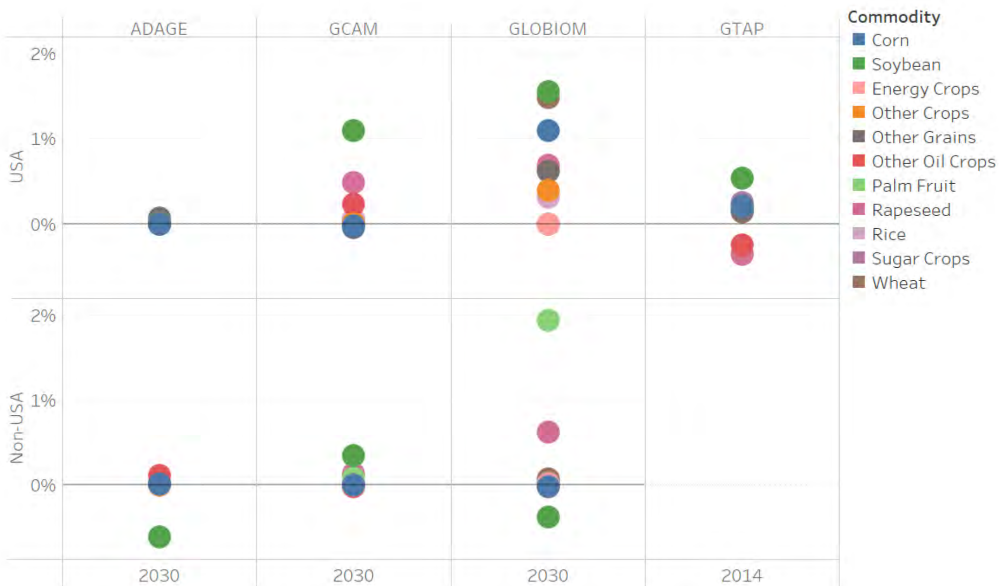
Figure 7.5-1: Difference in soybean yield in the soybean oil biodiesel shock relative to the reference case in 2014 (GTAP) and 2030 (ADAGE, GCAM, GLOBIOM, GTAP)



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]



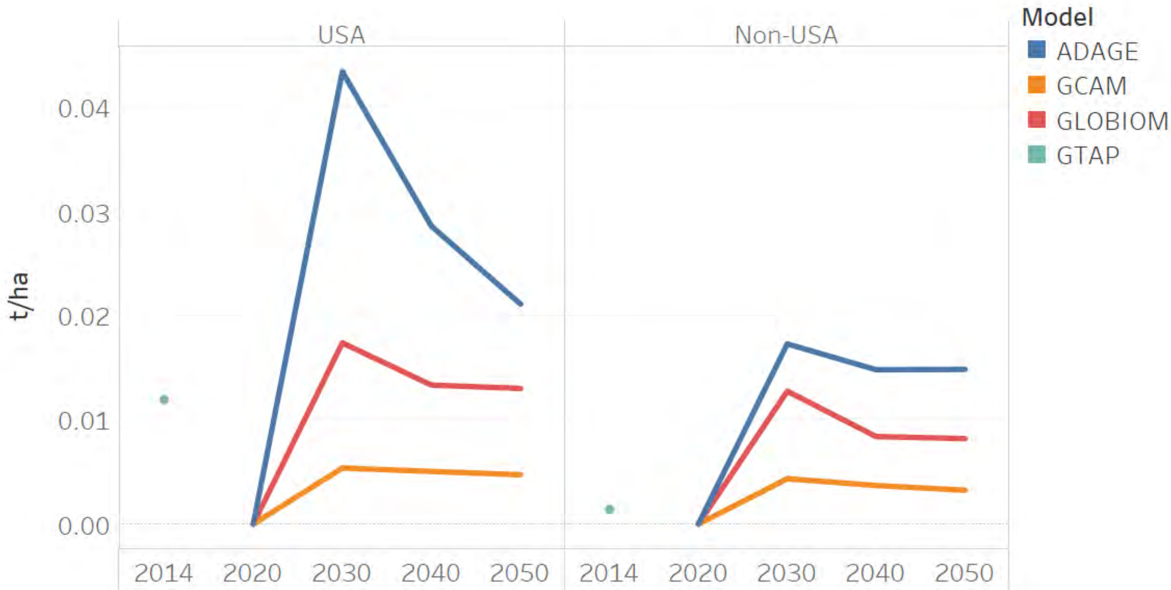
[207] Average commodity prices for non-USA regions in GTAP results were not available for this exercise.

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.

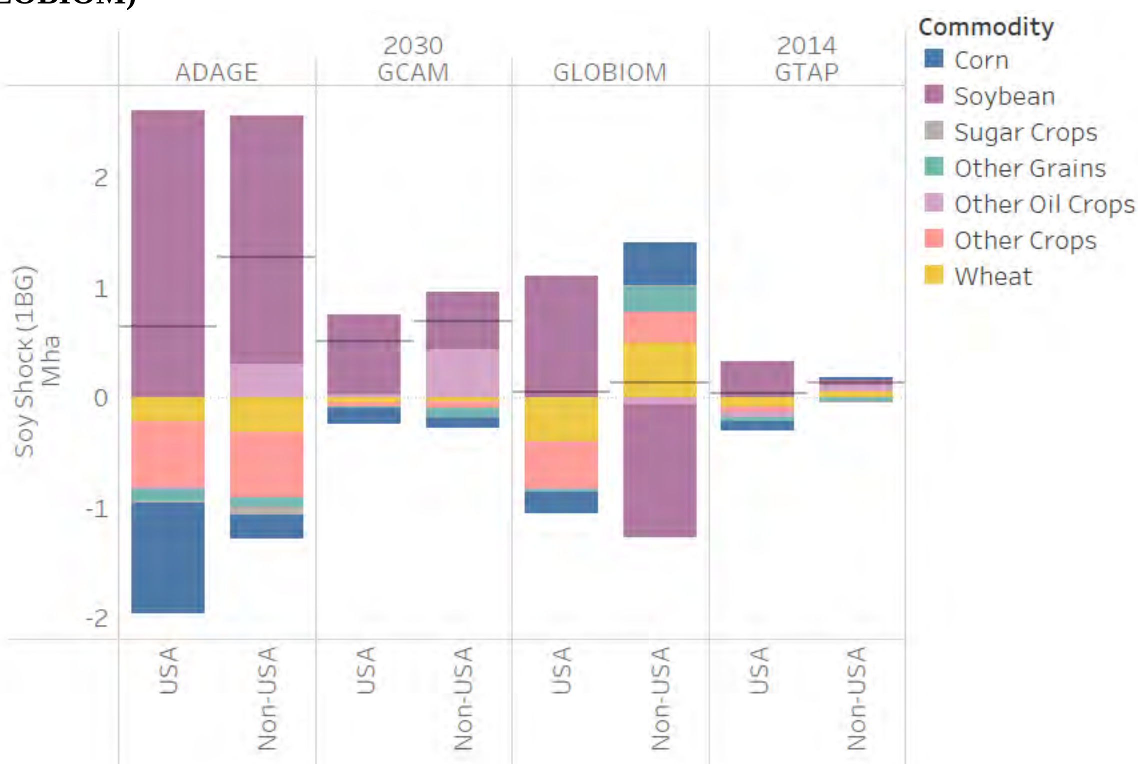
7.6 Land Use

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

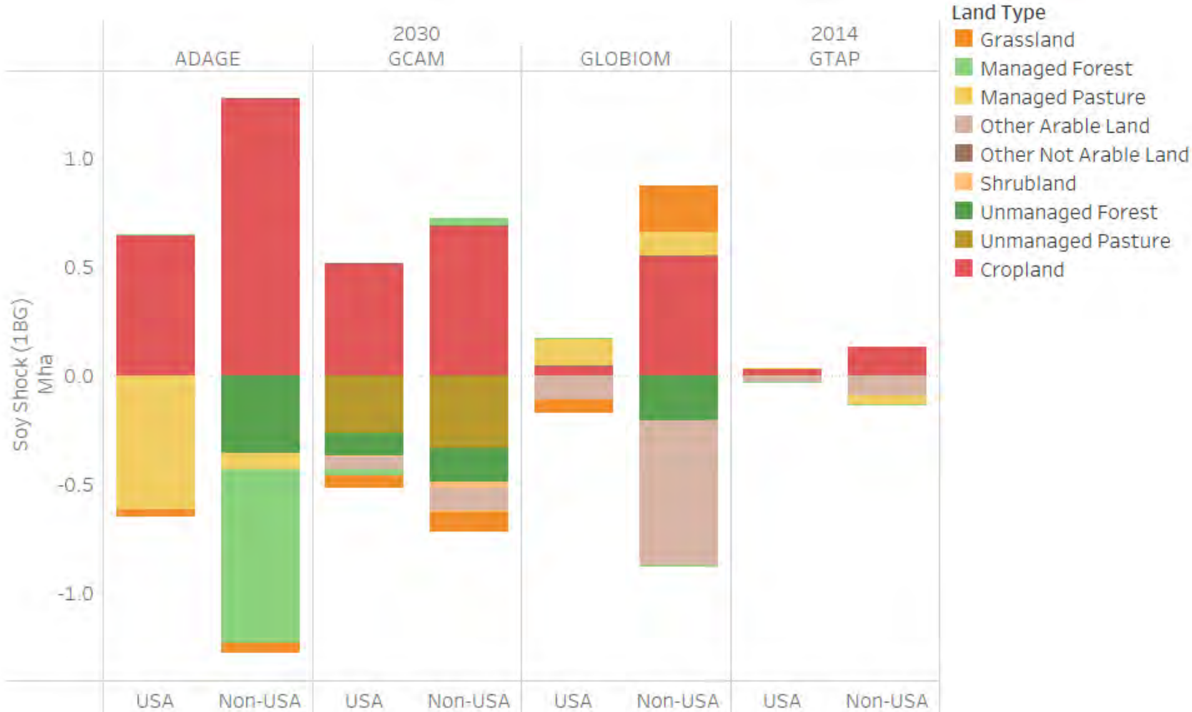
209 Horizontal lines show the net change in cropland. Cropland area shown represents land cultivated for row crops in ADAGE and GCAM and harvested area in GLOBIOM and GTAP. When a single unit of land is harvested multiple times in a single year, the area is counted multiple times as “harvested area” 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]



