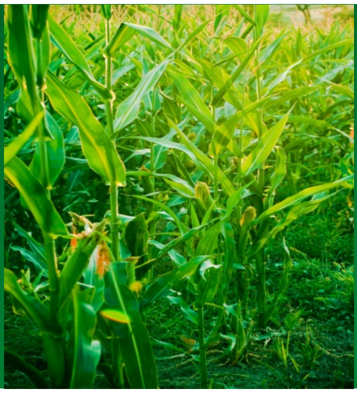

Advances in Estimation of Land Use Change Emissions Associated with Ethanol

LCA.6272.1.2025
November 3, 2025

Life Cycle Associates

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ACKNOWLEDGEMENT

Life Cycle Associates, LLC performed this study under contract to Renewable Fuels Association. Scott Richman was the project manager.

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Recommended Citation: Healy, B.D., Unnasch, S., Goyal, L., Duggal, Z. (2025). Advances in Estimation of Land Use Change Emissions Associated with Ethanol. Life Cycle Associates Report LCA.6272.1.2025. Prepared for Renewable Fuels Association.

CONTENTS

TABLES

FIGURES

TERMS AND ABBREVIATIONS

AEZ-EF	Agro-Ecological Zone Emission Factor Model
ANL	Argonne National Laboratory
ARB	Air Resources Board
BGY	Billion Gallons per Year
Btu	British Thermal Unit
CA	California
CARB	California Air Resources Board
CaRFG	California Reformulated Gasoline
CCLUB	Carbon Calculator for Land Use and Land Management Change from Biofuels Production
CGE	Computable General Equilibrium
CH_4	Methane
CI	Carbon intensity
CES	Constant Elasticity of Substitution
CET	Constant Elasticity of Transformation
CO	Carbon Monoxide
CORSIA	Carbon Offsetting and Reduction Scheme for International Aviation
CO_2	Carbon Dioxide
CO_2c	Fully oxidized fuel emissions including CO_2, VOC, and CO
CO_{2e}	Carbon dioxide equivalent
DGS	Distillers’ Grains
DOE	U.S. Department of Energy
EPA	U.S. Environmental Protection Agency
ETA	Elasticity of Area Expansion
ETL	Elasticity of Land Transformation
FAPRI	Food and Agriculture Policy Research Institute
FASOM	Forest and Agriculture Sector Optimization Model
g CO_2e	Grams of carbon dioxide equivalent
GHG	Greenhouse Gas
GLOBIOM	Global Biosphere Management Model
GREET	The Greenhouse gas, Regulated Emissions, and Energy use in Transportation Model
GTAP	Global Trade Analysis Project
GWP	Global Warming Potential
ICAO	International Civil Aviation Organization
iLUC	Indirect Land Use Change
IPCC	Intergovernmental Panel on Climate Change
IRA	Inflation Reduction Act
ISO	International Standards Organization
LCA	Life Cycle Analysis or Life Cycle Assessment
LCFS	Low Carbon Fuel Standard
LHV	Lower Heating Value

LUC	Land Use Change
mmBtu	million Btu
NRI	National Resource Inventory
OBBBA	One Big Beautiful Bill Act
RINs	Renewable Identification Numbers
RFS	Renewable Fuel Standard
RFS2	Revised Federal Renewable Fuels Standard
SAF	Sustainable Aviation Fuel
SAM	Social Accounting Matrix
SOC	Soil Organic Carbon
WHRC	Woods Hole Research Center
WTT	Well-To-Tank
WTW	Well-To-Wheel
YDEL	Yield Price Elasticity

EXECUTIVE SUMMARY

This study reviews how advances in land use change (LUC) and indirect land use change (iLUC) modeling over the past decade have reduced emissions estimates for U.S. corn and sorghum ethanol, with a focus on evaluating CARB's current assumptions. It systematically compares major models, GTAP, CCLUB, R&D GREET, GLOBIOM, and 45ZCF, along with supporting data sources such as AEZ-EF and IPCC factors, to identify how improvements in parameters like shock size, elasticities, and soil carbon dynamics have driven lower LUC estimates. Building on these comparisons, the report critically examines CARB's 2014–2015 LUC values, highlighting where they diverge from updated science, and uses standardized modeling assumptions to pinpoint the most impactful areas for revision. Strengths and weaknesses of leading LUC models are assessed relative to GTAP and CCLUB, with attention to interoperability challenges, methodological gaps, and opportunities to improve alignment across models for more accurate policy-relevant estimates.

The comparison of iLUC outcomes across regulatory frameworks and models highlights a wide variance in estimated emissions for corn and sorghum ethanol, underscoring how methodological choices drive results as shown in Figure S.1, with the most recent GTAP 2017 version showing substantially lower values.

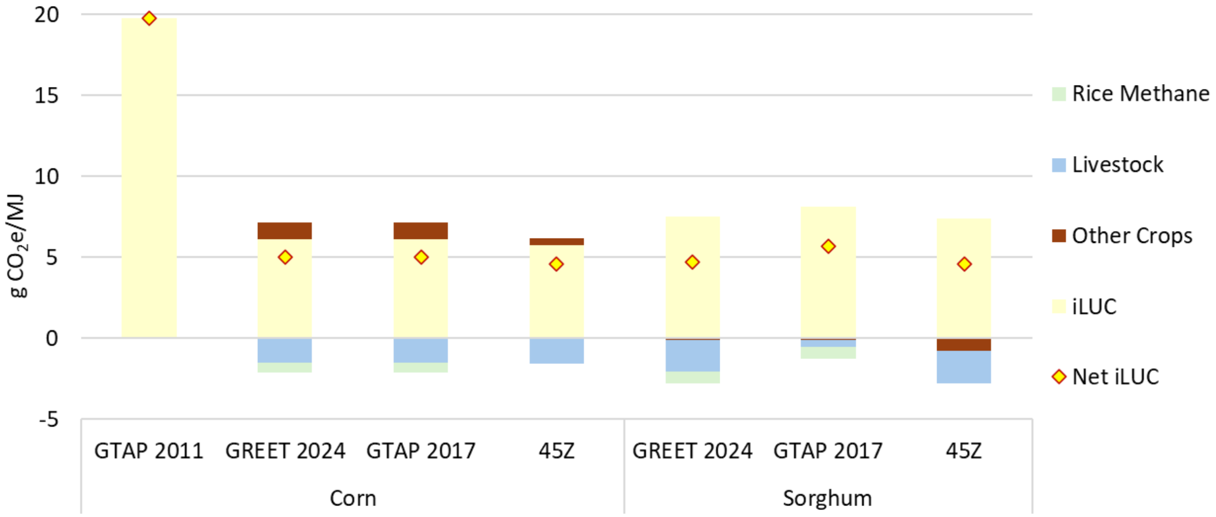

Figure S.1. Various iLUC modeling results for Corn and Sorghum Ethanol

Early applications such as GTAP 2011 and the LCFS analysis attribute iLUC values near 20 gCO$_2$e/MJ, consistent with CORSIA's default estimate for 2025. In contrast, more recent iterations, GREET 2024, GTAP 2017, and the 45Z model, incorporate updated data and refined treatment of co-products, livestock, and soil carbon, reducing net iLUC estimates to roughly 5 gCO$_2$e/MJ. The differences across vintages highlight how earlier models tended to overstate land conversion impacts due to limited data and co-product treatment, while refinements in GTAP 2017 and other updates better capture yield response, cropland-pasture dynamics, and feed substitution.

Key to these shifts are the underlying model drivers that determine how biofuel demand translates into land use change and emissions. Yield assumptions and yield price elasticities shape whether additional demand is met by intensifying production on existing cropland or expanding into new land, while elasticity factors more broadly capture market-mediated responses such as feed substitution with distillers' grains or shifts in protein consumption. Land transformation elasticities govern how readily land moves among cropland, pasture, and forest, with major implications for the type and carbon intensity of land converted.

These outputs are then linked to carbon accounting models like CCLUB, which apply emission factors and soil organic carbon stock data to quantify the greenhouse gas consequences of modeled transitions. The magnitude of the applied "shock", as shown in Table S.1, an exogenous increase in ethanol demand, further frames the results, while differences between static equilibrium models such as GTAP and dynamic frameworks such as FAPRI or FASOM determine whether the outcomes reflect a single snapshot or an evolving pathway. Together, these drivers explain why iLUC estimates can vary so widely and why updates to assumptions have consistently lowered emissions in more recent model iterations.

Table S.1. Biofuel Shocks from CARB 2014 iLUC Assessment

Shock	Shock Size (bgy)	Impact of Shock	LUC Impact
Corn Ethanol	11.59	Expands U.S. corn acreage; reduces soy/wheat; raises global corn price. DDGS offsets some feed demand.	Global forest & pasture conversion; moderate cropland-pasture shifts. Avg. iLUC = ~19.8 gCO$_2$e/MJ.
Sugarcane Ethanol	3.0	Expands cane in Brazil, mainly displacing pasture; some forest loss.	Dominated by pasture conversion. Avg. iLUC = ~11.8 gCO$_2$e/MJ.
Soy Biodiesel	0.812	Expands soy area; reduces other crops; vegetable oil market effects.	Moderate iLUC; sensitive to South American forest conversion. Avg. iLUC = ~29.1 gCO$_2$e/MJ.
Canola Biodiesel	0.4	Shifts oilseed balance; imports of soy/palm adjust.	Modest land use changes. Avg. iLUC = ~14.5 gCO$_2$e/MJ.
Sorghum Ethanol	0.4	Substitutes for corn; land response smaller; coproducts offset feed.	ILUC similar to corn but smaller scale. Avg. iLUC = ~19.4 gCO$_2$e/MJ.
Palm Biodiesel	0.4	Expands plantations in Malaysia/Indonesia; replaces forest/peatland.	Highest iLUC; tropical forest and peat conversion dominate. Avg. iLUC = ~71.4 gCO$_2$e/MJ.

In its 2014 iLUC assessment, CARB modeled biofuel impacts by applying exogenous volume shocks, expressed as increases in production measured in billion gallons per year, for each fuel pathway within the GTAP-BIO model. Each pathway was assessed independently, with 30 separate simulations run per biofuel type using varied parameter sets but a constant shock size, rather than modeling simultaneous increases across fuels as would occur under the LCFS. The resulting land use transitions were then converted into greenhouse gas emissions using the AEZ-EF spatial emission factors and averaged to produce pathway-specific iLUC values. CARB's update refined the 2009 approach with a newer GTAP baseline, explicit treatment of cropland pasture in the United States and Brazil, revised elasticity parameters, improved coproduct accounting, and more detailed AEZ-EF data, shifting predicted conversions away from forests and lowering overall iLUC estimates compared to earlier analyses.

CARB's analysis of land transformation highlights how cropland-pasture serves as the primary land source responding to biofuel demand. In GTAP-BIO, transformation elasticities govern how land shifts among cropland, pasture, and forestry, with cropland-pasture modeled as the most flexible category. CCLUB then applies carbon accounting to these outputs, translating land transitions into emissions impacts. As shown in Figure S.2, across multiple GTAP vintages and CARB scenarios, cropland-pasture consistently contracts while cropland expands to supply ethanol feedstock[1]. Forestry and pasture remain comparatively stable, indicating that the bulk of modeled land reallocation occurs between cropland-pasture and active cropland. The effect of shock size is also examined with the results presented per billion gallons/year of ethanol use.

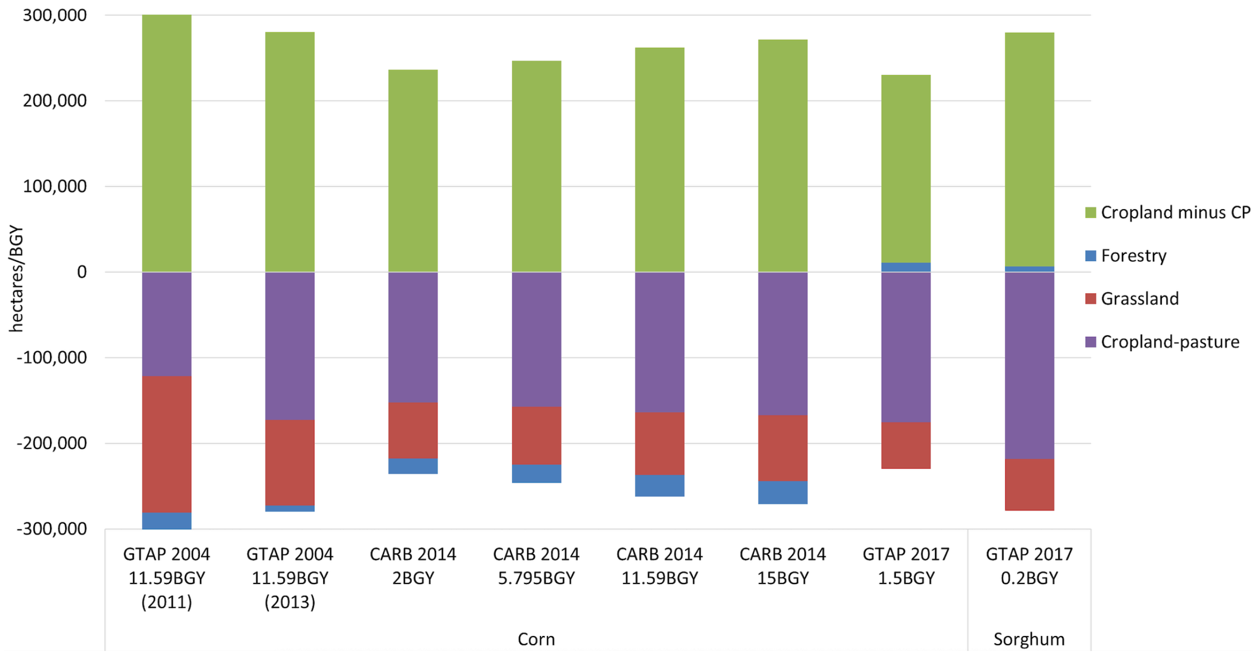

Figure S.2. Global Land Use Change for Corn and Sorghum Ethanol Across GTAP Models

In terms of total LUC (not per billion gallons per year), CARB's 2014 runs showed over one million hectares of cropland-pasture contraction at higher ethanol shocks, while GTAP 2011 allowed

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[1] The GTAP results are based on different versions of the GTAP database. The CARB 2014 study uses the GTAP 7 database with 2004 baseline data. The different study years (2011), (2013), and CARB 2014 use different land transformation functions.

somewhat more forest conversion under higher elasticities in Figure S.3. By GTAP 2017, the magnitude of shifts per unit ethanol is smaller, but cropland-pasture remains the dominant balancing category. In contrast, sorghum ethanol under GTAP 2017, modeled at a much smaller 0.2 BGY shock, produces negligible land reallocation, reflecting both the limited scale of the shock and sorghum's weaker substitution elasticities and market linkages compared to corn. Overall, the results demonstrate that large corn ethanol shocks generate broad global land adjustments through cropland-pasture conversion, while small sorghum shocks are absorbed within existing systems, underscoring the proportionality of GTAP's equilibrium structure and the importance of crop-specific market dynamics in shaping iLUC outcomes.

Figure S.3. U.S. Corn and Sorghum Ethanol Total Land Use Change

Figure S.4 shows how land use change emissions for corn and sorghum ethanol have declined across GTAP vintages as model assumptions and carbon accounting have improved. In the GTAP 2004 (2011 run), forestry dominates with nearly 9 million Mg C/BGY, yielding an iLUC intensity of about 13–14 g CO_2e/MJ. These results are based on an 11.59 BGY shock for the 2011 and 2013 studies and a 1.5 BGY shock for the 2017 database. The sorghum shock is 0.2 BGY.