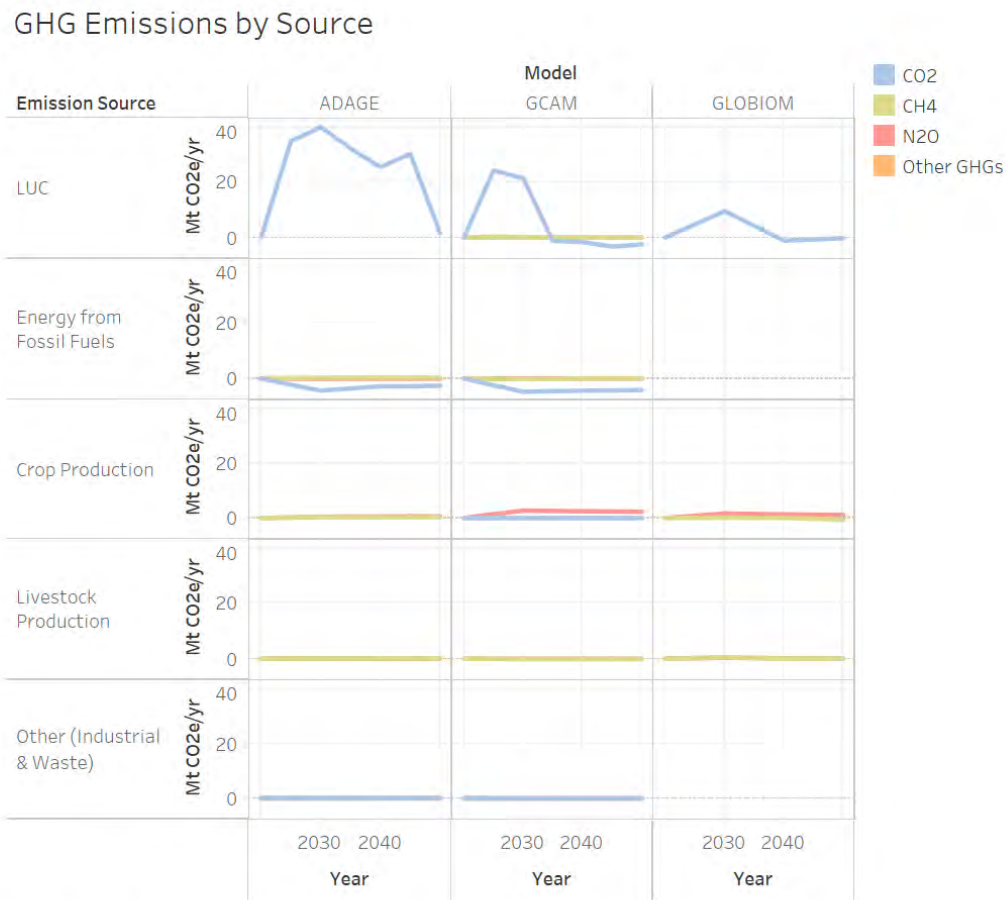
Following the trends observed in the crop production results, the models show variation in both the magnitude and location of land use change. As might be expected given their differences in land competition structure and land categorization, these four models also present diverse estimates regarding 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.

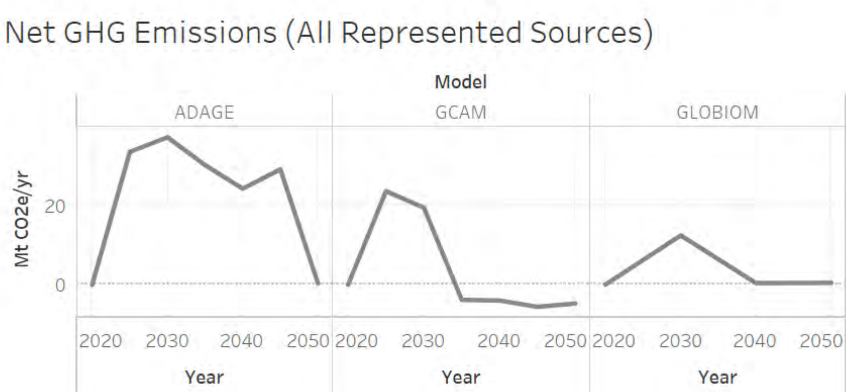
7.7 Emissions

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]

<table>
<tr><th></th><th colspan="4">Models with Energy Markets</th><th colspan="3">Models without Energy Markets</th></tr>
<tr><th></th><th></th><th>ADAGE</th><th>GCAM</th><th>GTAP</th><th></th><th>GLOBIOM</th><th>GREET</th></tr>
<tr><td rowspan="7">Sector/stage-specific emissions</td><td>Energy from Fossil Fuels</td><td>-28</td><td>-40</td><td>-46</td><td>Biofuel Production</td><td>x</td><td>13</td></tr>
<tr><td rowspan="2">Crop Production</td><td rowspan="2">7</td><td rowspan="2">21</td><td rowspan="4">-6</td><td>Crop Production</td><td>11</td><td>x</td></tr>
<tr><td>Feedstock Production</td><td>x</td><td>9</td></tr>
<tr><td>Livestock Sector</td><td>0.7</td><td>-1.3</td><td>Livestock Sector</td><td>3</td><td>x</td></tr>
<tr><td>Other</td><td>1</td><td>0</td><td>Fuel Use</td><td>x</td><td>0.4</td></tr>
<tr><td>Land Use Change</td><td>295</td><td>62</td><td>10</td><td>Land Use Change</td><td>23</td><td>10</td></tr>
<tr><td rowspan="3">Totals</td><td>Agriculture, forestry, and land use</td><td>303</td><td>82</td><td>4</td><td>Agriculture, forestry, and land use</td><td>38</td><td>19</td></tr>
<tr><td>Global GHG Impact</td><td>276</td><td>42</td><td>-42</td><td>Global GHG Impact</td><td>x</td><td>x</td></tr>
<tr><td>Supply Chain GHG Emissions</td><td>x</td><td>x</td><td>x</td><td>Supply Chain GHG Emissions</td><td>x</td><td>32</td></tr>
</table>

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.