By the 2013 run, emissions fall to 6–7 million Mg C/BGY, forestry's role diminishes, and cropland-pasture becomes more important, reducing the CI to 10 g CO_2e/MJ. GTAP 2017 shows a further drop to 2–3 million Mg C/BGY, with cropland-pasture as the primary source of emissions and a CI near 4–5 g CO_2e/MJ. Sorghum under GTAP 2017 follows a similar profile, dominated by cropland-pasture but with slightly higher total emissions, producing a CI near 6 g CO_2e/MJ. These results underscore how shifts in land transformation elasticities, category responsiveness, and carbon stock assumptions drive the steady decline in iLUC values across successive model updates.

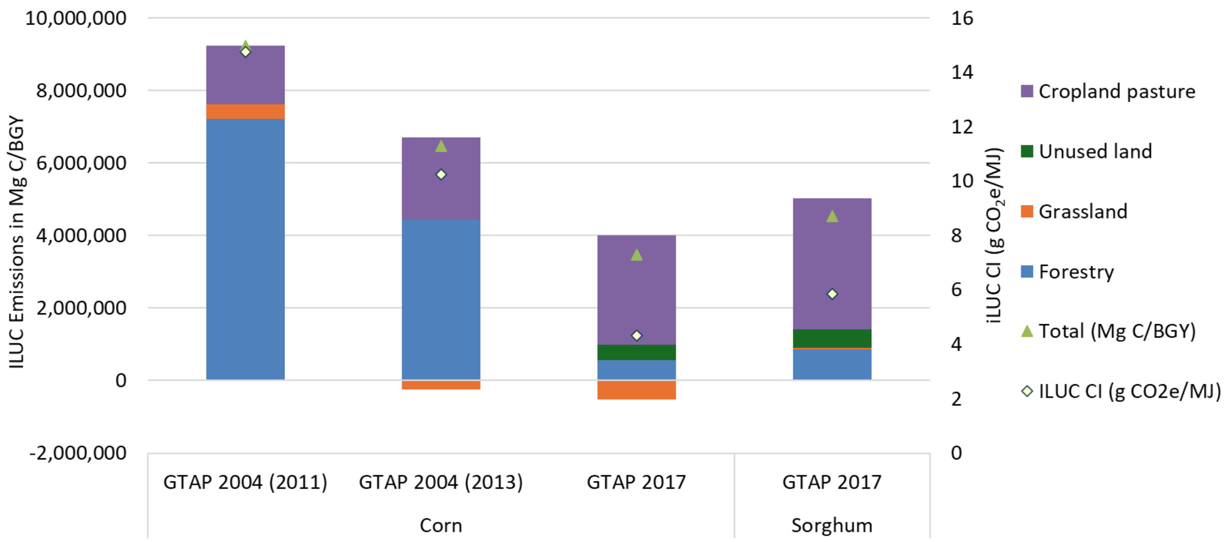

Figure S.4. Land Use Change Emissions of Ethanol Across GTAP Models

Key Takeaways

- **Methodology evolution:** Since ARB's first ILUC analysis in 2009, refinements have included more granular land transfer categories, improved accounting of grazing lands, and updated emission factors for forest, grassland, and cropland conversion. These changes reflect better data availability and research advancements.

- **Impact on results:** The cumulative effect of methodological improvements has been a steady reduction in estimated GHG emissions from corn ethanol land use change, producing results that are more consistent with observed global market behavior.

- **GTAP updates:** The GTAP database has been upgraded with more recent crop yields, land use, and trade data. It also incorporates the role of distillers grains in offsetting global feed demand and shifts in protein production that reduce net land requirements. Emission factors have been revised to align with newer IPCC research.

- **Energy system integration:** A major advance in recent GTAP modeling is tighter coupling with global energy systems. This allows the model to capture substitution not only among agricultural products but also across energy and industrial goods, producing more realistic simulations of how policies like increased ethanol blending ripple through economies and land use decisions.

- **Lower-impact factors:** Several frequently debated parameters, such as the size of the ethanol "shock," soil carbon emission factor variations, and the choice between static versus dynamic modeling, have been shown to have only minor effects on overall ILUC outcomes, with qualitative findings remaining robust across scenarios.

- **CARB Recommendations:** Analysts recommend using the GTAP 2017 model for its latest data and refinements, applying a 600 million gallon ethanol shock to simulate a California transition from E10 to E15, and focusing on AEZ 54, representing productive regions like the U.S. Midwest, to capture land carbon stock characteristics most relevant for iLUC estimates.

1. INTRODUCTION

Most biofuel policies around the world now require that eligible fuels achieve specific greenhouse gas (GHG) reductions compared to the fossil fuels they replace. These reductions are assessed using life cycle assessment (LCA), which accounts for all emissions from resource extraction through final fuel use. Results are expressed as carbon intensity (CI), in units of grams of CO_2-equivalent per megajoule (gCO_2e/MJ), enabling comparison across fuels on an energy-equivalent basis.

LCA results depend on numerous assumptions and inputs, which introduce uncertainty. One of the most debated sources of uncertainty is land use change (LUC). LUC occurs when land shifts from one use to another, such as forest or pasture converted to cropland, potentially releasing carbon depending on the land type and location. As biofuel demand grows to meet policy-driven volume targets, additional agricultural land may be required, either directly for biofuel feedstock production or indirectly through global market responses to changes in crop supply and demand. Price shifts in agricultural commodities may further incentivize indirect land conversions elsewhere.

Distinguishing direct from indirect LUC is not straightforward. Some biofuel pathways rely on feedstocks sourced from common commodity markets, while others depend on dedicated feedstock supply chains. Regardless, any expansion of arable land influences carbon fluxes both locally and globally. This report therefore uses “LUC” to refer to both direct and indirect effects. Concerns about the accuracy of LUC estimates persist, given the complexity of attributing land conversions to biofuel expansion and the uncertainties in modeling approaches.

1.1 LUC

The concept of LUC and its potential impact on the CI of biofuels was brought to prominence by Searchinger et al. in 2008, who argued in their paper that land conversion could significantly increase biofuel emissions (Searchinger, 2008). While debate continues over modeling methods and results, academic research has shown significant reductions in estimated LUC values from since 2008. Accordingly, regulators have incorporated LUC into policy frameworks like the U.S. Renewable Fuel Standard (RFS2) and California’s Low Carbon Fuel Standard (LCFS).

In agro-economic models designed for the agricultural sector, biofuel policy volume targets and other key inputs reflecting market and price dynamics are used to estimate the scale, location, and type of LUC. These model outputs are then combined with an emission factor database to calculate the resulting GHG emissions. Emission factor databases provide estimates of the carbon stored in vegetation and soils across different ecosystems and regions and quantify how much of that carbon is released when land is disturbed or converted.

While estimates of LUC from U.S. and EU biofuel policies vary widely depending on the modeling approach and assumptions used, their modeled values have declined significantly since 2008. Agro-economic models typically generate these estimates by incorporating parameters such as crop yields, price elasticities, and land transformation coefficients. Some studies provide regional detail, while others group results under “rest of world,” further highlighting the variability in outcomes.

These models not only estimate the scale and location of land conversion but also the types of land affected such as forest, pasture, or fallow. To calculate associated carbon intensity (CI) values, the outputs are paired with carbon stock datasets such as those from Winrock or the Woods Hole Research Center (WHRC). However, even when the same dataset is applied, differing assumptions can lead to widely divergent results. For example, multiple studies using WHRC data have produced inconsistent findings, and even repeated analyses by the same research group have yielded significantly different outcomes, largely due to how land cover changes are represented in the models.

iLUC

Indirect land use change (ILUC) refers to shifts in land cover that occur when expanding biofuel production increases demand for biomass, such as converting pasture to cropland to grow feedstock for biofuels. These land conversions release carbon stored in soils and vegetation, contributing additional GHG emissions to a fuel’s life cycle. Because iLUC emissions cannot be directly measured and occur through complex, global market interactions, they must be estimated through modeling.

To address this, both the U.S. Environmental Protection Agency (EPA) and the California Air Resources Board (CARB) developed methodologies that combine economic models of land use change with emission factors to calculate associated GHG releases. These approaches have undergone multiple reviews, including by the Coordinating Research Council. Since their initial adoption, CARB has significantly updated its iLUC methodology, most notably in 2015, by applying a newer version of the GTAP model and introducing a revised set of emission factors. EPA, by contrast, has not formally revised its methodology but has published updated GHG values for some biofuels.

1.2 Role of GHG Calculations

GHG calculations are a central component of LCA’S to quantify the emissions associated with each stage of a product's life cycle across various types of programs. Understanding the GHG implications within each framework is contingent upon a thorough analysis of the modeling requirements and the treatment of credits and co-products. This is crucial because the CI calculation is significantly influenced by how each model manages inputs, outputs, and the allocation of emissions. Credits may be issued for actions such as carbon sequestration or the use of renewable energy, while co-products can impact the overall GHG emissions profile if their production or utilization results in emission reductions elsewhere. Therefore, a detailed understanding of these components within each regulatory framework is essential for accurate LCA modeling and the comparative analysis of CI values across different methodologies.

1.2.1 Regulatory Programs & Modelling Efforts

Numerous regulatory programs, primarily for low carbon fuels, have been implemented nationally and internationally. These programs establish unique methodologies for quantifying emissions throughout the product lifecycle, establish reduction targets over time, and offer various incentives to reduce emissions relative to a petroleum fuel baseline. To ensure these programs meet their emissions reductions requirements, they impose penalties for non-compliance. The following is a list of regulatory programs and the associated LCA modeling tool that greatly impact U.S. corn and sorghum ethanol:

- U.S. EPA Renewable Fuel Standard (RFS) Program/EPA Fuel Pathway Analyses
- California Low Carbon Fuel Standards (LCFS)/CARB Look Up Tables and Tier 1 Calculators
- Carbon Offsetting and Reduction Scheme for International Aviation (CORSIA)
- The U.S. Inflation Reduction Act (IRA)/GREET
- One Big Beautiful Bill Act (OBBBA)/GREET

The RFS, expanded in 2007, sets annual volumetric requirements for renewable fuels with minimum lifecycle GHG reduction thresholds relative to petroleum baselines (EPA, 2025). The RFS aims to reduce greenhouse gas emissions, decrease dependence on imported oil, and support the development of advanced biofuels and renewable fuel infrastructure. The program uses a credit trading system where refiners and importers can buy and sell renewable identification numbers (RINs) to meet their blending obligations.

California’s LCFS, adopted in 2009, requires reductions in the carbon intensity of transportation fuels over time (CARB, 2020). Compliance is based on lifecycle carbon intensity scores calculated using CA-GREET and iLUC values derived from GTAP-BIO and AEZ-EF modeling. CARB provides default lookup table values and calculator tools for Tier 1 pathways, while customized Tier 2 analyses allow producers to claim lower CI scores.

CORSIA is a global program under the International Civil Aviation Organization (ICAO) that requires airlines to offset emissions growth above 2020 levels (ICAO, 2025). Lifecycle analysis under CORSIA is standardized across countries, with approved methodologies, including GREET-based options, used to determine the carbon intensity of aviation fuels. These values determine eligibility for emissions units and credits in the international aviation sector.

The 2022 IRA provided tax credits for low-carbon fuels under Section 45Z and sustainable aviation fuel (SAF) under Section 40B, with eligibility determined through lifecycle GHG analysis measured against a baseline CI reduction requirement (Treasury, 2025). Under the IRA, the U.S. Departments of Treasury and Energy adopted tailored GREET models (45ZCF-GREET, 40BSAF-GREET) to calculate carbon intensities of fuels. The IRA linked financial incentives directly to lifecycle emissions performance, making GREET a central tool in credit generation and compliance.

The 2025 OBBBA updates the IRA framework and adjusts incentive structures and qualification timelines for various renewable fuels (Congress, 2025). Like the IRA, GREET serves as the primary lifecycle model to evaluate program eligibility. The Act's alignment with GREET ensures continuity with existing policy while modifying credit structures and cost-sharing requirements for renewable fuel producers.

1.3 Objectives

The objective of this study is to assess how advances over the past decade in LUC and iLUC modeling and data have led to lower emissions estimates for U.S. corn and sorghum based ethanol. The analysis will focus on GTAP and CCLUB models to critically evaluate CARB's current LUC assumptions. The analysis also identifies which elements of CARB's 2015 LUC values most significantly diverge from current science and are priorities for updating. The report includes a comparison of leading LUC models, highlighting their relative strengths and weaknesses versus GTAP and CCLUB.

1.4 Scope of Report

To achieve the objectives of this study, this report reviews advances in LUC modeling over the past decade, focusing on how improvements in models such as GTAP, CCLUB, R&D GREET, GLOBIOM, and 45ZCF-GREET as well as data sources like AEZ-EF and IPCC factors have lowered LUC emissions estimates. Key drivers such as shock size, elasticity parameters, and soil carbon dynamics are systematically compared to establish a foundation across models. Building on this, the analysis critically reviews CARB's LUC estimates, examining assumptions, elasticity factors, and modeling structures, and align CARB's inputs with CCLUB to highlight sources of divergence and issues with CARB's 2014-2015 iLUC analysis.

The report identifies aspects of CARB's 2014 analysis that diverge from more recent estimates and assesses which assumptions are most impactful to update by running models under standardized assumptions. The report compares the strengths and weaknesses of major LUC models relative to GTAP and CCLUB, identifying gaps, interoperability challenges, and areas for methodological improvement.

The report covers iLUC for both corn and sorghum ethanol as labelled. If there is no separate specification for sorghum ethanol, the content and graphic are referring to corn ethanol. Labeling for models such as "GTAP 2004 (2011)" is used throughout the report. In this instance, 2004 refers to the vintage of the GTAP model, while 2011 refers to the regulation year.

2. LAND USE CHANGE MODELS

Land use change models are a critical component of life cycle assessment for biofuels. Their purpose is to estimate the GHG emissions that result when increased biofuel demand alters land-use patterns, specifically when new cropland is created by converting forests, grasslands, or other non-agricultural lands (IPCC, 2006). LUC models simulate complex economic, agronomic, and ecological responses across local and global systems, making them essential tools for evaluating the carbon intensity of biofuel. By capturing both direct and indirect pathways of land conversion, these models aim to ensure that fuel policy accurately reflects real-world environmental impacts.

Indirect Land Use Change accounts for the GHG emissions related to the conversion of land, such as forests or agricultural land, that theoretically occur indirectly as a result of biofuel production. It also considers the potential displacement of crops caused by the expansion of biofuel feedstock cultivation, which may lead to additional land being converted from non-agricultural use to compensate for the increased demand (CARB, 2015). As a result of the modeled conversion, carbon stored in above-ground biomass and in the soil is released to the atmosphere, resulting in an increase in CO_2 emissions relative to business-as-usual. There is also a modeled loss of on-going carbon sequestration in the vegetation that has been removed. This section of the report first presents background information on modeling of iLUC, which is followed by details of the iLUC models used in the LCA methodologies evaluated in this report.

The following is a list of LUC models associated with regulatory programs that greatly impact U.S. corn and sorghum ethanol:

- Global Trade Analysis Project (GTAP)
- Carbon Calculator for Land Use and Land Management Change from Biofuels Production (CCLUB)
- Global Biosphere Management Model (GLOBIOM)
- IRA Clean Fuels Production Credit 45ZCF-GREET

2.1 iLUC Modeling Background

Estimating iLUC emissions requires many assumptions as compared to estimation of direct emissions and can differ widely between models and modeling systems. According to (Xin Zhao, 2021), “Induced land use change includes both direct and indirect land use change, as the two cannot be distinguished given the complexity of the market-mediated responses”.

Figure 2.1 summarizes the general approach to calculating the carbon intensity of iLUC. A biofuel “shock” through increased demand is modeled via agro-economic models to determine how much and what kind of land is converted as a result of the increased biofuel demand. Emission factors, above-ground and below-ground carbon, are applied to the converted land to determine the GHG impact of changing the land from, for example, native vegetation to crop production. Emissions are then allocated over a certain time period, 30 years in U.S. policies like the RFS and

LCFS, assumed to be consistent with the length of the fuel program. Notably, the appropriate time period for amortizing land use change emissions remains a source of some disagreement and debate, especially as many U.S. ethanol facilities have been in continuous operation for more than 30 years.