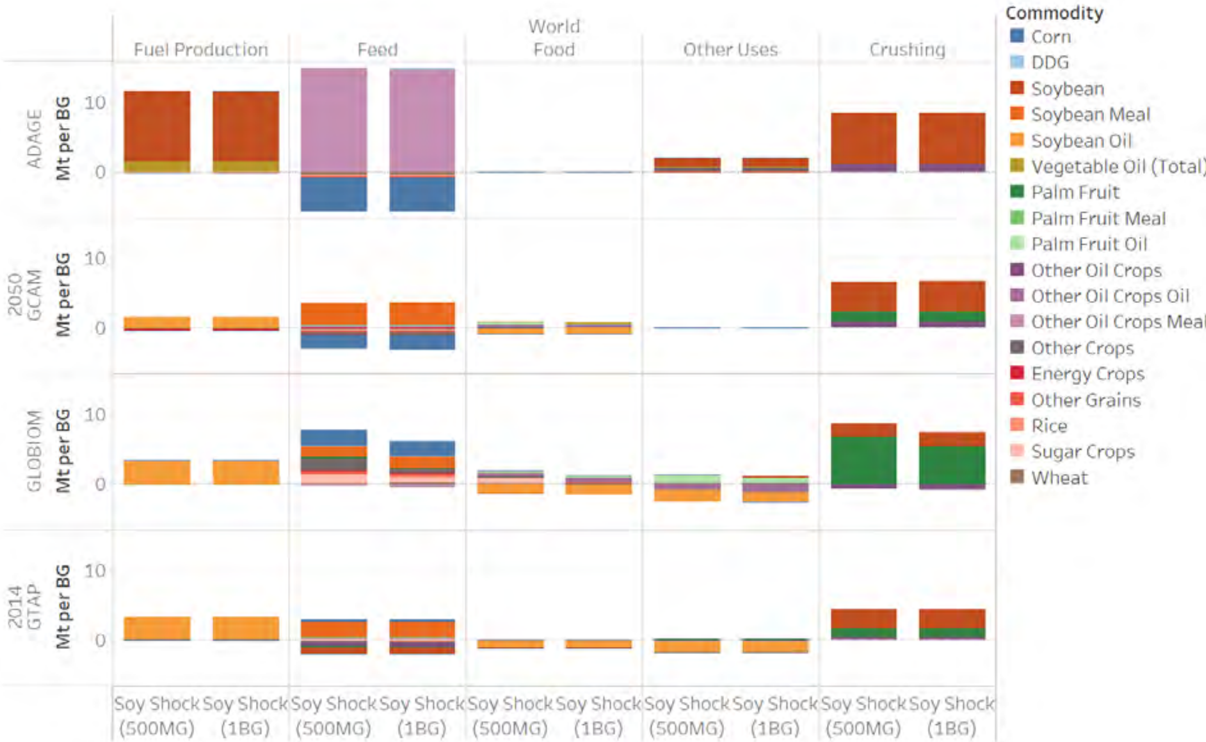
However, in the 2050 time step, GLOBIOM results show nonlinearities in the global crushing of palm fruit and the consumption of sugar crops and other crops for feed, with the 500 MG shock showing higher consumption per billion gallons.[217] The nonlinearity for palm fruit is attributable to the commodity 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.

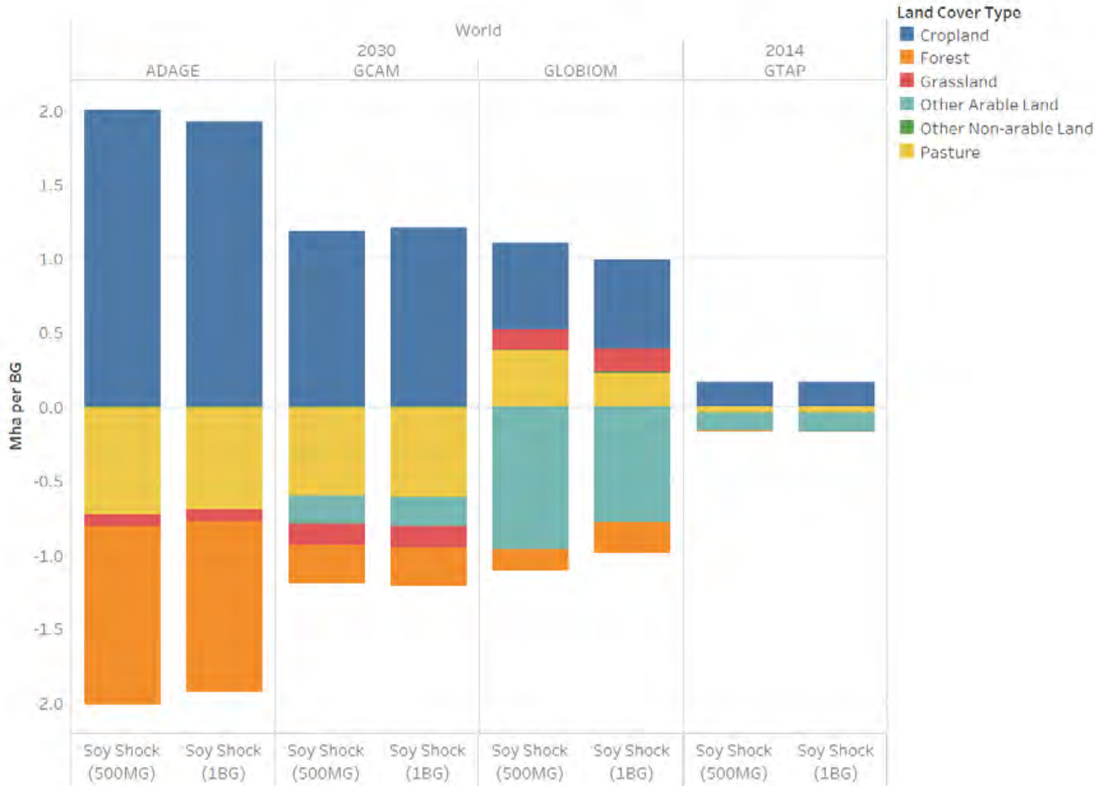
Figure 8.1.2-1: Difference in global commodity consumption by end use (Mt per BG of shocked soybean oil biodiesel consumption) in the 500 MG and 1 BG soybean oil biodiesel scenarios relative to the reference case in 2050 (ADAGE, GCAM, and GLOBIOM) and 2014 (GTAP)



8.1.3 Land Use

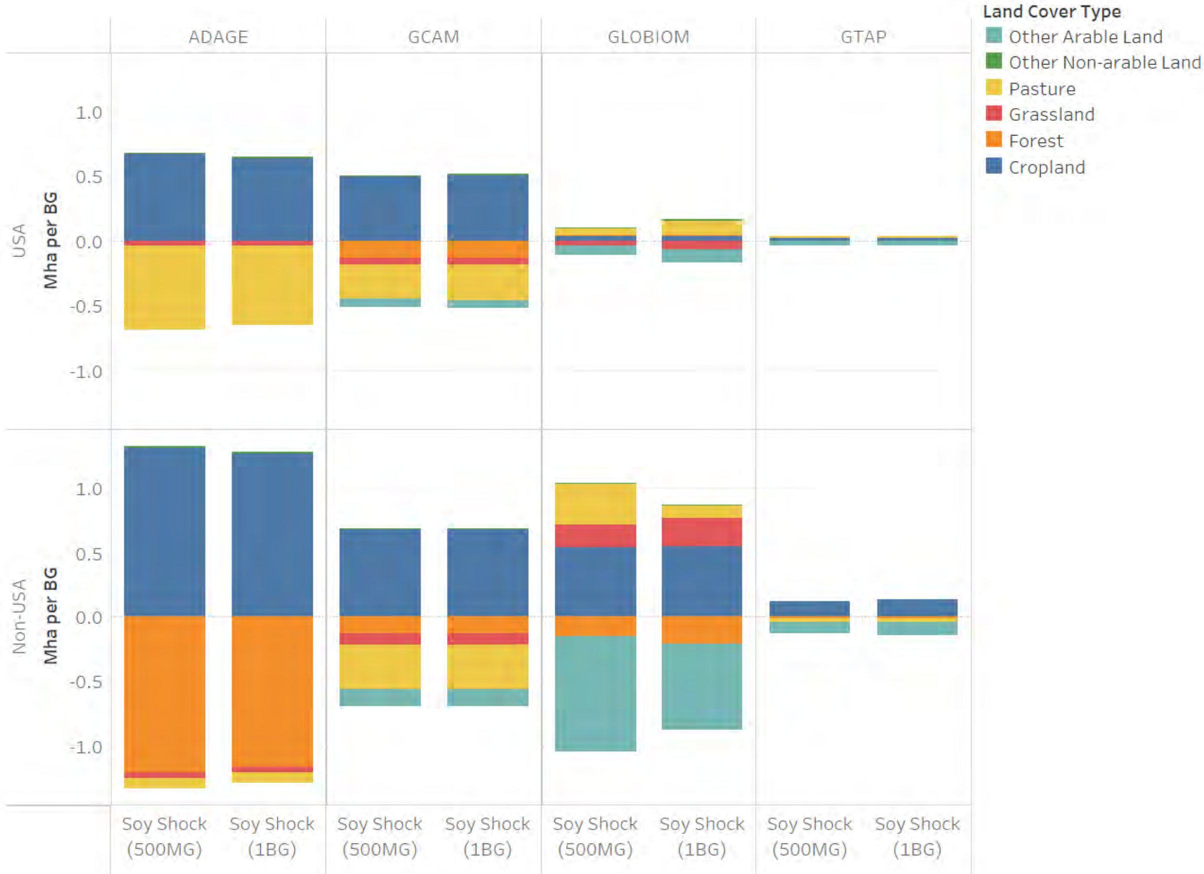
The global land use change by land cover type in the 500 MG soybean oil biodiesel shock has a relatively linear relationship in ADAGE, GCAM, and GTAP results, as seen in Figure 8.1.3-1. However, GLOBIOM results show an increase in global land converting to pasture per billion gallons in the 500 MG shock (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