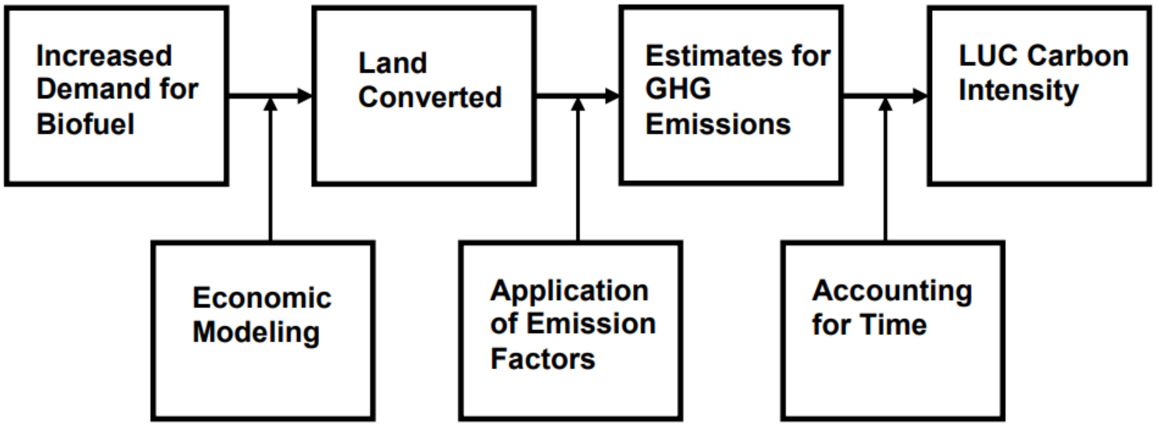

Figure 2.1. Simplified Block Flow Diagram of iLUC Modeling (CARB, Detailed Analysis for Indirect Land Use Change, 2014).

A typical model-derived land use change emissions profile is shown in Figure 2.2. Year 1 has the highest emissions as a result of land clearing and burning of the native vegetation. Most of the below-ground carbon, from roots and organic material, is released in years 1 to 5, with a slower release in years 6 to 20. Finally, foregone sequestration occurs during the entire project period, which as noted above, is assumed to be 30 years under U.S. policies.

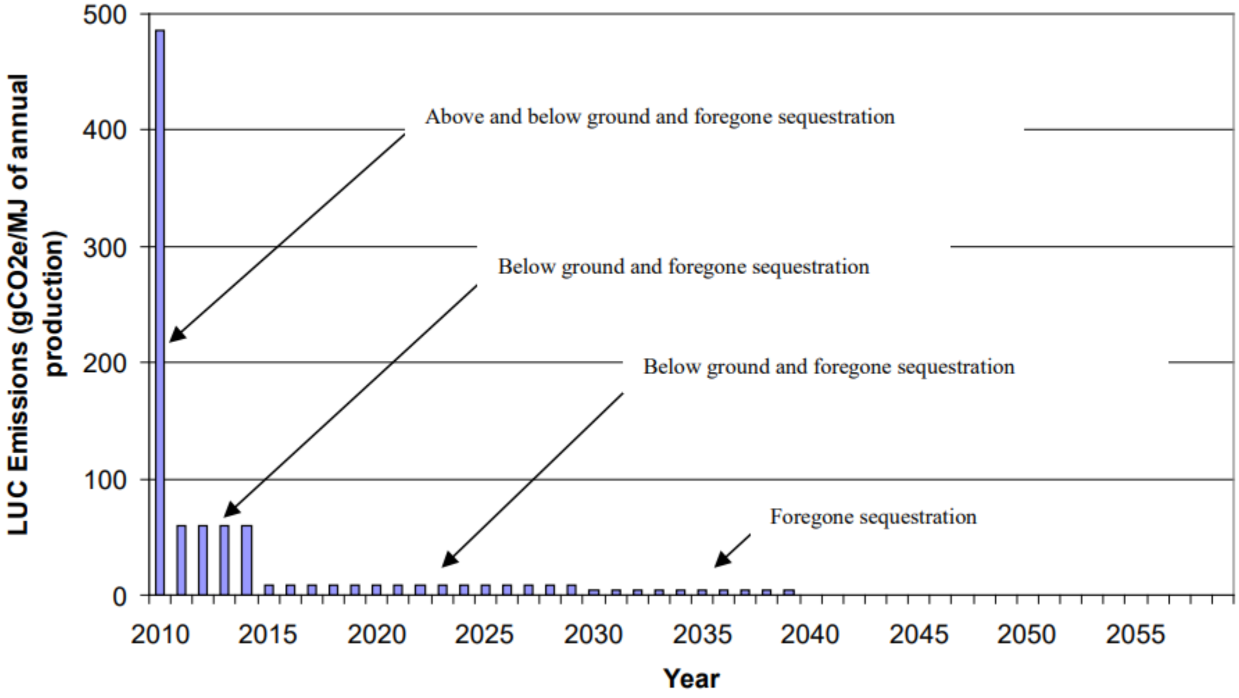

Figure 2.2. Emission Profile of ILUC (CARB, 2014)

Land use conversion is modeled by assessing the carbon emissions associated with the assumed transformation of one type of land use to another, such as converting forests or wetlands into agricultural land. The carbon released from soil and vegetation during land conversion is a key factor, as the carbon that was previously stored in biomass or soil organic matter is emitted as CO_2, contributing to Global Warming Potential (GWP).

Economic general equilibrium models like GTAP form the backbone of many LUC analyses, including the LCFS, as shown in Figure 2.3 (CARB, 2014). GTAP-based approaches model the global agricultural economy to predict how biofuel-driven demand shocks redistribute land uses worldwide, considering trade, crop switching, yield responses, and land conversion costs. Emissions from these land conversions are then estimated using biophysical models and emission factors, such as the Agro-Ecological Zone Emission Factor (AEZ-EF) model that reflects carbon stocks in soils and vegetation, as well as foregone carbon sequestration.

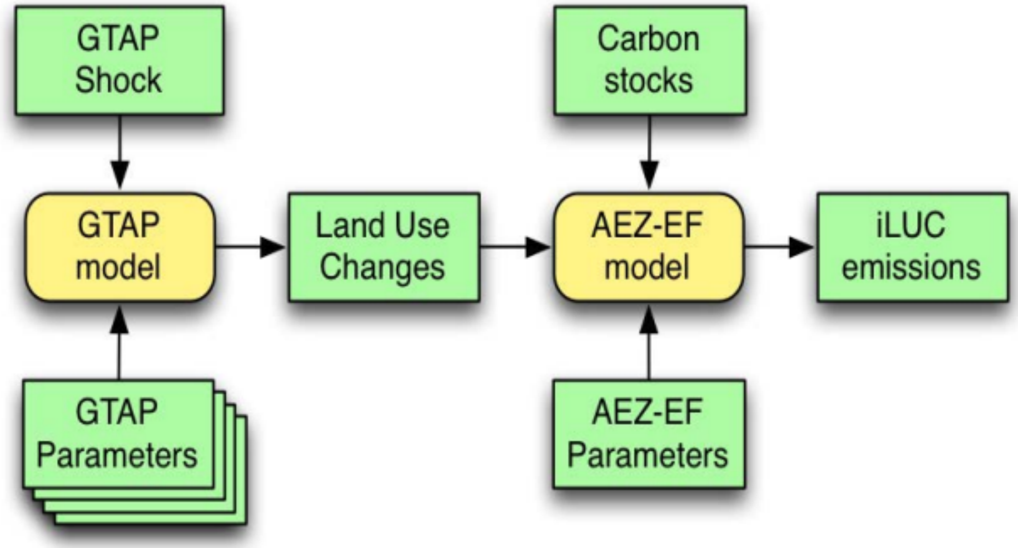

Figure 2.3. GTAP-BIO Model Integration with AEZ-EF Model for LCFS iLUC Calculation

Tools such as Argonne National Laboratory's CCLUB model also integrate GTAP outputs with detailed regional emission factors to generate refined carbon intensity values, capturing both international and domestic land use change effects (DOE, 2021). In the CCLUB model, land use change is quantified by calculating the direct and indirect carbon fluxes associated with land conversion. This includes emissions from the loss of carbon stored in vegetation and soils when land is cleared for agriculture or other uses. CCLUB employs detailed data on land cover types and the carbon sequestration potential of different land types to model these emissions.

Over the past decade, substantial advances have improved the quality of these models and their underlying data. Key improvements include refined land cover and land use databases, better representation of yield responses to price signals, enhanced regional differentiation in land transformation elasticities, and updated emission factors reflecting more granular soil and biomass carbon stocks.

These refinements have led to lower estimates of LUC-related emissions for major biofuel pathways, such as corn ethanol. This review will assess how these scientific advances have led to lower emissions estimates, with particular attention to GTAP and CCLUB modeling improvements, while critically evaluating which aspects of CARB's existing LUC assumptions remain outdated and are highest priority for revision.

2.1 Model Review

Indirect land use change modeling relies on integrated frameworks that link global economic dynamics with biophysical carbon accounting. The Global Trade Analysis Project (GTAP-BIO) is the primary tool used by CARB under the LCFS to simulate how biofuel demand reshapes agricultural production, trade, and land allocation worldwide, with land conversions translated into CO_2 emissions through the AEZ-EF model. CCLUB incorporates GTAP-BIO by applying detailed U.S. data on vegetation and soil carbon stocks to estimate emissions from specific land transitions. Together with other modeling approaches, these frameworks provide the regulatory basis for assigning iLUC values, while also highlighting the sensitivity of results to assumptions about yields, trade elasticities, and carbon stocks.

2.1.1 GTAP

The Global Trade Analysis Project (GTAP) is the most widely applied model for estimating iLUC. It is a computable general equilibrium (CGE) model originally designed for global trade policy analysis, adapted in the late 2000s to evaluate biofuels. Its core mechanism is to impose a biofuel demand "shock" and trace how global markets rebalance across agriculture, land use, and trade. The resulting land conversion estimates are then coupled with emission factors to generate iLUC values.

GTAP Modeling History

The GTAP model has evolved since its inception through various updates that impact iLUC values as shown in Table 2.1. The earliest applications (2008–2010) used GTAP-BIO with a 2001 social accounting matrix (SAM). Land was treated as a relatively homogeneous factor of production, with limited differentiation between cropland, pasture, and forest. Yield elasticities were set low (0.15–0.2), implying that most of the response to higher crop demand came from expanding cropland rather than intensifying production. These assumptions generated high iLUC values, often in the range of 25–30 gCO_2e/MJ for corn ethanol.

Table 2.1. Evolution of GTAP Model and Impact on iLUC

Timeframe	Model Evolution	iLUC Values
2008-10[a]	Biofuel sectors, DDGS co-product, 2001 SAM. Basic representation of biofuels	25-30 gCO_2e/MJ
2011-14[a]	AEZ's cropland pasture, elasticity refinements, 2004 SAM, reflecting heterogeneity and land refinements	Reduced iLUC by 20-30%
2015 (CARB)[a]	GTAP-BIO 2014, AEZ-EF, conservative elasticities applied to LCFS	Corn ethanol, 19.8 gCO_2e/MJ
2016-19[b]	2011/2014 SAMs, revised elasticities, improved land cover, econometric calibration	10-15 gCO_2e/MJ
2020-Present[c]	Higher yield elasticity, endogenous intensification, new land data, empirical studies and remote sensing.	7-12 gCO_2e/MJ

[a] LCFS Land Use Change Assessment (CARB, 2025)

[b] The GTAP Data Base: Version 10 (GTAP, GTAP Data Bases: GTAP 10 Data Base Documentation, 2019)

[c] The GTAP Data Base: Version 11 (GTAP, 2023)

Subsequent iterations addressed several shortcomings. Beginning in 2011, GTAP-BIO introduced agro-ecological zones (AEZs), which allowed land to be disaggregated by productivity class. This innovation recognized that not all land is equally suitable for crop production, reducing the model's reliance on high-carbon land, like tropical forest as a marginal supply source. Around the same time, cropland–pasture was introduced as a distinct land category. Empirical work by Taheripour and colleagues had demonstrated that much of U.S. cropland expansion occurred on existing cropland–pasture rather than pristine forest, and this refinement allowed the model to reflect those dynamics. As a result, deforestation estimates declined and iLUC penalties dropped by roughly 20–30 percent.

By 2015, when CARB adopted GTAP-BIO for its LCFS update, the model incorporated AEZs and cropland–pasture but remained reliant on a 2004 SAM and conservative elasticity assumptions. Yield elasticities below 0.2 and limited trade responsiveness forced more land expansion than updated empirical evidence supported. The resulting estimate for corn ethanol (19.8 gCO_2e/MJ) was lower than EPA's earlier RFS2 assessment (~30 gCO_2e/MJ), but higher than what more recent GTAP versions would later produce. Figure 2.4 shows the evolution of iLUC values for corn and sorghum ethanol for various regulatory schemes.

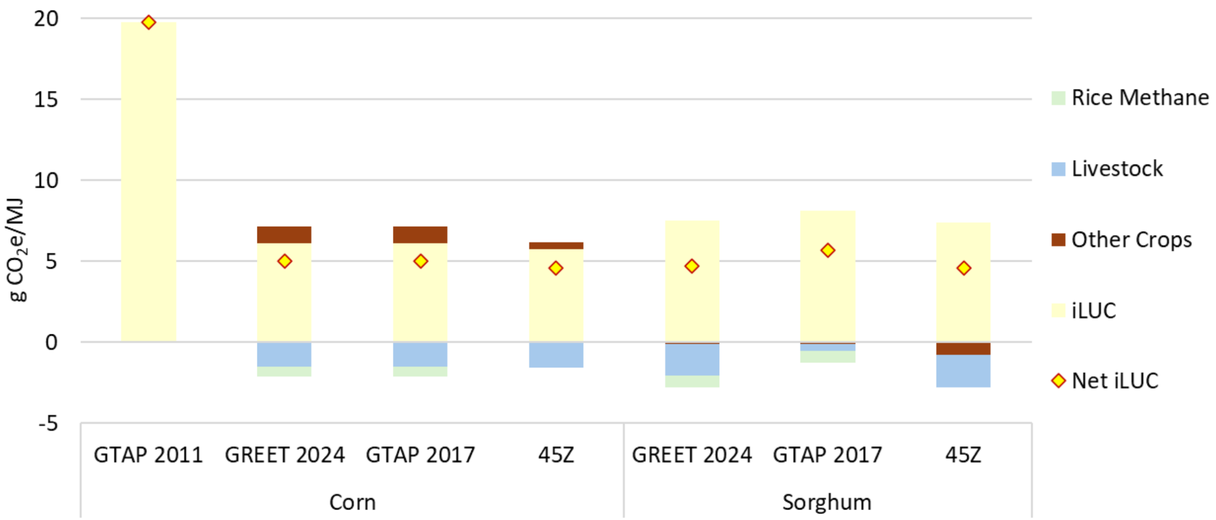

Figure 2.4. Various iLUC modeling results for Corn and Sorghum Ethanol

From 2016 onward, GTAP-BIO underwent major improvements. The database was updated to 2011 and 2014 SAMs, elasticities were recalibrated based on new econometric studies (Berry & Schlenker, Rosas et al.), and land cover data were refined with FAO and IFPRI inputs. Yield elasticities were raised into the 0.25–0.35 range, reflecting stronger farmer responses to price incentives. Transition probabilities among land types were recalibrated against observed historical changes, reducing the likelihood of high-carbon land conversion. These updates produced iLUC values in the 10–15 gCO_2e/MJ range.

The most recent versions (2020 onward) include even more substantial revisions. Land cover maps and carbon stock data were improved with remote sensing and inventory-based estimates. Yield elasticities now fall in the 0.3–0.5 range, consistent with a growing body of evidence that intensification plays a major role in meeting new demand. Pasture-to-cropland conversions are assigned lower emission factors to reflect empirical SOC measurements. Regional disaggregation of key trade partners, Latin America, Africa, and Asia, provides more accurate representation of global market adjustments. Collectively, these advances have reduced iLUC estimates for U.S. corn ethanol to ~7–12 gCO_2e/MJ, less than half of CARB's 2015 value[2].

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[2] LUC modeling in Section 4 explores different shock sizes for the more readily accessible GTAP 2011 files.

Model Inputs

Key inputs to GTAP include the baseline economic database, which specifies global production, consumption, and trade flows for a given year, and the biofuel production shock, which represents the increase in output being modeled. The model also requires parameters such as the yield price elasticity (YDEL), which defines how crop yields respond to changes in crop prices; the elasticity of area expansion (ETA), which sets the productivity of newly converted cropland relative to existing cropland; and the elasticity of land transformation (ETL), which governs the extent to which land shifts between cropland, pasture, and forest.

Additional inputs include demand and supply elasticities for energy and agricultural sectors, regional land transformation coefficients, and assumptions about co-product substitution effects such as distillers' grains replacing animal feed. Together, these inputs determine the amount and type of land converted when biofuel demand increases.

Model Structure

The GTAP-BIO model is structured as a global computable general equilibrium framework that links production, consumption, and trade across multiple regions and sectors. Land use is represented through a nested structure, where land can shift between forest, pasture, cropland, and cropland-pasture categories depending on economic signals. Within cropland, additional substitution occurs among different crop types, allowing the model to simulate how increased demand for one crop influences allocation of land to others.

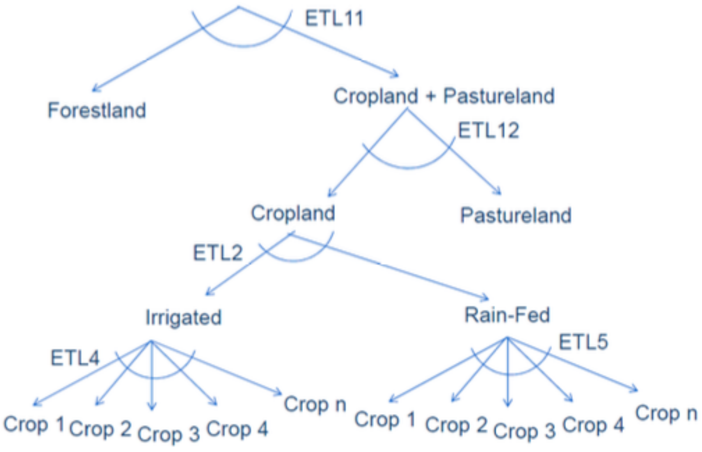

Figure 2.5. Modified Land Transformation Tree Structure, CARB 2014

The model also incorporates a land transformation tree that defines substitution possibilities and elasticities between land cover types and distinguishes between rain-fed and irrigated cropland as shown in Figure 2.5. Regional disaggregation is done by AEZs, which provide geographic specificity to land conversion processes. This structure enables the model to allocate biofuel-driven demand shocks across regions, crops, and land types in a consistent equilibrium framework.

2.1.2 CCLUB

The Carbon Calculator for Land Use Change from Biofuels model, developed at Argonne National Laboratory, is not an economic model but a carbon accounting framework. Its purpose is to translate GTAP land allocation outputs into carbon intensity estimates. Over the last decade, CCLUB has steadily replaced older approaches such as AEZ-EF by incorporating updated carbon stock data, better soil dynamics, and conservation practices. The model structure, data sources, and calculations are shown in Figure 2.6.

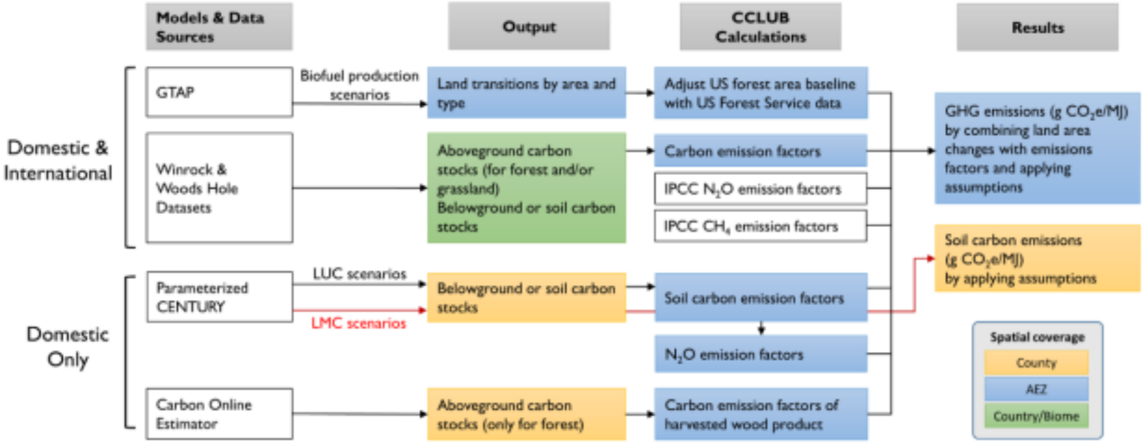

Figure 2.6. CCLUB Model Calculations and Data Sources Including GTAP Model Integration

The earliest version (2010–2013) directly implemented AEZ-EF factors within GREET, using IPCC Tier 1 defaults for biomass and soil carbon. This approach assumed immediate, permanent loss of carbon stocks, which tended to overestimate emissions.

Between 2014 and 2016, CCLUB introduced several major refinements. Forest biomass estimates were updated using Pan et al. (2011), while soil organic carbon (SOC) stocks were revised with Gibbs et al. (2014). Land transition pathways were distinguished, recognizing that forest-to-cropland conversions have higher emissions than pasture-to-cropland. A 30-year amortization period was introduced, spreading emissions over time rather than front-loading them. These changes lowered iLUC relative to AEZ-EF.

From 2017 to 2019, CCLUB became more regionally specific. SOC values were calibrated with USDA and FAO data. Cropland–pasture transitions were explicitly treated, with lower SOC losses relative to earlier assumptions. Forest regrowth dynamics were added, allowing for partial recovery of biomass stocks over time. These refinements further lowered iLUC estimates, with corn ethanol typically around 10–12 gCO_2e/MJ when coupled with updated GTAP results.

The most recent versions (2020 onward) have integrated conservation practice scenarios. No-till and cover crop adoption can be explicitly modeled, allowing SOC gains to offset some land conversion emissions. This update was especially important for the 45Z Clean Fuel Production Credit framework. With these practices considered, corn ethanol iLUC drops into the 7 to 9 gCO_2e/MJ range.

Model Inputs

CCLUB requires data on land transition areas, typically provided by agro-economic models such as GTAP. These specify the type and extent of land converted including forest to cropland and grassland to cropland. Additional inputs include regionally specific carbon stock values for aboveground biomass, belowground biomass, and soil organic carbon. Parameters defining carbon flux rates from biomass decay, soil disturbance, and foregone sequestration are included, along with assumptions about time horizons for carbon release and recovery. Management practices, crop productivity factors, and regional climate or ecosystem data are also used to refine estimates of carbon dynamics following land conversion.

Model Structure

The model is organized into modules that track carbon fluxes from vegetation, soils, and foregone sequestration. Land conversion data are allocated across regions and land cover types, which are then linked to carbon stock databases. Aboveground carbon losses are modeled as immediate emissions from clearing, while belowground emissions are represented as gradual releases over time. Soil carbon fluxes are estimated separately and combined with biomass emissions. The model applies time accounting to integrate emissions over a standard horizon, producing carbon intensity values. Its structure emphasizes the linkage between land transition areas and region-specific carbon pools, ensuring that both direct emissions and lost sequestration potential are captured.

2.1.3 Other Models

Several major policy frameworks incorporate land use change modeling to determine the greenhouse gas impacts of biofuels, but they differ in scope, structure, and units of measurement. The U.S. RFS applies a threshold-based approach, linking partial equilibrium models like FASOM and FAPRI to carbon stock data to estimate direct and indirect land use change. GLOBIOM, developed for European policy assessments, integrates global agriculture, forestry, and bioenergy markets in a partial equilibrium model to project land allocation shifts and associated carbon emissions. More recently, the Inflation Reduction Act introduced the 45Z Clean Fuel Production Credit, which uses the 45ZCF-GREET model; this framework integrates GTAP-BIO land conversion results with CCLUB carbon stock estimates and expresses outcomes in kilograms of CO_2-equivalent per million Btu of fuel energy. Together, these approaches illustrate the evolving methodologies for quantifying land use change emissions in biofuel policy.

RFS

In the expanded Renewable Fuel Standard (RFS2), land use change is modeled using a combination of U.S. Department of Agriculture and university-based economic models. Domestic land use effects are estimated with the Forest and Agricultural Sector Optimization Model

(FASOM), while international effects are captured with the Food and Agricultural Policy Research Institute (FAPRI) model. These agro-economic models simulate how increased biofuel demand alters crop production, prices, trade, and land allocation both in the U.S. and abroad.

The modeled land transitions, such as forest or pasture converted to cropland, are then paired with emission factors developed by Winrock International to estimate associated carbon releases from vegetation and soils. The resulting direct and indirect land use change emissions are integrated into the life cycle greenhouse gas assessments of biofuels under the RFS. Notably, the FASOM-FAPRI modeling framework has not been used to estimate land use changes since its initial application for the RFS2 regulations.

GLOBIOM

In GLOBIOM, land use change is modeled through a global partial equilibrium framework that represents the interactions between agriculture, forestry, and bioenergy sectors. The model divides the world into regions and grid cells, simulating how changes in demand for food, feed, and bioenergy influence land allocation among crops, pasture, and forests. It incorporates biophysical data on crop yields, soil types, and management practices, along with economic drivers such as prices and trade flows.

When biofuel demand increases, the model projects how much land is converted from one type to another to meet the new feedstock requirements. These land transition estimates are then linked to carbon stock data for vegetation and soils, allowing the calculation of greenhouse gas emissions from both carbon release and foregone sequestration. Through this integration of economic and biophysical modeling, GLOBIOM generates estimates of direct and indirect land use change emissions associated with biofuel expansion.

45ZCF-GREET

In the 45Z Clean Fuel Production Credit framework, lifecycle greenhouse gas emissions, including land use change, are modeled with the 45ZCF-GREET tool developed by Argonne National Laboratory for the Inflation Reduction Act. The model incorporates feedstock-specific data such as crop type, region of origin, and farming practices, while applying iLUC factors derived from GTAP-BIO and CCLUB modeling. Default iLUC values are built into the calculator for major feedstocks like corn ethanol, soy biodiesel, and sugarcane ethanol, though applicants can request updated values if supported by EPA- or CARB-approved modeling.

The results are expressed in kilograms of CO_2-equivalent per million British thermal units (kg CO_2e/MMBtu) of fuel energy. GTAP-BIO provides estimates of land conversion triggered by modeled changes in biofuel demand, which are paired with regional soil and biomass carbon stock changes from CCLUB. Modeled emissions from above- and below-ground carbon losses, along with forgone sequestration, are allocated over a 30-year horizon and averaged to yield an iLUC factor. This value is then integrated with other lifecycle components, farming, transport, conversion, and distribution, to generate the compliance-grade carbon intensity used for determining credit eligibility under Section 45Z.

2.2 Key Model Drivers

Several key model attributes strongly influence how LUC is estimated, particularly in frameworks such as GTAP and CCLUB. Among the most important drivers are assumptions about future crop yields. In GTAP, yield projections and yield price elasticities determine whether additional biofuel demand is met through intensification on existing cropland or through the conversion of new land. Higher yield responses to price increases reduce the need for expansion, while lower responses result in greater land conversion and higher associated emissions. CCLUB incorporates these outcomes by linking the modeled land transitions to region-specific carbon stock changes in soils and biomass, which are highly sensitive to whether land is converted from forest, grassland, or marginal areas.

Elasticities also play a central role in shaping modeled outcomes. GTAP relies on a set of elasticity factors to capture market-mediated effects such as crop switching, trade substitution, and feed use. For example, the displacement of corn and soybean meal by distillers' grains (DGS) in livestock feed directly reduces cropland requirements, while substitution between beef and poultry consumption reflects shifts in land intensity across protein sources. These market responses directly affect the magnitude and type of land converted in the GTAP framework. When coupled with CCLUB, the location and type of conversion identified by GTAP are linked to detailed carbon pools, producing estimates of emissions from soil disturbance, aboveground biomass loss, and foregone sequestration.

Another critical set of parameters governs land allocation decisions across competing uses. GTAP uses transformation elasticities to determine the likelihood of land moving between cropland, pasture, and forest. Low elasticities imply limited substitution, leading to higher commodity price responses, while higher elasticities allow land to shift more freely among categories. The consequences of these land allocation assumptions flow directly into CCLUB, where the emissions impact of converting high-carbon stock forest versus lower-carbon marginal land can differ by orders of magnitude. Together, the treatment of yield responses, feed substitution, and land transformation elasticities make GTAP and CCLUB highly sensitive to input choices, and these parameters explain much of the variability in published estimates of biofuel-induced LUC.

2.2.1 Model Perspective (Equilibrium vs Dynamic)

Equilibrium models solve for the point where supply and demand functions intersect across sectors of the economy, ensuring that all resources and outputs are balanced. Because closed-form solutions are not available, these models iteratively converge on equilibrium values for prices and quantities. Static equilibrium models, such as GTAP, provide results for a single point in time using a fixed database. In comparative static analysis, the model is rerun with different exogenous inputs, such as changes in income, population, or fuel demand, to observe how outcomes vary. Dynamic models, such as FAPRI and FASOM, extend this approach by solving equilibria over multiple time intervals, capturing the transitions between states. In practice, this allows dynamic models to trace how agricultural and energy markets evolve over years or decades, rather than providing a single snapshot.

The dynamic version of GTAP is also available which applies shocks sequentially across multiple periods, allowing the model to trace the pathway of adjustment over time. This feature can represent a staged implementation, such as gradual ramp-ups in renewable fuel standards, rather than one-time shocks.

Another important distinction lies in how models represent economic scope. General equilibrium models capture all sectors of the economy, agriculture, energy, manufacturing, finance, transportation, and others, thereby reflecting interactions across industries. Partial equilibrium models, by contrast, focus on a subset of sectors while treating the rest as fixed. For example, FAPRI is a partial equilibrium model that emphasizes agricultural commodities but does not explicitly incorporate forestry or pastureland in most regions, which limits its ability to reflect land competition across uses. General equilibrium models like GTAP, however, include all major sectors and allocate land across competing uses, making them better suited to capture the broader system-wide effects of biofuel expansion.

The EPA has examined LUC analysis with the GLOBIOM and GCAM models citing their dynamic nature as a key feature. However, introducing dynamic economic assumptions adds further assumptions to the iLUC analysis with limited useful information. Dynamic models provide predictions that take into account future economic projections; however, the data and assumptions required to make such predictions introduce additional uncertainty into the analysis.

2.2.2 Land Conversion Emission Factors

Land use emission factors are essential for translating modeled land transitions into estimates of greenhouse gas emissions. While economic models like GTAP predict how much land shifts among crops, pasture, and forest in response to biofuel demand, they do not inherently quantify the carbon consequences of these shifts. This translation step requires linking land use changes to carbon stock data for vegetation and soils, and applying emission factors that represent the release of stored carbon or the foregone sequestration potential of land converted.

2.2.3 Shock Size

In LUC modeling, a “shock” refers to an exogenous change applied to the system, such as a rise in biofuel demand caused by a policy, a shift in trade policy, or an adjustment in crop productivity, that forces the model to recalculate global or regional equilibria. By design, these shocks are applied under ceteris paribus conditions, meaning that all other variables are held constant, so that the model isolates the impacts of the specified change. This approach is especially important for iLUC modeling, where the goal is to understand how a single policy action, like mandating additional corn ethanol, translates into changes in agricultural markets, land allocation, and ultimately greenhouse gas emissions. Without this mechanism, the model would not be able to separate the effect of the policy from the myriad other changes occurring in the global economy.