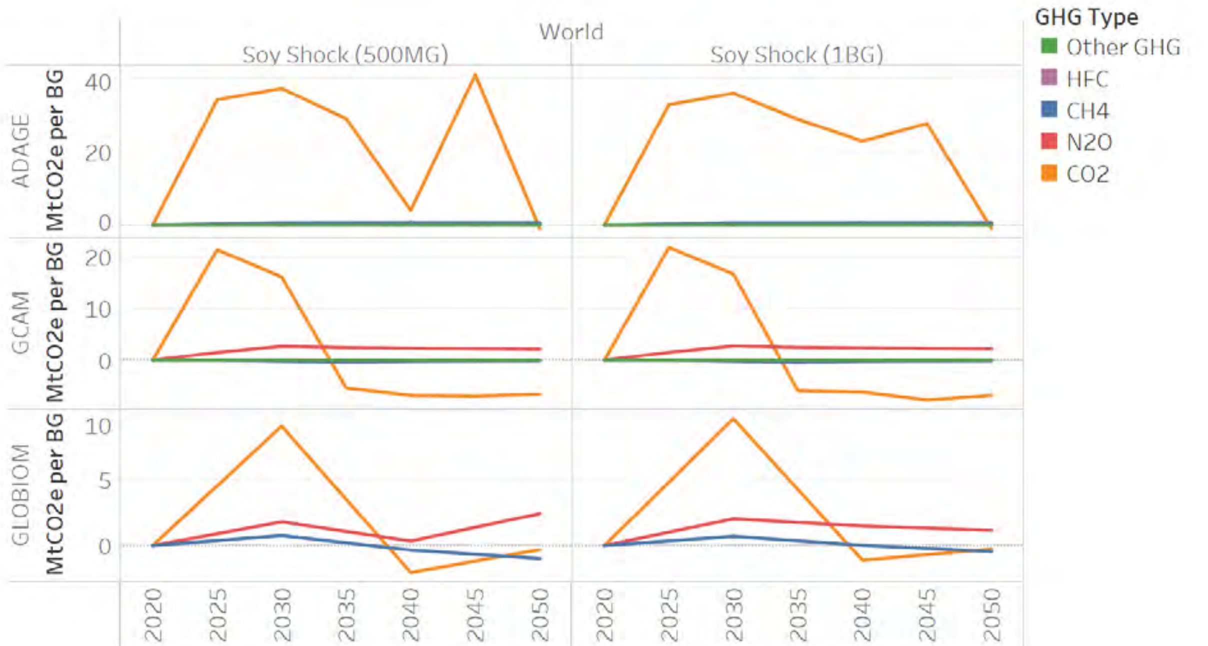
In the 500 MG scenarios, ADAGE, GCAM, and GTAP results indicate a relatively linear relationship between shock size and global GHG emissions. These models estimate a slight percentage decrease in total cumulative GHG emissions in the 500 MG scenarios relative to the 1 BG scenarios, but these results 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.

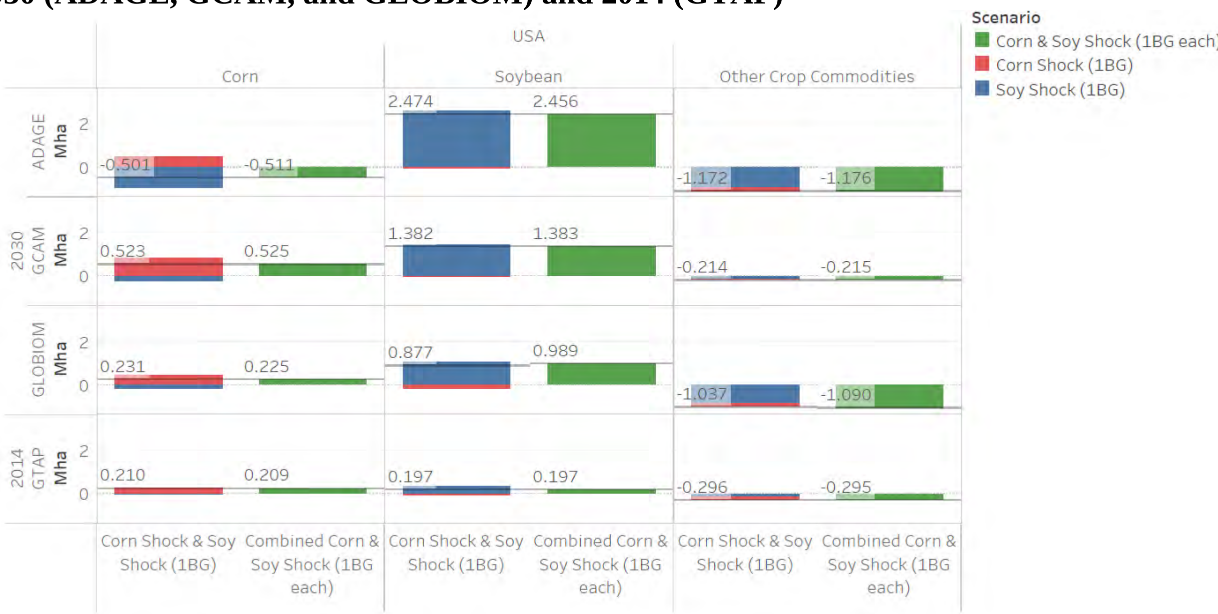
8.2.1 Land Use

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.

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[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.

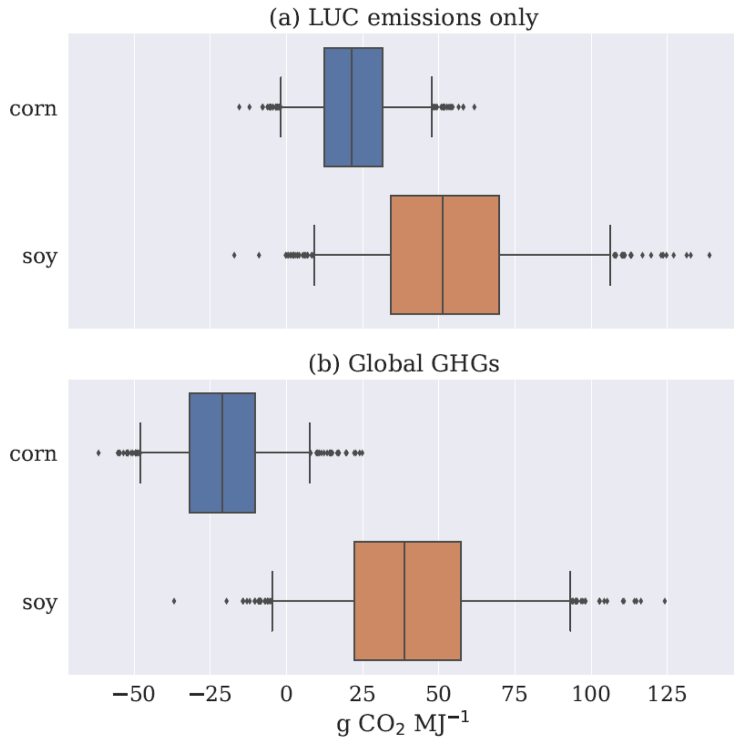
crop-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of cropland.
Grass-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of unmanaged grass land.
Mgd-forest-soil-c	Triangle(0.7, 1, 1.3)	Soil carbon density of managed forest land.
Mgd-pasture-soil-c-linked	Linked(grass-soil-c)	Soil carbon density of 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

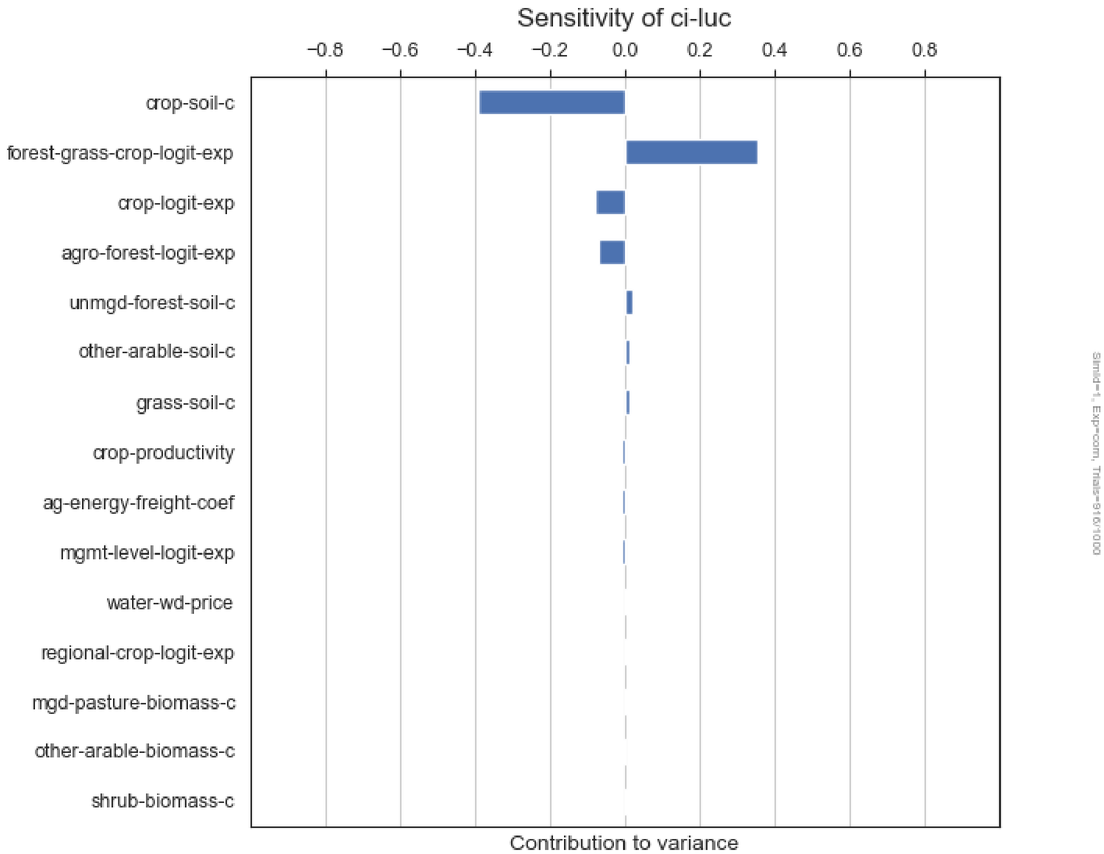


Figure 9.1.1-3: Tornado chart of most the influential parameters on corn ethanol overall carbon intensity estimates with GCAM

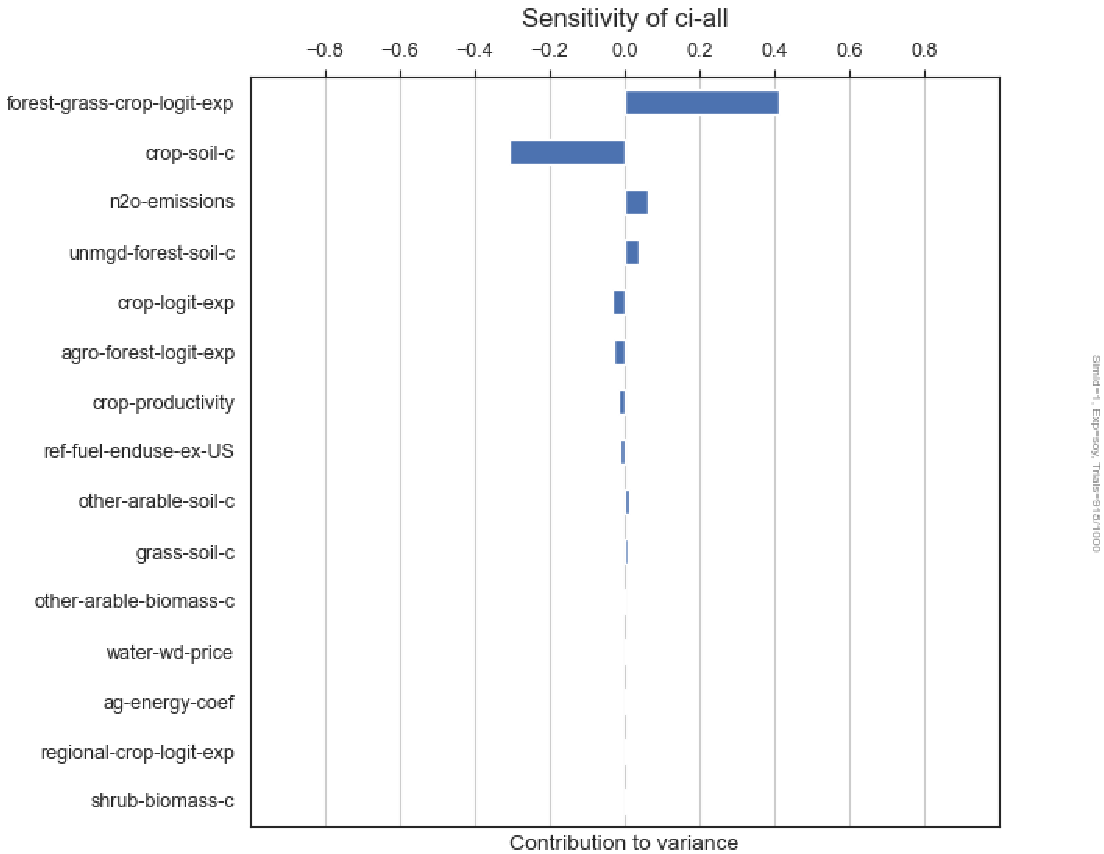


Figure 9.1.1-4: Tornado chart of most the influential parameters on soybean oil biodiesel land use change carbon intensity estimates with GCAM

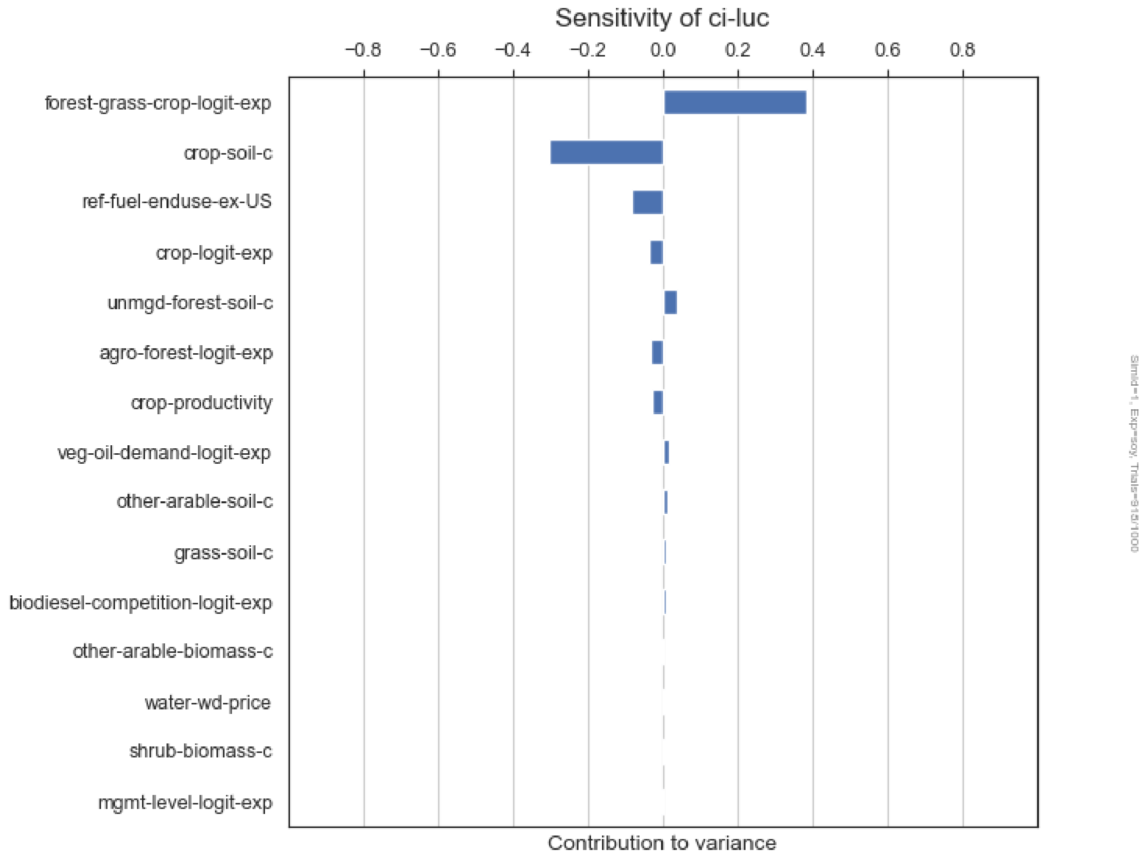
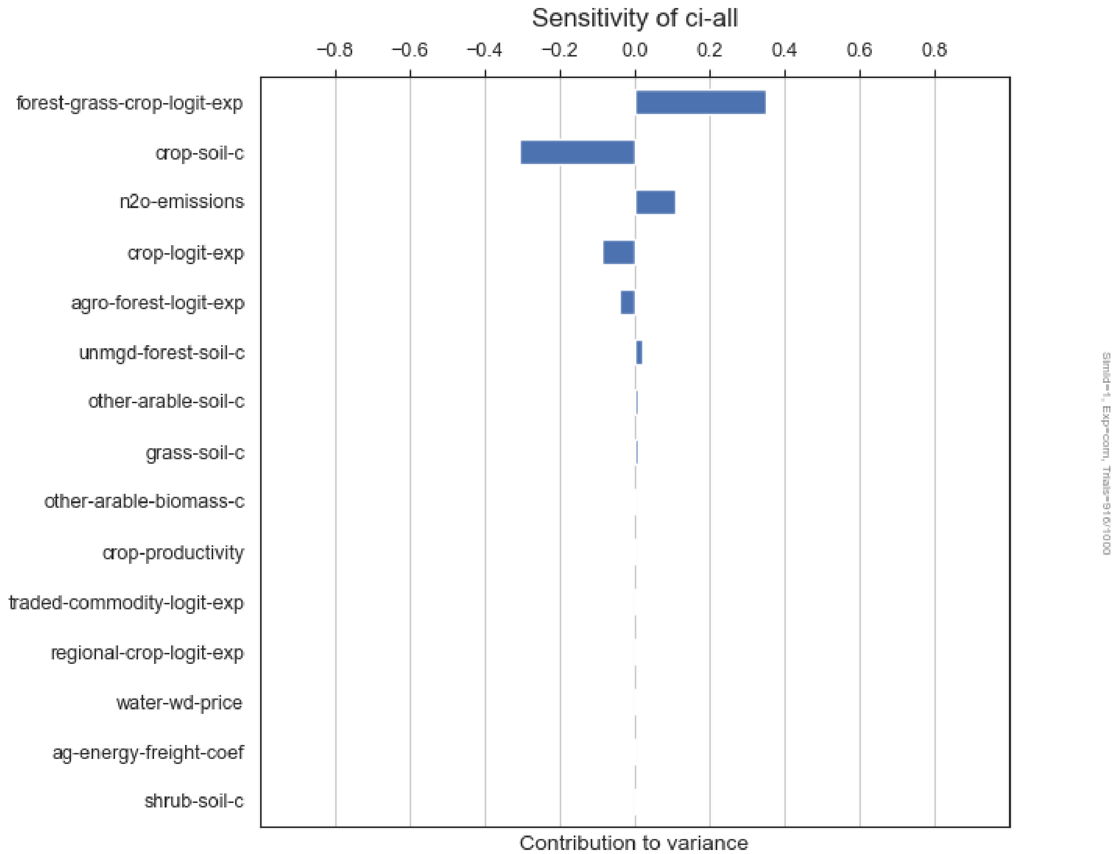