The shock size ideal reflects the volume of biofuel which is induced by a policy action. For example, about 15 billion gallons of ethanol are consumed annually or 10% of gasoline sales at the national level. Some analyses incorrectly assume this level of ethanol consumption is solely related to the RFS (Taheripour, 2022). In California, a 10% blend rate is required to achieve reformulated gasoline requirements. Changing the blend rate from 10% to 15% could be modeled as a shock; however, a switch to E15 may have to do more with market forces and refinery closures. Ethanol usage in the U.S. is also not solely due to the RFS as ethanol provides a high-octane, zero aromatic blending component which helps achieve benzene and sulfur standards and other fuel requirements.

In the GTAP framework, shocks are most commonly applied using the comparative static version of the model, which provides a snapshot of how the global economy and land use would adjust to a new equilibrium if only the specified shock occurred. For example, a biofuel shock might be defined as an additional 11.6 billion gallons of corn ethanol, which is then modeled as an exogenous increase in fuel demand. The model estimates how this additional demand raises crop prices, shifts trade flows, induces yield responses, and reallocates land between cropland, pasture, and forest. These land-use outputs are then linked to carbon stock changes via AEZ-EF or CCLUB to produce iLUC emissions.

Beyond GTAP, the concept of shocks is applied across other LUC models and contexts. In partial equilibrium models such as FAPRI or FASOM, shocks might include changes in feed demand, shifts in protein consumption from beef to poultry, or productivity gains from technology adoption. In dynamic land-use models like GLOBIOM, shocks can represent both policy interventions and environmental stressors, such as weather extremes or changes in livestock stocking rates, which alter the availability of land for crops. Regardless of the framework, shocks serve as the critical input that connects external drivers to endogenous model behavior, providing a transparent way to evaluate how policy or market changes ripple through agricultural systems and translate into land conversion and carbon emissions. This shock-response structure underpins regulatory modeling for programs like the LCFS and RFS, where modeled iLUC values depend on the magnitude, timing, and specification of the applied shocks.

This study shows GTAP results based on a range of shock sizes which have been analyzed in the literature as well as a parametric assessment of shocks ranging from 2 to 15 BGY.

2.2.4 Elasticity Factors

Elasticities are among the most influential parameters in LUC modeling, as they describe how markets respond to changes in prices and returns. In general terms, elasticity measures the percentage change in one variable resulting from a one percent change in another, expressed as a unit-free ratio. Demand elasticities, for example, determine how much consumption falls when prices rise. Goods with many substitutes, such as economy cars, exhibit high elasticities, while necessities like milk or gasoline tend to be inelastic, showing limited response to short-term price changes. These parameters provide a practical way to capture behavioral responses without requiring complete demand curves, and they are typically calibrated from historical market data.

In LUC modeling, a number of specialized elasticity functions are used to capture interactions in trade, production, and land allocation. The Constant Elasticity of Substitution (CES) governs how easily different inputs can be exchanged in production processes, such as substituting one feed component for another. The Armington elasticity, widely applied in global trade modeling, distinguishes goods by country of origin to reflect the persistence of trade relationships even when price differences exist. Its treatment has major implications for LUC outcomes: higher Armington values imply stronger substitution across borders and more dispersed land use change, while lower values concentrate land conversion within the biofuel-producing country.

Land allocation elasticities are especially important for estimating the extent and type of land conversion. Many computable general equilibrium models use a Constant Elasticity of Transformation (CET) function to govern shifts among land categories. In GTAP-BIO, this is represented as a nested structure: land is first allocated among broad categories such as cropland, pasture, and forest, and then cropland is further divided among competing crops. The CET elasticity determines how much land in one category expands in response to changes in land rents, directly influencing both the magnitude and distribution of predicted land conversion. The CET function models how land is allocated across competing uses, such as cropland, pasture, or forest, based on the relative returns of each use. Higher prices for one land-intensive activity incentivize land shifts toward that use.

Major changes have been made to the CET to improve the representation of land use and land use changes. The 2011 analysis used single-level CET structure for land allocation, but subsequent updates include empirically grounded formulations to more accurately model policy impacts. An advanced version of the model, GTAP-BIO-ADV, includes a multi-level CET, into one version.

Because these elasticities are uncertain and vary by region, they are a key focus of sensitivity analyses, and differences in their specification across studies are a major reason why LUC estimates can diverge so widely.

2.2.5 SOC Impacts

In both GTAP and CCLUB, soil organic carbon (SOC) plays a central role in determining the greenhouse gas impacts of land use change, but it is incorporated at different stages of the modeling chain. GTAP, as an economic equilibrium model, does not track carbon stocks directly. Instead, it estimates the magnitude and location of land conversions across cropland, pasture, forest, and cropland-pasture categories. These land conversion outputs are then passed into carbon stock models such as AEZ-EF or CCLUB. In this sense, GTAP defines where and how much land changes, while CCLUB applies SOC emission factors to translate those conversions into carbon intensity values. The GTAP side of the system therefore shapes the exposure of SOC pools to disturbance but does not specify the amount of SOC lost.

CCLUB provides the biophysical accounting for SOC emissions by combining global soil datasets, primarily the Harmonized World Soil Database, with IPCC Tier 1 stock change factors. It calculates baseline SOC levels at 0–30 cm and 30–100 cm depths for each region and applies depletion factors when natural land is converted to cropland or intensively grazed pasture. These factors typically assume a 20–52% reduction in SOC depending on the land cover type and climate zone. SOC loss is then annualized over a 30-year period, consistent with IPCC guidance, and expressed as gCO_2e/MJ when linked with biofuel demand shocks. In addition, CCLUB accounts for N_2O emissions from nitrogen mineralization after soil disturbance, adding a modest but important non-CO_2 component to total iLUC emissions.

The treatment of SOC has a significant effect on iLUC outcomes. Conversions from high-SOC land, such as temperate pasture or tropical soils, generate some of the largest modeled emission factors in both AEZ-EF and CCLUB. Sensitivity analyses show that assumptions about SOC depletion rates can swing corn ethanol iLUC values by several grams of CO_2e per MJ, while in soy biodiesel or palm biodiesel pathways, SOC accounting is often the dominant contributor to total iLUC emissions. Conversely, policies or land transitions that avoid high-SOC land conversion can substantially reduce modeled iLUC scores. Thus, even though GTAP does not directly handle carbon, its allocation of land use change feeds directly into CCLUB's SOC calculations, making soil carbon treatment one of the most consequential linkages between the two models.

3. REVIEW OF CARB 2014 LAND USE CHANGE RESULTS

This section presents the findings from the review of the 2014 assessment of ILUC by CARB for the California LCFS program. The detailed analysis from the CARB 2014 assessment has been published by CARB (CARB, 2014). The CARB report explicitly argues that the only indirect effect identified by CARB to be significant was iLUC, resulting from potential changes in land use due to increased biofuel production following the re-adoption of the LCFS.

The 2014 ILUC study conducted by CARB was an improvement from and built on top of its 2009 assessment, estimating the quantitative GHG impact from the increased biofuel production based on numerous simulations of global land use change scenarios following a sudden increase in biofuel production. No other potential indirect effects were quantified or presented by CARB, though evidence was presented by stakeholders that other indirect GHG effects associated with other fuel pathways may warrant examination.

3.1 Inclusion of iLUC in LCFS

More tailored to iLUC, the California LCFS GREET model, another variant of the GREET model, is tailored specifically to meet the requirements and objectives of California's LCFS program (CARB, 2024). Implemented by the California Air Resources Board (CARB), the LCFS aims to reduce the carbon intensity of transportation fuels used in the state, thereby decreasing greenhouse gas emissions from the sector. The California LCFS GREET model adopts a well-to-wheels (WTW) framework, like the original GREET model, but with adjustments specific to California's conditions and policies. The model includes detailed pathways for conventional and alternative fuels, including gasoline, diesel, natural gas, electricity, hydrogen, and a variety of biofuels like ethanol and biodiesel. The model incorporates California-specific data on electricity generation, fuel production, and transportation infrastructure, ensuring that the assessments accurately reflect the state's unique energy landscape of renewable energy sources.

The California LCFS program imposes CI targets on transportation fuels that are expected to be met through the substitution of lower CI renewable fuels for higher CI conventional fuels and by technology substitution such as battery electric vehicles displacing internal combustion engine vehicles. LCA analysis is performed using CA-GREET3.0 and the Tier 1 Calculators. The LCI data in CA-GREET3.0 and the Tier 1 Calculators are derived from GREET1_2016 with LUC values developed by CARB in 2015 based on the GTAP model (CARB, 2015).

The current version of the model, CA-GREET3.0, was made effective in January 2019 and is based on the GREET1_2016 version of the GREET model. A proposed update to the model, CA-GREET4.0, was released in December 2023, and has now been approved for use beginning in 2025 (CARB, 2023), but no changes to land use change estimation were included. The LCFS pathway includes several simplified CA-GREET3.0 model Tier 1 simplified CI calculators for several approved feedstock pathways. For corn, these include ethanol production from starch and fiber as well as biodiesel and renewable diesel production from corn oil. The simplified calculators contain built-in assumption factors around farming, meaning that corn farming data is fixed, as well as energy, fertilizer inputs, and yields of ethanol and co-products for each production pathway. The simplified calculators were updated along with the finalized CA-GREET4.0 model (CARB, 2024).

Figures 3.1 and 3.2 show the predicted land transformation and land use emissions from CARB's 2014 analysis for corn ethanol. Subsequent charts are also for corn ethanol unless labeled as sorghum ethanol. The changes are categorized by geographic grouping as well as land conversion category. The model predicts cropland conversion in the U.S. with primarily pasture and cropland conversion in Brazil and sub-Saharan Africa. The largest land use emissions are predicted in sub-Saharan Africa.

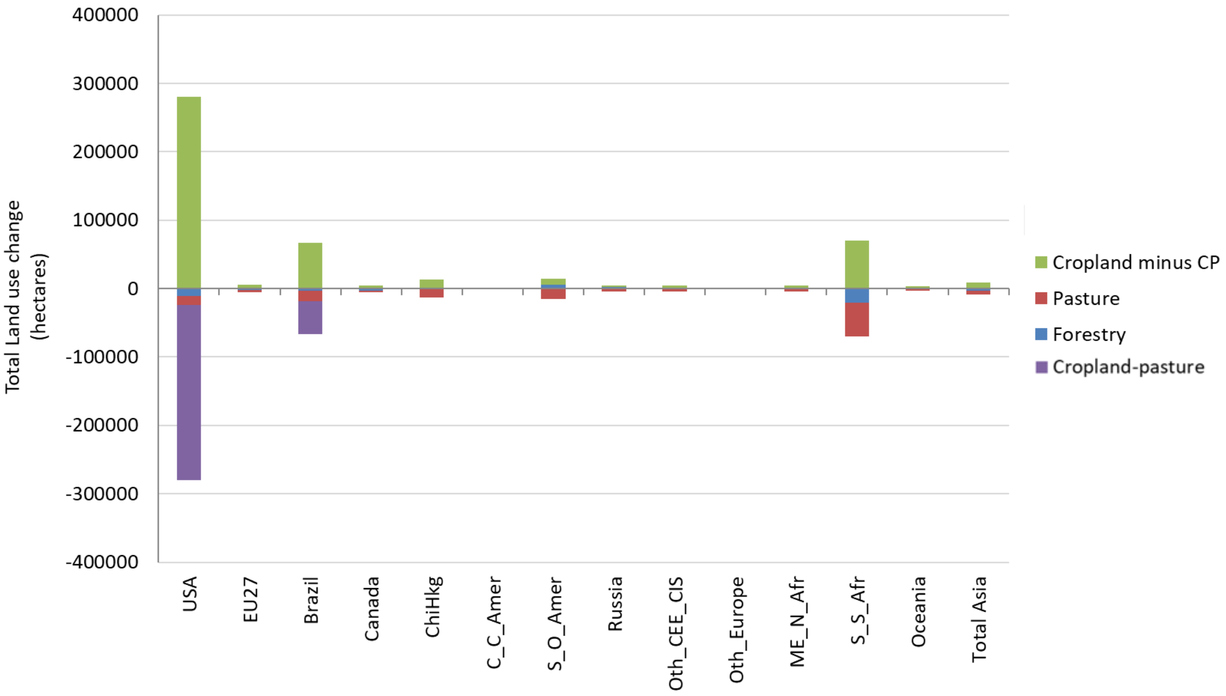

Figure 3.1. Land use Conversion for GTAP 2004 (2013)

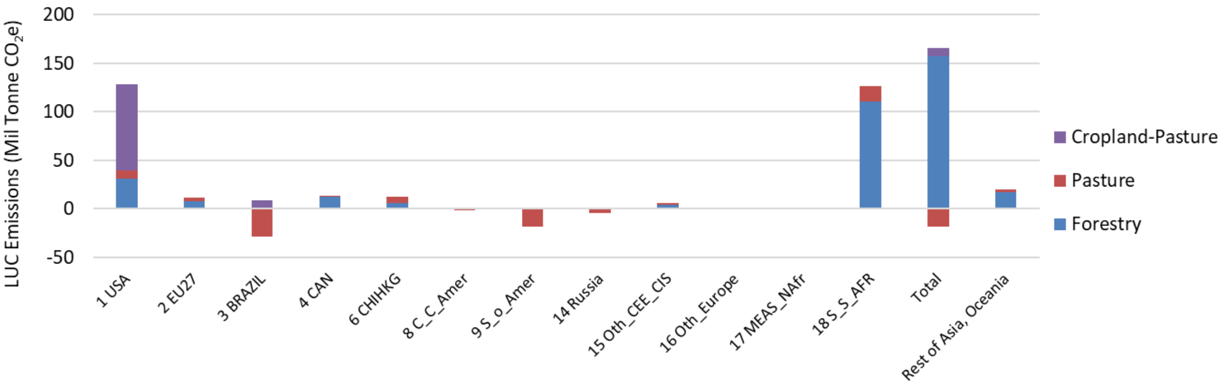

Figure 3.2. LUC Emissions for GTAP 2004 (2013)

3.2 Key Model Inputs

General equilibrium models such as GTAP estimate ILUC by first quantifying the global economy and associated land use changes resulting from a user-defined shift away from its baseline equilibrium. The differences of global land use patterns in the baseline equilibrium from the computed equilibrium following the user-defined biofuel shock represent the estimated indirect land use change due to the increased biofuel production. Such ILUC computed by GTAP model are exported and subsequently combined with external GHG emission factors respective to various regions, original and new land use, soil carbon and other factors to result in ILUC GHG emission factor.

Beyond the biofuel shock itself, the GTAP simulation requires many other inputs and parameters which significantly affect the simulation results. Some of the most important GTAP model parameters CARB customized for its 2014 study are presented below.

3.2.1 Baseline Year

While the 2009 CARB study used the baseline year of 2001, the 2014 study updated the baseline year to 2004 which was the latest available GTAP database at the time. The baseline year represents the global economy and associated land use as point-in-time snapshot assumed to be at an equilibrium. Currently, the latest baseline data available in GTAP is for 2017, meaning the baseline data was updated several years after CARB's last analysis was conducted. While the model simulations estimate the future snapshot of the global economy, the update in the baseline year data represents the actual changes that have taken place. Even after a careful selection of model inputs and parameters, the model simulation results can present a vastly different result than the actual response of the global economy due to various factors externalities.

3.2.2 Biofuel Production Increase

The user-defined increase in the biofuel production quantity, biofuel volume/year, often referred to as a "shock", is the primary input for CARB's ILUC simulations. For each type of biofuel covered under LCF, CARB conducted 30 independent GTAP simulations with varying sets of model parameters, while keeping the shock constant. None of the GTAP simulations by CARB included an increase in biofuel production of various types simultaneously, departing away from the practical impact of a policy like LCFS.