Figure 9.1.1-5: Tornado chart of most the influential parameters on soybean oil biodiesel overall carbon intensity estimates with GCAM



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.

[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.

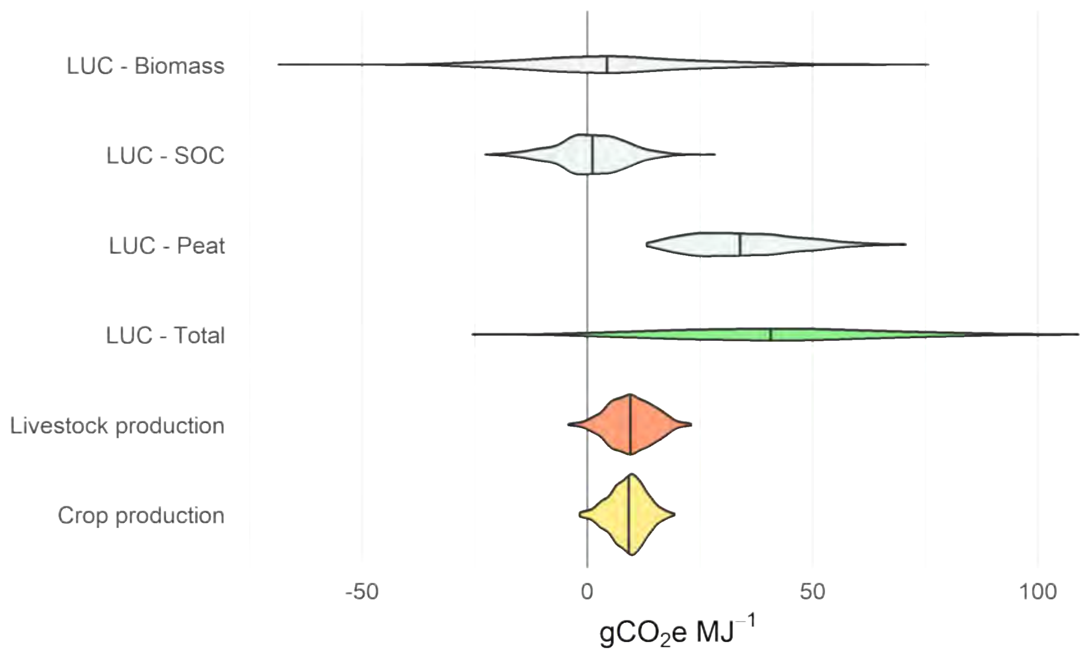
[231] Note that some of the scalar distributions in this MCS are not balanced around the central value (scalar of 1). For example, in the distribution for trade elasticity of vegetable oils (Log-uniform(0.75, 4)), roughly 17 percent of the draws would be expected to be below one, and thus decrease the 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.

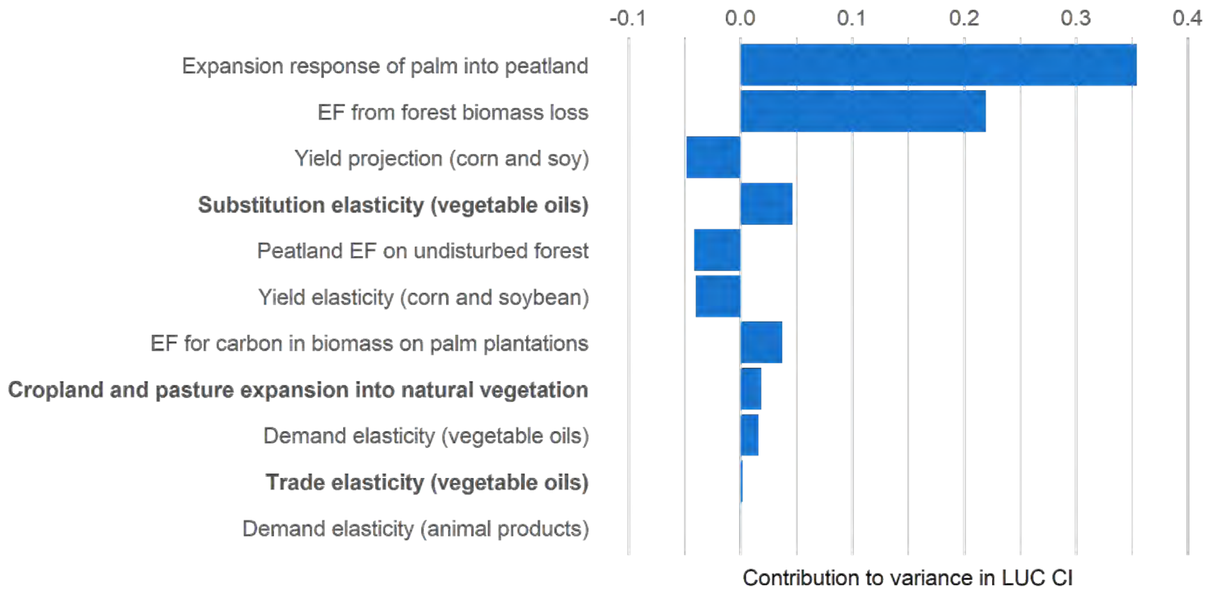
[235] Vertical lines within distributions represent mean values. "LUC – Biomass" includes emissions changes from biomass loss from land use change, changes in agricultural biomass, natural reversion of land, and carbon sequestered in harvested wood products. "LUC – SOC" emissions are land use change 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

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[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

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[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

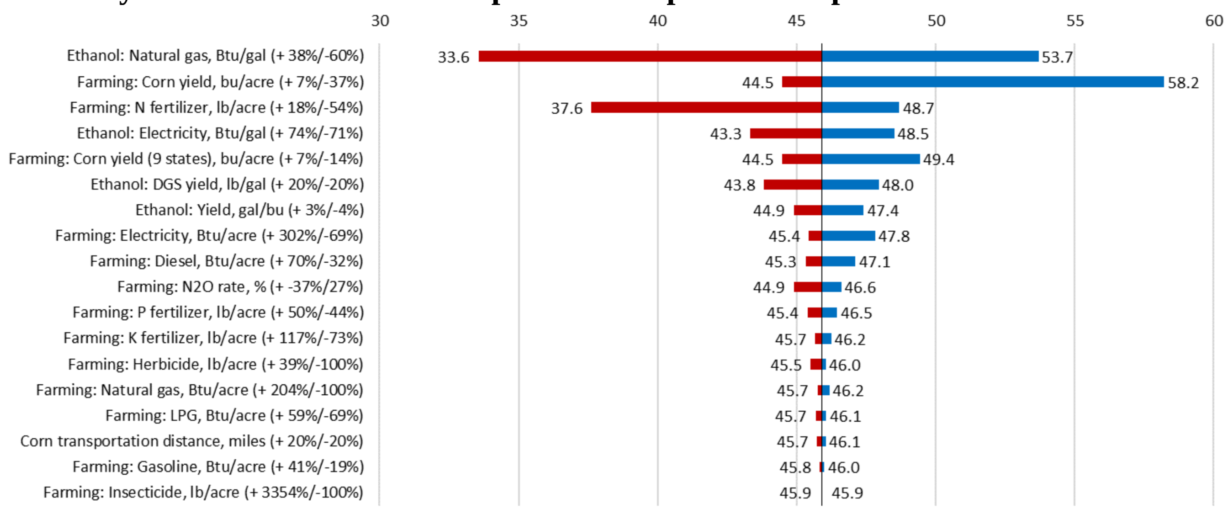
9.1.3.2 Parameter Sensitivity Scenario Analysis