The shock size, being the primary input to such an assessment, must be selected carefully to represent the expected change in the fuel market due to the introduction/extension of the policy. The independent shock sizes for each biofuel type used by CARB under its 2014 ILUC study are presented in the table below.

Table 3.1. Biofuel Shocks from CARB 2014 iLUC Assessment

Shock	Shock Size (bgy)	Impact of Shock	LUC Impact
Corn Ethanol	11.59	Expands U.S. corn acreage; reduces soy/wheat; raises global corn price. DDGS offsets some feed demand.	Global forest & pasture conversion; moderate cropland-pasture shifts. Avg. iLUC = ~19.8 gCO_2e/MJ.
Sugarcane Ethanol	3.0	Expands cane in Brazil, mainly displacing pasture; some forest loss.	Dominated by pasture conversion. Avg. iLUC = ~11.8 gCO_2e/MJ.
Soy Biodiesel	0.812	Expands soy area; reduces other crops; vegetable oil market effects.	Moderate iLUC; sensitive to South American forest conversion. Avg. iLUC = ~29.1 gCO_2e/MJ.
Canola Biodiesel	0.4	Shifts oilseed balance; imports of soy/palm adjust.	Modest land use changes. Avg. iLUC = ~14.5 gCO_2e/MJ.
Sorghum Ethanol	0.4	Substitutes for corn; land response smaller; coproducts offset feed.	ILUC similar to corn but smaller scale. Avg. iLUC = ~19.4 gCO_2e/MJ.
Palm Biodiesel	0.4	Expands plantations in Malaysia/Indonesia; replaces forest/peatland.	Highest iLUC; tropical forest and peat conversion dominate. Avg. iLUC = ~71.4 gCO_2e/MJ.

CARB modeled iLUC by imposing an exogenous “volume shock”, an increase in production in bgy, for each pathway in the GTAP-BIO economic model, then converting the model’s land-transition outputs into GHG emissions with AEZ-EF spatial emission factors and averaging 30 scenario runs to get the pathway iLUC value. CARB’s 2015 update incorporated: a newer GTAP baseline (2004), explicit cropland-pasture in U.S./Brazil, revised elasticities, improved coproducts, and a far more spatially detailed AEZ-EF set. These changes shift land conversion away from forests toward cropland-pasture/pasture in many cases and lower overall iLUC relative to 2009.

3.2.3 Yield Price Elasticity

Yield price elasticity (YPE), is a central parameter in indirect land use change modeling because it determines how much of a production shock is absorbed through higher yields rather than through expansion of cropland. In computable general equilibrium models such as GTAP-BIO, an increase in demand for corn or soy for biofuel raises crop prices. Farmers can respond by producing more from existing land or by bringing new land into production. YPE governs the balance between these two responses. A higher value implies that more of the adjustment occurs through yield increases, which reduces cropland expansion and lowers estimated iLUC emissions. A lower value shifts the adjustment toward land expansion, which amplifies iLUC impacts.

In early applications such as the 2009 California Low Carbon Fuel Standard, GTAP-BIO used YPE values in the range of 0.2 to 0.6, reflecting econometric studies available at the time. Researchers at Purdue synthesized several estimates and proposed 0.25 as a representative medium-term response. When California revisited the analysis in 2014 and 2015, the agency used a lower range of values from 0.05 to 0.35. This decision was influenced by consultant studies that estimated yield responses over very short periods, often a single year. Purdue and other modelers argued that the GTAP framework should be calibrated to medium-term elasticities, since yield improvements are realized through adoption of better seeds, machinery, and management practices that take several years to materialize.

The sensitivity of iLUC results to YPE is significant. Lower elasticity values produce disproportionately higher iLUC emissions. California’s choice to average results across multiple scenarios with low YPE values raised the reported iLUC carbon intensity for corn ethanol compared to what would have been obtained using the GTAP default. By contrast, Purdue has consistently defended the 0.25 default as more representative of medium-run farmer responses. CCLUB does not parameterize YPE independently but instead inherits the land conversion outputs from GTAP. When GTAP assumes a lower elasticity and allocates more land to new cropland, CCLUB translates that increase into higher carbon releases. YPE illustrates how a single parameter can materially change the estimated carbon intensity of biofuels and underscores the importance of aligning elasticity assumptions with the appropriate economic time frame.

3.2.4 Emission Factors by AEZ

For CARB, this process is carried out through the AEZ-EF model, which pairs GTAP outputs with carbon stock values differentiated by region and land cover type. AEZ-EF draws from global soil and biomass datasets to assign CO_2-equivalent emissions to transitions such as forest-to-cropland or pasture-to-cropland. CARB justifies the use of AEZ-EF as providing transparent, region-specific emission factors consistent with IPCC guidelines, while also allowing uncertainty analysis by varying the key parameters. The resulting iLUC factors, expressed in grams CO_2e per megajoule of fuel, are averaged across scenarios and incorporated into LCFS carbon intensity values.

The GTAP simulation results are in the form of estimated land area types and amount changes as a result of the specified biofuel production increase. The land area conversion estimates for each native vegetation type, in hectares, are disaggregated by 19 geographic regions and 18 AEZ regions, creating 3-dimensional matrix. This output from GTAP is then combined with the corresponding emission factors in a separate spreadsheet-based AEZ-EF model. The emission factors reflect average GHG emissions per unit land area for both above & below ground biomass and carbon sequestered in the soil. Based on the land area conversion from a native vegetation to a different use thus results in an increase or decrease in carbon sequestration capacity, referred to as ILUC.

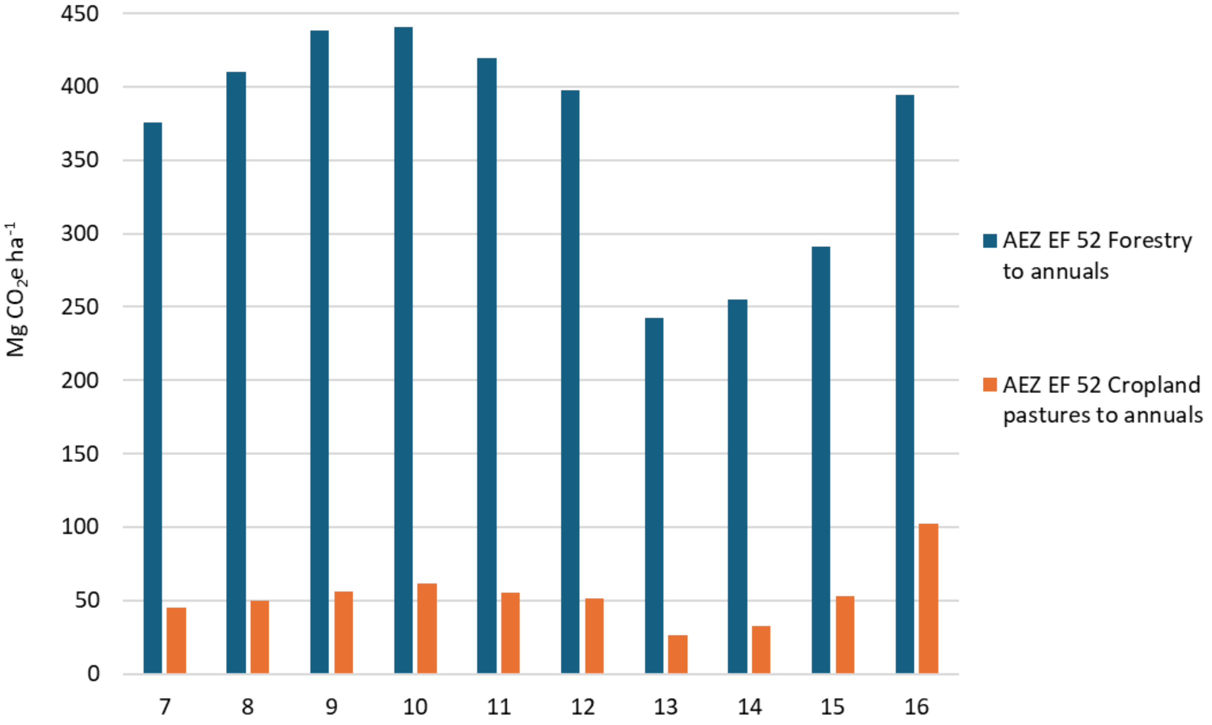

Figure 3.3. AEZ-EF 52 Carbon Stock Factors

The AEZ-EF model combines carbon stock data with many factors affecting the carbon stock such as original and new land use type, mode of conversion, and carbon remaining in harvested wood products, shown in Figure 3.3. This model relies heavily on the default land characterization values from IPCC. The latest IPCC publication on the subject at the time as from 2006, which have since been updated in 2019.

Table 3.2. Shared AEZ-EF and CCLUB Inputs

Input Category	AEZ-EF Values	CCLUB Values
Above-Ground Live Biomass (AGLB)	Forest AGLB by AEZ: 50–250 MgC/ha (temperate forest ~120, tropical >200). Cropland AGLB ≈ 2–10 MgC/ha. Pasture ≈ 2–5 MgC/h	Winrock/IPCC datasets. Identical AGLB ranges (forest 50–250 MgC/ha; cropland/pasture <10)
Below-Ground Biomass (BGB)	Calculated with root:shoot ratio = 0.24–0.28 depending on biome. So tropical forest BGB ≈ 50–70 MgC/ha.	Same IPCC ratio (0.24–0.28). CCLUB directly applies the same coefficients to AGLB
Dead Organic Matter (DOM: litter, deadwood, understory)	Forest DOM = 15–25 MgC/ha litter, 10–40 MgC/ha deadwood. Understory typically 5–10 MgC/ha	Same Pan et al. and IPCC defaults. Litter ~20 MgC/ha, deadwood 10–40, understory ~7
Soil Organic Carbon (SOC)	HWSD baseline: 0–30 cm ~40–90 MgC/ha (temperate), up to 150+ MgC/ha in tropical AEZs. 30–100 cm adds ~50–100 MgC/ha. Loss factors: 20–52% SOC decline when converted to cropland	Identical HWSD source. Applies same Tier 1 loss factors (0.48–0.80 multipliers → 20–52% loss)
Harvested Wood Products (HWP)	~20–30% of above-ground forest biomass retained over 30 yrs (decay curves applied; e.g., timber half-life 35 yrs)	Same 20–30% retention assumption
Peatland Emissions	95 $MgCO_2$/ha/yr (≈25 MgC/ha/yr) for drained peat. Assumes 33% of palm expansion occurs on peat	Same updated factor (replaces older IPCC 73 $MgCO_2$/ha/yr)
N_2O from SOC Loss	IPCC Tier 1: 1% of mineralized N → N_2O-N. Applied to SOC loss flux	Same Tier 1 EF

The chart on shared inputs shows that the AEZ-EF model developed by Plevin and the CCLUB model are built on nearly identical foundations for carbon stock and emission factor data. Both models use IPCC 2006 defaults and Winrock/Gibbs datasets for above-ground and below-ground biomass, with consistent root-to-shoot ratios and carbon densities for forests, cropland, and pasture. Soil organic carbon values and loss factors are also directly carried over, as are assumptions for harvested wood product retention and foregone sequestration rates. Even high-impact categories such as peatland emissions and N_2O from soil disturbance are treated with the same factors. This alignment means that differences in iLUC results between AEZ-EF and CCLUB stem less from the baseline carbon pools and more from how each model structures land transitions and accounts for uncertainty.

3.3 Data Omissions

The 2014 CARB iLUC analysis improved on the 2009 version but also left important data omissions. GTAP-BIO did not include unmanaged or inaccessible forests, excluding a significant land pool that other models treated as convertible. Carbon stock inputs were also incomplete. The AEZ-EF model relied on broad biomass and soil carbon estimates not matched to the specific lands converted in GTAP, and soil data in regions like North America and Australia were based on outdated sources. Forest carbon accounting was coarse, with limited treatment of understory, litter, deadwood, and forest age.

Parameter testing was also narrowed. Although early concept papers suggested a broad exploration of elasticities, CARB fixed land transformation elasticities at baseline values and only varied yield price elasticity, cropland productivity, and cropland-pasture responses. The analysis relied on a limited set of scenarios rather than a full uncertainty distribution, reducing insight into the sensitivity of iLUC outcomes to these parameters.

Finally, the reporting of results lacked complete regional resolution. The 2014 work could not fully distinguish between forest and pasture conversions by geography because the earlier 2009 results were not consistently documented. These omissions limited the transparency and comprehensiveness of the iLUC estimates, even as the analysis incorporated significant methodological advances.

3.4 GHG Emission Results

To quantify the GHG impacts associated with corn ethanol expansion, a series of GTAP model experiments were conducted following CARB’s established framework. These experiments were designed to estimate iLUC effects under varying production shock scenarios consistent with the methods used in CARB’s prior assessments.

CARB's ARB1409 GTAP model has a few built-in experiments, each with a complete set of inputs, parameter values, and shock size to model land use changes. The experiment labelled "Corn Ethanol with constraint and ETL11 different from ETL12" was loaded and solved using the solution method "Gragg 2-4-6 steps extrapolation" for multiple shocks. First, the default experiment and a pre-programmed corn ethanol shock of 11.59 BGY was solved and its results saved. Next, the same experiment but with modified shocks was solved one at a time while exporting each solution. The modified shocks include 2 BGY, 5.975 BGY, half of 11.59 BGY, and 15 BGY, for a total of 4 experiments and respective solutions.

To calculate the ILUC impacts for each experiment, the steps laid out in the CARB's 2014 ILUC assessment report were followed. For each experiment, the baseline land area for each relevant land use category, forestry, livestock, crops, pasturecrop, sugarcrop & oilpalm, was subtracted from the corresponding land area after the new equilibrium from exported solution files. The difference represented changes in the land use , measured in hectares, for each respective land use category due to the applied corn ethanol shock.

The calculated land use changes were then organized in the same structure as required by the AEZ-EF v52 model, which was the latest publicly available version of the AEZ-EF model, and was developed specifically for CARB's 2014 assessment for corn ethanol. The results of this run are shown in Figure 3.4. It should be noted that the current CCLUB model includes the AEZ-EF v54 model, but we intended to re-trace the steps followed by CARB during its 2014 assessment.

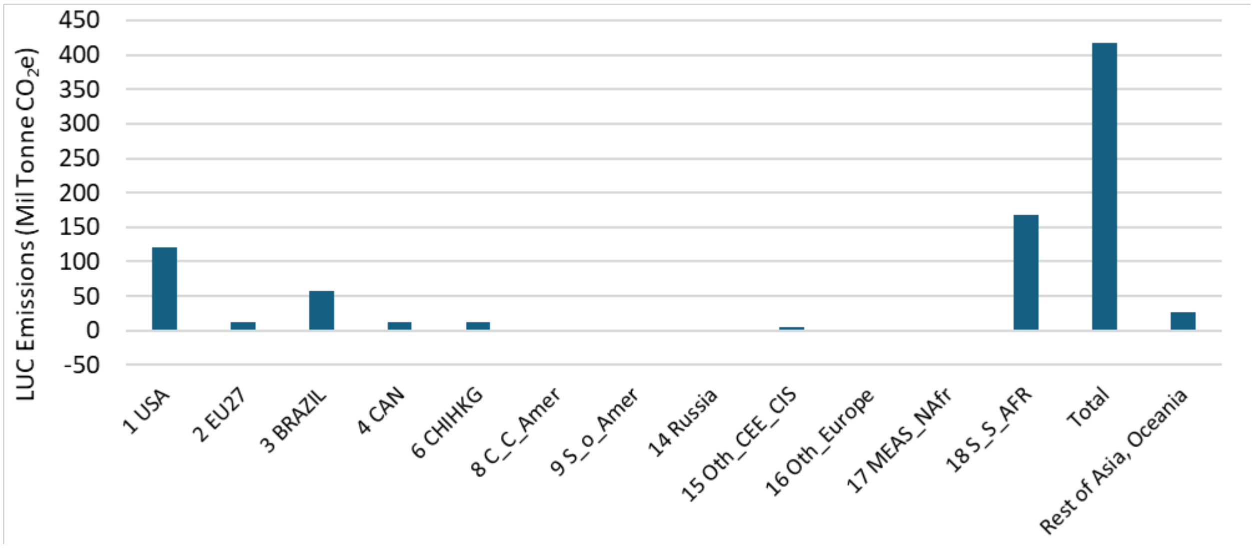

Figure 3.4. iLUC Emissions, ARB 2014 11.59 BGY

The structured land use changes were saved in the designated "GTAP_results" xls file, which was then plugged into the AEZ-EF v52 model to result in the calculation of the LUC emissions in CO_2e by AEZ. Due to the structure of the AEZ-EF v52, this study was not able to disaggregate the CO_2e emissions into land use categories, forest/pasture/cropland-pasture, similar to the GTAP experiments documented in CCLUB.