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



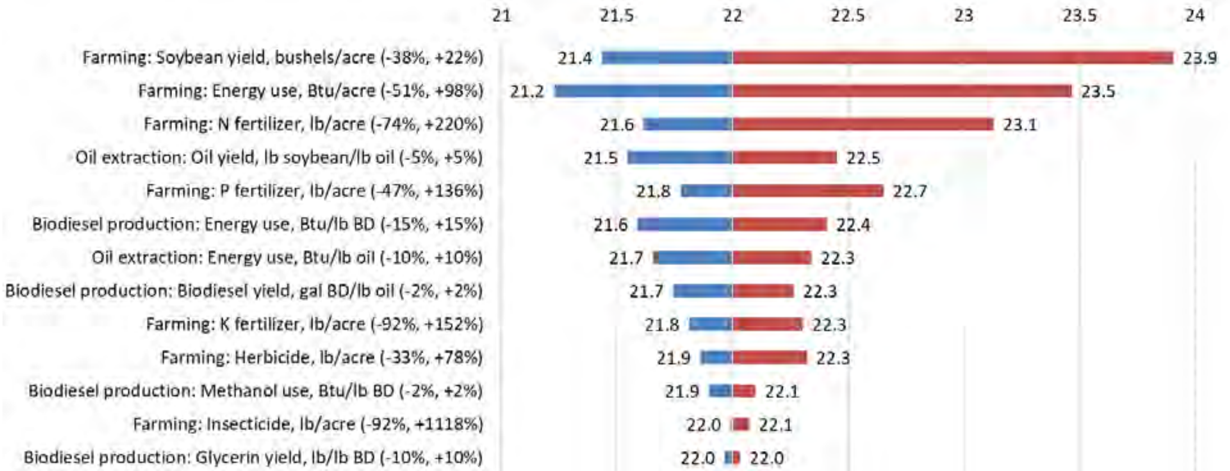
Based on the data provided, overall CI for corn ethanol saw the largest variation and influence in this exercise from the amount of natural gas used in processing and producing ethanol in facilities with a wide range of efficiencies representing a difference of roughly 20 grams of CO_2 per MJ of ethanol 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.

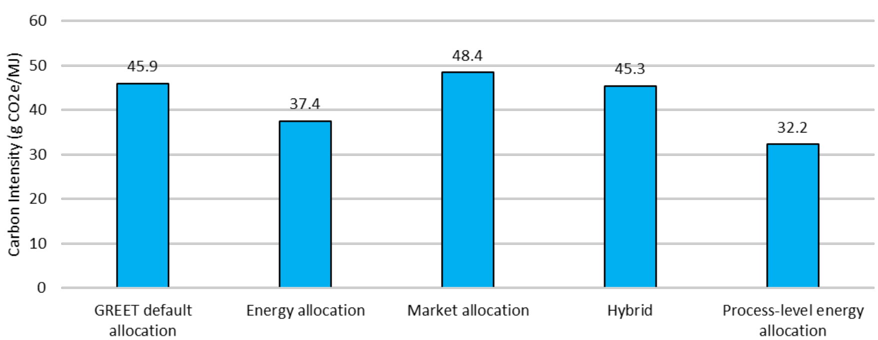
9.1.3.3 Allocation Sensitivity Analysis

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

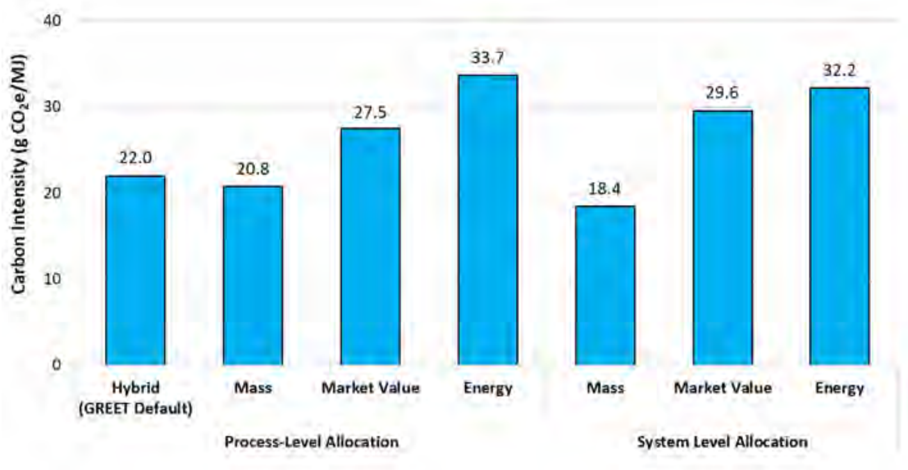


For soybean oil biodiesel, Argonne presents further delineations of LCA allocation methods used either at the *process* level (assigning the GHG impacts based on the individual steps that are involved, in this case soybean oil and soybean meal at the crushing facilities and then between biodiesel and 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



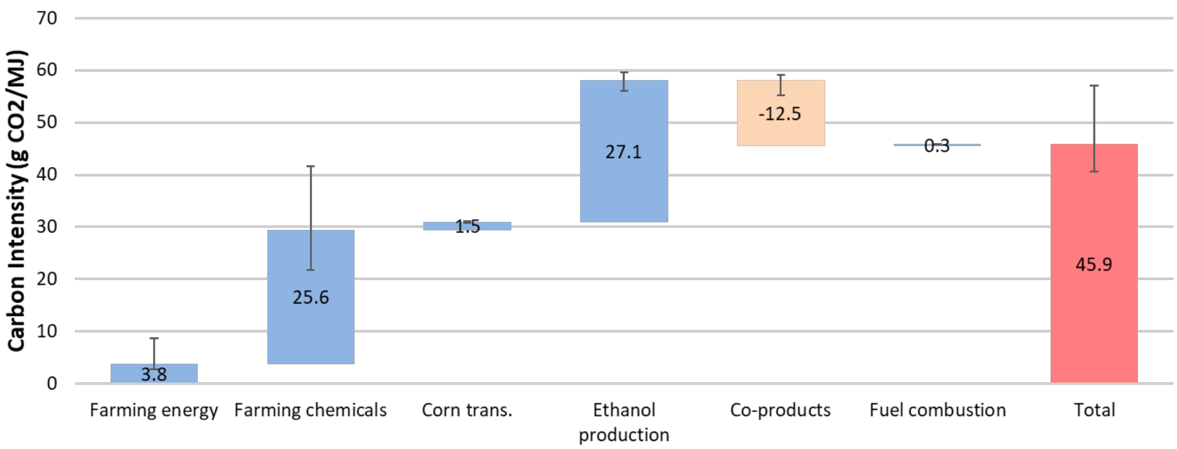
As illustrated by the figures above in this allocation sensitivity analysis section, coproduct allocation methods can have a significant impact on biofuel LCA estimates when using a supply chain LCA model such as GREET. As with the above sections, these results did not include GREET's reported LUC GHG 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.

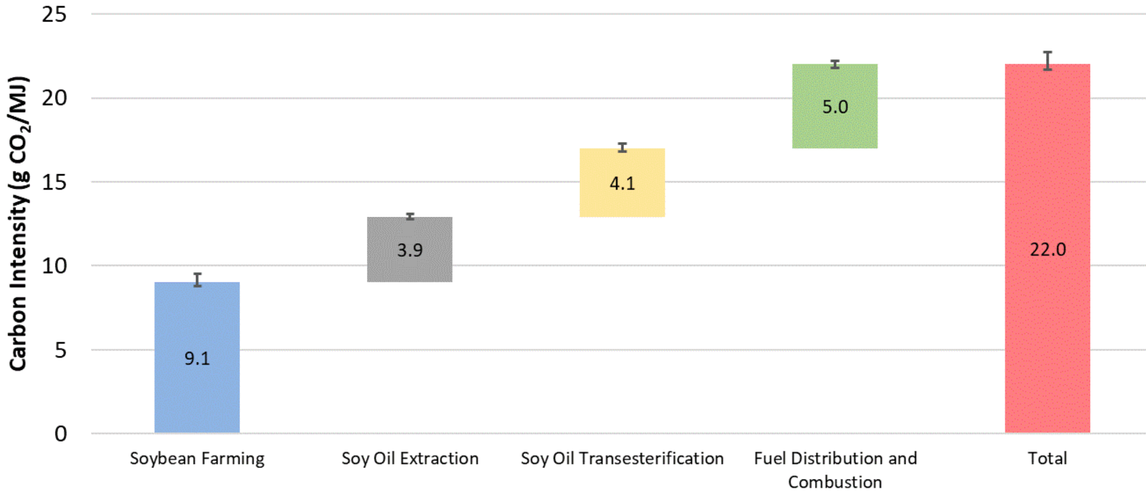
Figure 9.1.3-5: Stochastic analysis results of USA corn ethanol by lifecycle stage in GREET (whiskers indicate P10 and P90 values)



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

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[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.