Figure 3.5 shows U.S. iLUC emissions from the 2011 GTAP analysis when paired with different carbon stock models, including DayCent, AEZ-EF, Century, Woods Hole, and Winrock. The results vary widely because each model uses different assumptions about soil and biomass carbon. Forest conversion dominates across all datasets, but emissions range from about 100 million metric tons of CO_2 under Winrock to nearly 200 million under Woods Hole. Grassland and cropland-pasture conversions are smaller, with some models such as Century even showing negative emissions due to soil carbon uptake assumptions.

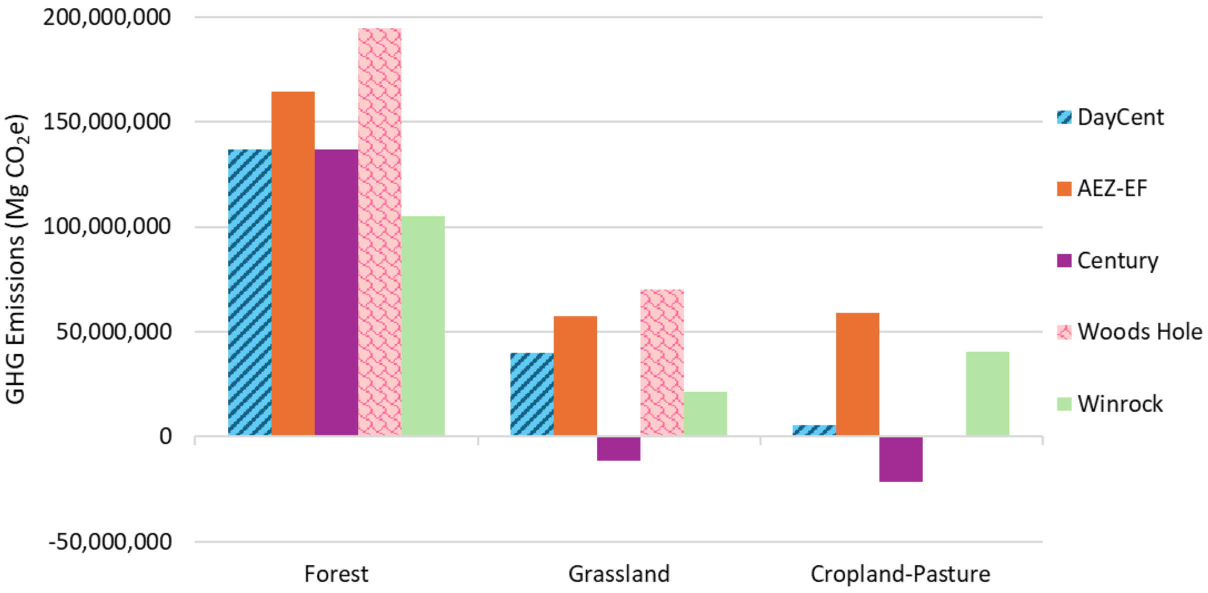

Figure 3.5. GTAP 2004 (2011) Domestic GHG Initial Shock

Differences also arise because each dataset classifies and maps land areas differently, so the same GTAP land transitions yield different emission totals. AEZ-EF assigns emission factors by agro-ecological zone, Woods Hole emphasizes higher forest carbon stocks, and Winrock uses more conservative values. These methodological differences explain why land areas and resulting emissions diverge across models, underscoring that forest carbon assumptions are the key driver of uncertainty in the 2011 U.S. iLUC results.

Figure 3.6 presents the international greenhouse gas emissions from the initial land use change shock in the 2011 GTAP analysis, broken out by carbon stock model. It highlights how global emissions estimates differ substantially depending on the dataset applied. Forest conversion again dominates the results, with Woods Hole showing the highest emissions close to 800 million metric tons of CO_2, while Winrock and AEZ-EF report considerably lower totals. Grassland and cropland-pasture conversions contribute smaller amounts, and in some cases, certain models even show near-zero or negative values due to soil carbon assumptions.

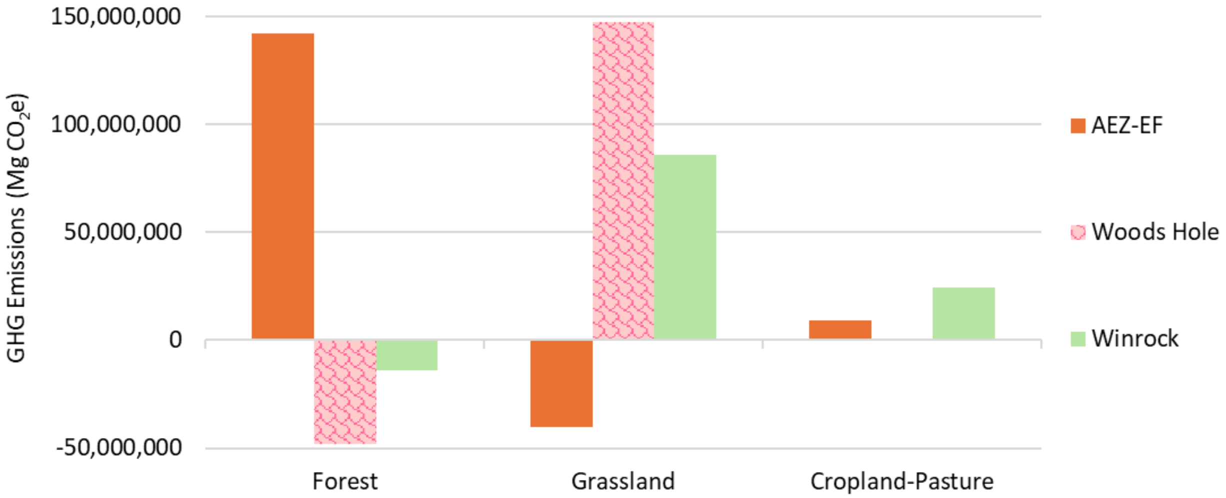

Figure 3.6. GTAP 2004 (2011 analysis) International GHG Initial Shock

The variation across models reflects differences in how they define land classes and characterize biomass and soil carbon stocks globally. Woods Hole assumes very high forest carbon densities, producing larger emissions when forests are converted, while Winrock applies more conservative values and AEZ-EF differentiates results by agro-ecological zones. Because GTAP provides only the land area transitions, the emissions outcomes depend heavily on which carbon stock dataset is used. This chart underscores that in international modeling, as in the U.S. case, forest carbon assumptions dominate the overall iLUC results and remain the largest source of uncertainty in emissions estimates.

This comparison reveals that the AEZ-EF carbon factors result in LUC emissions that are somewhat above the average of the factors examined here.

4. COMPARING CARB 2014 LUC TO OTHER MODELS

This section examines how CARB's 2014 iLUC analysis can be better understood when compared to other modeling approaches such as CCLUB. While CARB relied on GTAP-BIO with AEZ-EF factors, other models incorporate different methods for linking land use changes to carbon outcomes. Comparing these approaches highlights how differences in model design influence iLUC results and provides context for evaluating the robustness of CARB's estimates within the broader modeling landscape.

4.1 Key Model Inputs

CARB's 2014 iLUC framework, based on GTAP-BIO with AEZ-EF, differs from CCLUB most clearly when examining specific inputs. For graphical regions, GTAP aggregates the world into broad economic and agro-ecological zones to capture trade and land use shifts, while CCLUB refines these outputs by applying carbon accounting at finer regional scales, especially within North America. With respect to shocks, CARB's GTAP modeling imposed biofuel demand increases in billion-gallon increments, reallocating land globally to meet new crop requirements, whereas CCLUB does not generate shocks itself but instead takes the land area changes from GTAP as a starting point for emissions calculations.

The choice of land cover type also diverges between the two systems. GTAP categorizes land broadly as cropland, pasture, forestry, and cropland-pasture, with transitions occurring between these types. CCLUB uses the same land transitions but overlays them with more detailed land cover data to determine how soil and biomass carbon changes unfold. Carbon stocks highlight another contrast: AEZ-EF applies average values for biomass and soils by agro-ecological zone, while CCLUB incorporates dynamic soil organic carbon data, vegetation stocks, and management-specific adjustments such as no-till or cover cropping.

Elasticities are central to GTAP, where parameters like yield-price elasticity and land transformation elasticities govern how strongly markets respond to biofuel shocks. CARB's 2014 results were highly sensitive to these elasticity assumptions. CCLUB does not simulate market elasticities directly, but the emissions it calculates are strongly shaped by the elasticity-driven land use outputs it inherits from GTAP. Together, the comparison shows that CARB's 2014 approach, built on GTAP with AEZ-EF, relies on aggregated regions, broad land types, static carbon stock values, and highly influential elasticity settings, while CCLUB provides finer regional carbon accounting and management-specific detail to translate those economic shifts into more precise emissions estimates.

4.2 Biofuel Shocks

CARB's 2014 iLUC approach applied biofuel shocks directly within the GTAP-BIO framework, specifying demand increases for ethanol in terms of billion gallons per year and tracing the global reallocation of land required to satisfy that additional demand. These shocks were implemented as exogenous increases in biofuel consumption, which then drove higher crop prices, altered trade flows, and shifted land between forestry, pasture, cropland, and cropland-pasture. The magnitude of the shock and the elasticity parameters governing supply responses determined the scale and distribution of land use change. Once these land transitions were calculated, AEZ-EF applied average carbon stock factors to estimate emissions.

CCLUB does not generate or impose shocks itself but instead uses the land area transitions from GTAP runs as inputs. In this way, the biofuel shock is fully defined within GTAP, and CCLUB's role is to calculate the carbon consequences. The distinction is that CARB's 2014 framework coupled the shock definition and carbon outcome within a GTAP–AEZ-EF system, where the carbon response was directly tied to broad average stock values. CCLUB, by contrast, separates the economic shock mechanism from the carbon accounting. While it relies on the same GTAP shock design to quantify land conversions, it refines the emissions outputs by incorporating dynamic soil organic carbon responses, vegetation carbon stocks, and management effects.

The result is that CARB's 2014 method treated the biofuel shock as both the driver of land use change and the anchor for emissions calculations, but with limited resolution in carbon accounting. CCLUB, when paired with GTAP, uses the same shock-driven land reallocations but translates them into more nuanced emissions estimates. This separation provides greater transparency: GTAP defines how the shock alters land allocation, while CCLUB determines how those land changes translate into carbon fluxes, offering a more detailed assessment of iLUC than CARB's 2014 GTAP–AEZ-EF framework.

4.2.1 Requirements for Ethanol

California places specific technical requirements on ethanol blending in its reformulated gasoline program, commonly referred to as California Reformulated Gasoline (CaRFG). The fuel must comply with several interlocking standards, each tied to air quality, performance, and predictive modeling.

CaRFG is subject to California's predictive model, which requires refiners to demonstrate that their gasoline formulation meets emissions standards for pollutants such as NOx, hydrocarbons, and toxics. Ethanol, as an oxygenate, interacts with this model through its effects on combustion chemistry and evaporative emissions. California also maintains an octane requirement, which ethanol helps refiners achieve because of its high blending octane value. The baseline requirement for ethanol blending is effectively E10 in California. E15, which was recently approved for use in the state but is undergoing regulatory review, would increase ethanol demand in the state by 600 million gallons, if adopted as the baseline requirement (CARB, 2025).

From a modeling perspective, changes in ethanol blending can be represented as discrete policy shocks that alter both fuel composition and refinery optimization behavior. The first major shift, from 5.7 percent ethanol by volume to 10 percent, corresponds to the nationwide adoption of E10. Ethanol fulfills multiple roles in this system by satisfying the federal oxygenate requirement, contributing to octane supply, and enabling compliance with RFS2 mandates. Refiners have increasingly gravitated toward sub-octane blending strategies, producing lower-octane base gasoline that relies on ethanol's high blending octane to meet finished-grade specifications

(Hirshfeld, 2014). This practice reduces refinery costs and helps maintain compliance with constraints on T90 distillation temperature and benzene content, since ethanol replaces higher-aromatic components that contribute to toxics and emissions. A subsequent increase from E10 to E15 represents a second shock, requiring further refinery and distribution adjustments for fuel properties including Reid Vapor Pressure, distillation curves, and emissions profiles.

Taken together, the technical requirements for ethanol in California center on compliance with the predictive model, meeting minimum oxygen content rules during specific winter months in designated areas, and maintaining ethanol blending within the 0 to 10 percent volume range currently authorized under CaRFG3.

4.3 Elasticity Factors

Elasticity parameters in computable general equilibrium models are central to how induced land use change is estimated, particularly for U.S. corn ethanol. The two most influential are yield price elasticity, which measures how much yield per acre increases when crop prices rise, and land transformation elasticity, which governs how easily land can shift between cropland, pasture, and forest. These elasticities determine whether a demand shock from biofuel production is met through intensification on existing land or through expansion into new land. When yields are assumed to be more responsive to prices, more of the adjustment occurs through intensification, reducing the need for new cropland and lowering iLUC emissions. When yield responsiveness is assumed to be very low, the model pushes more of the adjustment onto land expansion, which increases iLUC emissions.

In the early years of iLUC modeling, yield price elasticities were highly uncertain. Early applications of GTAP-BIO for the 2009 California Low Carbon Fuel Standard used values ranging from 0.2 to 0.6, informed by limited econometric studies. Later regulatory updates tested much lower values, from 0.05 to 0.35, based on short-term econometric evidence. Researchers argued that such low values understated the role of technology adoption and management improvements that occur over multiple years. As the debate evolved, sensitivity analyses showed that lowering yield price elasticity values significantly increased iLUC estimates, while values closer to 0.25 yielded much lower results.

Yield price elasticity and land transformation elasticity remain the largest drivers of iLUC outcomes. A medium-term yield elasticity of about 0.25, with reasonable ranges between 0.175 and 0.325, reflects the capacity of farmers to respond to higher prices through intensification. Land transformation elasticity, which controls how land moves between uses, interacts with yield elasticity to shape iLUC estimates. As model calibration improved to reflect these medium-term dynamics, iLUC estimates for U.S. corn ethanol declined significantly. Early estimates, from 2010, that exceeded 80 grams of carbon dioxide equivalent per megajoule gave way to values updated in 2017 to 15 grams. This decline reflects the shift toward more realistic assumptions about how agricultural systems respond to price incentives.

The overall conclusion is that elasticity assumptions are the most important determinants of iLUC for corn ethanol. When yield responses are assumed to be minimal, iLUC scores rise sharply. When yield responses are calibrated to medium-term evidence, iLUC scores fall to much lower levels. Over the past decade, as empirical evidence and model calibration improved, U.S. corn ethanol's iLUC values have stabilized in the lower range. This trajectory shows that economic behavior, as represented by elasticity parameters, is the key to understanding and improving the accuracy of iLUC modeling.