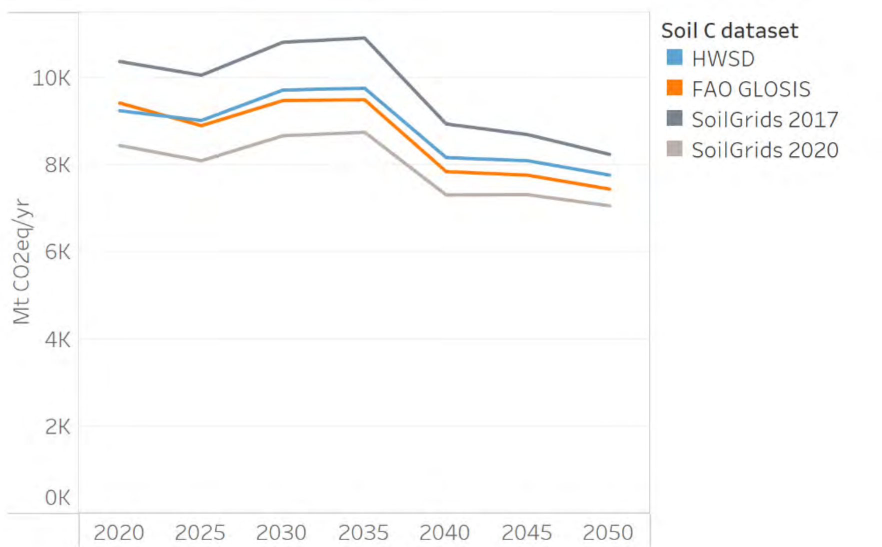
[261] Poggio, L., de Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., and Rossiter, D.: SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty, SOIL, 7, 217–240, 2021.

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.

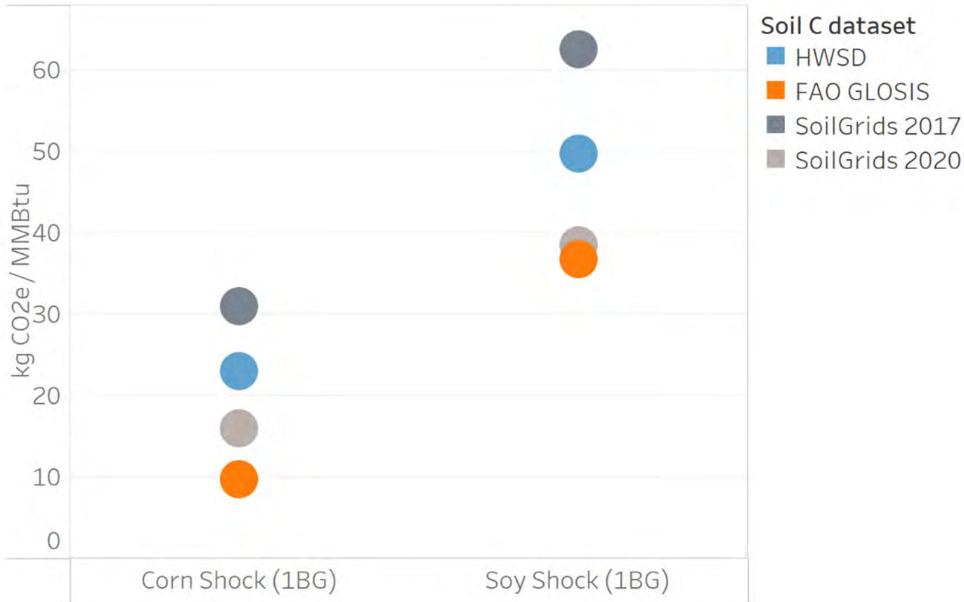
Figure 9.2-1: Global emissions from land use change in the reference case using four soil carbon datasets



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.

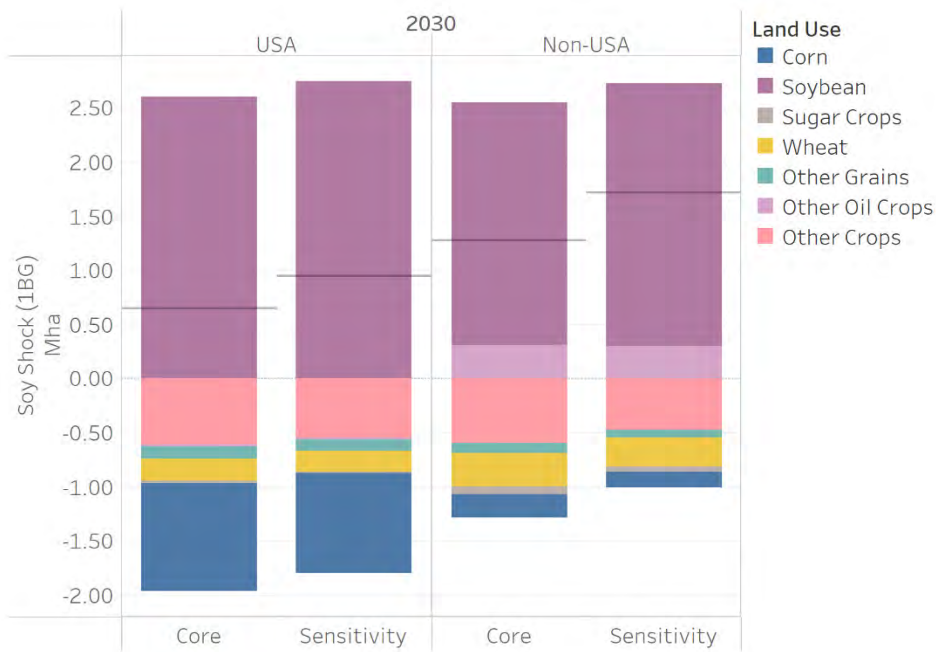
Table 9.3-2: Fixed factor elasticity between land types in ADAGE sensitivity runs

Land Conversion		From: Cropland	From: Pastureland	From: Managed Forestland	From: Natural Forestland	From: 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]

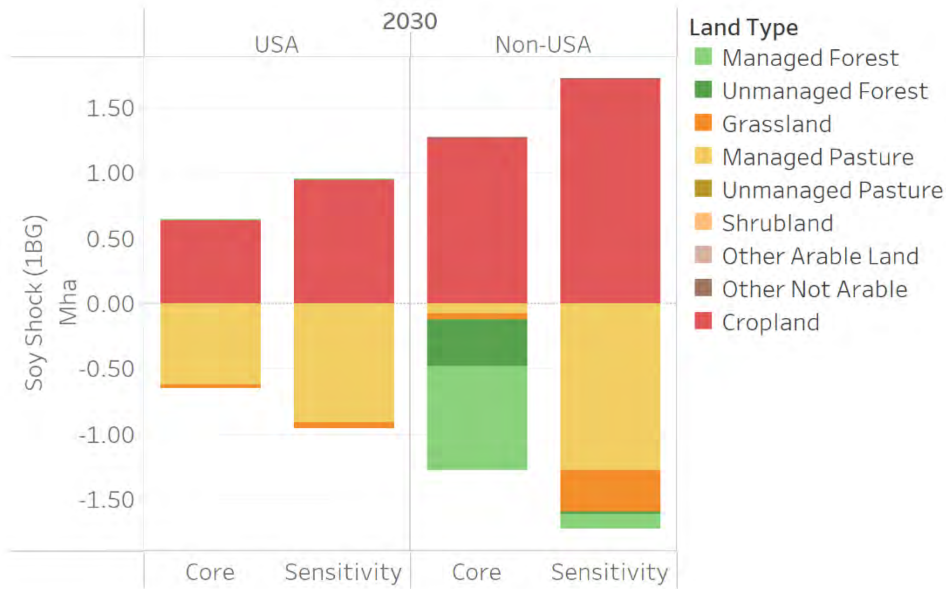


In the sensitivity runs, there is a large change in the type of land converted to cropland, relative to the core runs (Figure 9.3-2). In the USA region, managed pasture is still the primary

[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.

[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.