4.4 Range of Land Conversion Emission Factors

Comparisons of emission factor datasets including AEZ-EF, TEM, Winrock, and Woods Hole, show wide variation in estimated greenhouse gas emissions from land use conversions such as forest-to-cropland and pasture-to-cropland as shown in Figure 4.1 (Taharipour, 2024). While all sources agree that forest conversion releases more carbon than pasture conversion, the magnitude of emissions differs substantially across regions due to variations in vegetation and soil characteristics. Even within a single region and land type, emission factors diverge sharply among datasets, reflecting differences in assumptions, system boundaries, carbon stock data, and ecosystem classifications. These disparities are especially large for pasture conversions, where factors can differ by threefold or more, with TEM often producing higher estimates in Brazil and Asia, and Woods Hole yielding higher values in China, India, Russia, and parts of Europe. Forest conversion estimates also vary significantly across models, though the spread is narrower than for pasture. This variability highlights the substantial uncertainty in land use emission factors and underscores the need for targeted research to reconcile datasets and improve confidence in indirect land use change assessments.

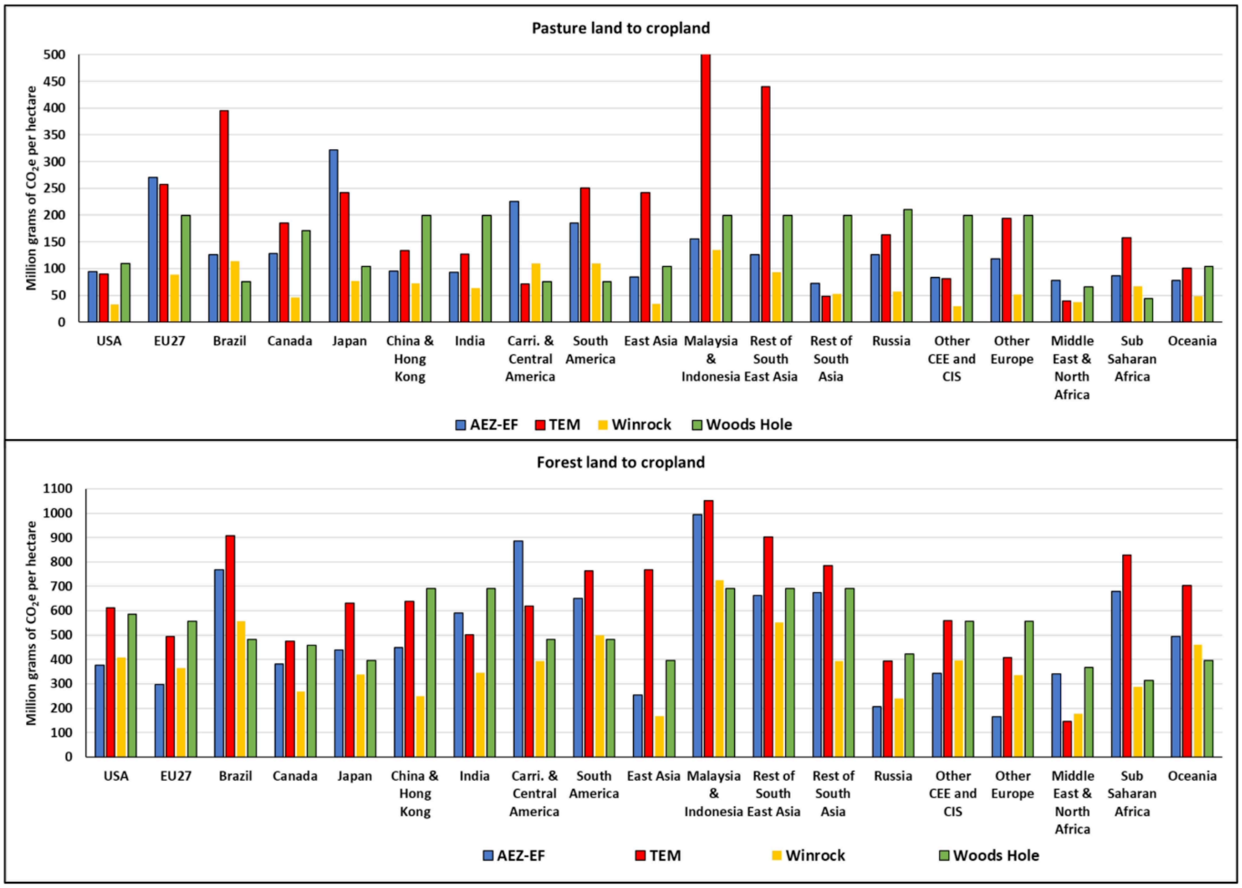

Figure 4.1. Emission factors for converting forest and pasture to cropland by region.

The EPA, in contrast, has historically relied on Winrock International carbon stock data to pair with land use shifts projected by its FASOM and FAPRI modeling framework for the RFS. Winrock provides empirically based carbon stock estimates for vegetation and soils across major global regions. EPA justified its choice by emphasizing consistency with U.S. national GHG inventory methods and the availability of peer-reviewed, regionally disaggregated data.

The CCLUB model, developed by Argonne National Laboratory, provides another key approach. Unlike AEZ-EF, which is global in scope, CCLUB focuses on U.S. land transitions and incorporates the Century soil carbon model to simulate changes in soil organic carbon over time. This allows for more detailed tracking of belowground carbon dynamics following land conversion, including gradual decomposition and regrowth processes. In practice, CCLUB is often used in conjunction with GTAP outputs: GTAP estimates the scale and location of land converted, while CCLUB translates those shifts into carbon fluxes using its regionally detailed stock and soil carbon accounting framework.

At a high level, CARB's approach emphasizes global consistency and scenario-based uncertainty analysis through AEZ-EF, while EPA has leaned on Winrock data for transparency and alignment with inventory methods. CCLUB adds further resolution to U.S. estimates by embedding process-based soil modeling through Century. Together, these tools highlight the central role of emission factors in bridging economic modeling with biophysical carbon accounting, a step that is often the largest source of variability in land use change emissions estimates.

AEZ-EF

The GTAP-BIO model simulates how biofuel expansion changes agricultural markets and land allocation across regions and AEZs. However, GTAP only produces land-area shifts, not carbon emissions. To translate those results into greenhouse gas impacts, CARB couples GTAP outputs with the AEZ-EF model. AEZ-EF assigns carbon fluxes to each hectare of land conversion based on region- and AEZ-specific factors for above-ground biomass, below-ground carbon, soil organic carbon, foregone sequestration, and in some cases clearing by fire. The result is a set of emissions profiles that are averaged over a 30-year accounting period and normalized by fuel energy, producing compliance-grade iLUC values expressed in gCO_2e/MJ under the LCFS. CARB justifies AEZ-EF on its alignment with GTAP's AEZ structure, its reliance on IPCC-based carbon stock data, and its ability to capture uncertainty by running multiple parameter scenarios. Table 4.1 describes the various conversion processes in AEZ-EF and impacts.

Table 4.1. AEZ-EF Emissions from Land Conversion.

Conversion	Description	Values	Impact on AEZ-EF
Forest → Cropland	Large above- and below-ground biomass, litter, deadwood	Stock values vary by AEZ; forest AGLB up to >200 Mg C/ha; SOC losses significant	One of the largest emission sources in AEZ-EF; drives high ILUC values when GTAP predicts forest conversion.
Forest → Pasture	Similar to forest→cropland but with lower soil disturbance	Forest stock values with partial soil release	Substantial emissions, though somewhat lower than cropland conversion because tillage is absent
Pasture → Cropland	Loss of grass biomass and soil carbon	IPCC default SOC loss factors applied; ~25–50% SOC depletion	Significant in regions with high SOC pasture, sensitive to soil assumptions
Pasture → Forest	Sequestration via afforestation	Forest growth rates (Mg C/ha/yr) applied	Negative emissions (sequestration), but rarely modeled as induced by biofuel shocks
Cropland → Forest/Pasture	Abandonment → regrowth sequestration	Growth rates by AEZ for secondary forest or grass	Provides a sink term; offsets some gross emissions.
Cropland-Pasture ↔ Cropland	Intermediate carbon density; treated as 50% of pasture conversion	EF ratio = 0.5 (pasture→cropland)	Highly uncertain but influential for U.S./Brazil; major sensitivity driver for corn ethanol and soy biodiesel.
Peatland conversion	Draining peat releases large, sustained CO_2	Default EF ≈ 95 Mg CO_2/ha/yr; factor 33% applied to oil palm peat	Extremely high emissions dominate palm biodiesel ILUC; uncertainty treatment is critical
Soil carbon changes	SOC depletion upon conversion	Stock change factors by AEZ (Table 21/22)	Major uncertainty driver, especially for pasture→cropland

CCLUB performs a similar translation for U.S. land-use changes but with more detailed carbon accounting. It can take GTAP-BIO land-area changes and apply its own, more spatially explicit stock factors and soil carbon modeling, via Century, to simulate time-dependent emissions from forest-to-cropland, pasture-to-cropland, or cropland-pasture transitions. This provides a more refined view of soil carbon loss and regrowth in U.S. contexts. While AEZ-EF is the foundation of CARB's iLUC values, EPA under the RFS has relied on Winrock datasets instead of AEZ-EF to apply carbon factors to land conversion estimates from FASOM and FAPRI. Thus, under the LCFS, iLUC factors such as 19.8 gCO_2e/MJ for corn ethanol (2015 values) derive directly from GTAP outputs combined with AEZ-EF carbon accounting, while under the RFS, EPA reports results in kg CO_2e/MMBtu using Winrock-based factors. The difference in emission factor frameworks explains much of the divergence between CARB's and EPA's published iLUC values, with AEZ-EF introducing region/AEZ specificity and scenario analysis, and Winrock emphasizing transparency and inventory consistency.

IPCC Factors

In addition to specialized tools like AEZ-EF and CCLUB, many regulatory agencies and modelers rely on IPCC emission factors as a baseline for assigning carbon releases to land use transitions. The Intergovernmental Panel on Climate Change (IPCC) guidelines provide globally recognized default values for carbon stocks in above-ground biomass, below-ground biomass, litter, deadwood, and soil organic carbon across broad land categories. These defaults were designed for use in national GHG inventories but have been widely adopted in LUC modeling where region- or country-specific data are lacking. Their appeal lies in transparency and consistency: every country submitting an inventory under the UNFCCC references the same framework, allowing regulatory agencies to justify the use of internationally accepted data.

In GTAP-based applications such as CARB’s LCFS, IPCC Tier 1 factors serve as a foundation for some of the carbon stock values used in AEZ-EF. While AEZ-EF introduces regional detail through agro-ecological zones, its emission factors are benchmarked against or supplemented by IPCC defaults where local data are sparse. In the U.S. RFS framework, EPA has historically drawn on Winrock data for vegetation and soil carbon, but those data are also cross-referenced against IPCC Tier 1 guidelines to ensure alignment with national GHG inventory practices. For CCLUB, which models U.S. land conversions with greater soil specificity, IPCC defaults are less central than Century-based soil simulations, but they remain an important reference for above-ground biomass pools and for validating regional carbon stock assumptions.

Ultimately, the role of IPCC emission factors in LUC modeling is to provide a transparent, standardized benchmark that complements more detailed region-specific datasets. CARB justifies their inclusion as a way to ensure methodological credibility under the LCFS, while EPA relies on them for consistency with inventory reporting under the RFS. The result is that, whether directly applied or used as a reference point, IPCC values underpin much of the emission factor structure that translates modeled land conversions from GTAP or CCLUB into compliance-grade iLUC carbon intensity values.

4.4.2 Improved Agriculture

Climate-smart agricultural practices such as no-till or reduced tillage, cover cropping, and manure application have the potential to materially alter the iLUC values assigned to corn ethanol under the LCFS, but these practices are not currently incorporated into the program’s modeling framework. In the LCFS system, iLUC is estimated using GTAP-BIO to simulate land use responses and the AEZ-EF model to assign carbon stock changes. These models assume average management practices across large regions and do not differentiate between conventional and conservation-oriented farming. As a result, the additional soil carbon storage and emission reductions achieved through improved practices are not captured in the regulatory values, leading to a more generalized and potentially conservative estimate of iLUC.

Technically, adoption of climate-smart practices would shift both the carbon accounting and the economic parameters underlying iLUC. On the carbon side, no-till and cover crops increase soil organic carbon, reduce decomposition rates, and enhance belowground biomass inputs, while manure provides additional organic matter and reduces synthetic fertilizer use. These effects raise the carbon carrying capacity of cropland and reduce the emissions intensity of converting land into corn production. On the economic side, practices that stabilize or enhance yields under stress effectively increase the yield response to prices, which in GTAP terms raises the yield-price elasticity. A higher elasticity channels more of the adjustment to increased biofuel demand into yield gains rather than land expansion, thereby reducing the modeled scale of land conversion.

In contrast to CARB's approach, the CCLUB model incorporates pathways to account for management practices such as no-till, reduced tillage, and cover cropping. By integrating soil carbon dynamics and management-specific sequestration rates, CCLUB can differentiate the emissions impacts of conventional versus conservation-oriented farming on converted and existing cropland. This allows for a more nuanced estimate of iLUC emissions that reflects the real-world variability in agricultural systems. Incorporating these practices into LCFS iLUC modeling would lower the carbon intensity penalty currently assigned to corn ethanol by reducing both the area of land that must be converted and the emissions per hectare of converted land. Since CARB's framework does not yet include these management-specific parameters, current LCFS values likely overstate corn ethanol iLUC emissions relative to CCLUB outputs that recognize the benefits of conservation practices.

4.5 Land Transformation

Land transformation in iLUC modeling refers to how land shifts between categories such as cropland, pasture, and forestry in response to biofuel demand, governed by transformation elasticities that set how easily one land type can convert to another. In CARB's 2014 framework, GTAP-BIO determines these transitions using fixed elasticity parameters, with cropland-pasture modeled as the most responsive category. CCLUB does not simulate land transformation directly but takes GTAP's land use outputs and applies detailed carbon accounting to those transitions. The key difference is that CARB's approach emphasizes economic rules of land reallocation, while CCLUB emphasizes the emissions consequences of those reallocations.

Figure 4.2 shows global land use change per billion gallons of ethanol across several GTAP vintages, including GTAP 2004 (2011 and 2013 runs), CARB 2014 scenarios with shocks from 2 to 15 BGY, and GTAP 2017. Life Cycle Associates configured the GTAP model to replicate CARB's 2014 corn ethanol shock as well as a range of demand shocks to test sensitivity. Shocks of 11.59-15 BGY push models to extremes, and GTAP has adopted what appears to be a modular approach with a smaller shock for which the results can be scaled up or down to fit the policy being assessed.

The baseline run applied an 11.59 BGY corn ethanol expansion, replicating CARB's reference case, and subsequent runs used smaller and larger shocks, 2 BGY, 5.975 BGY, half of 11.59 BGY, and 15 BGY, to evaluate how total and category-specific land use responses scaled with ethanol demand.

For each run, the model produced new equilibrium land-area outputs for cropland-minus-cropland-pasture, cropland-pasture, grassland, and forestry, which were compared to the baseline to calculate net changes in hectares per BGY.

Results are broken into forestry, pasture, cropland minus cropland-pasture, and cropland-pasture and normalized to billion gallons per year (BPY). In every case, cropland-pasture contracts sharply, serving as the main land source converted into active cropland, while cropland minus cropland-pasture expands to meet rising ethanol feedstock demand. Forestry and pasture remain relatively stable, with only minor adjustments across scenarios. Actual hectare predictions are shown in Section 4.5.1.

The resulting values were normalized by shock size and plotted to illustrate the relative distribution of land-use change across categories for both corn and sorghum. Because these experiments were primarily diagnostic, the intent was to assess the model's internal consistency and response sensitivity. The applicable LCFS-related ethanol change for California, from E10 to E15, is about 600 million gallons per year.

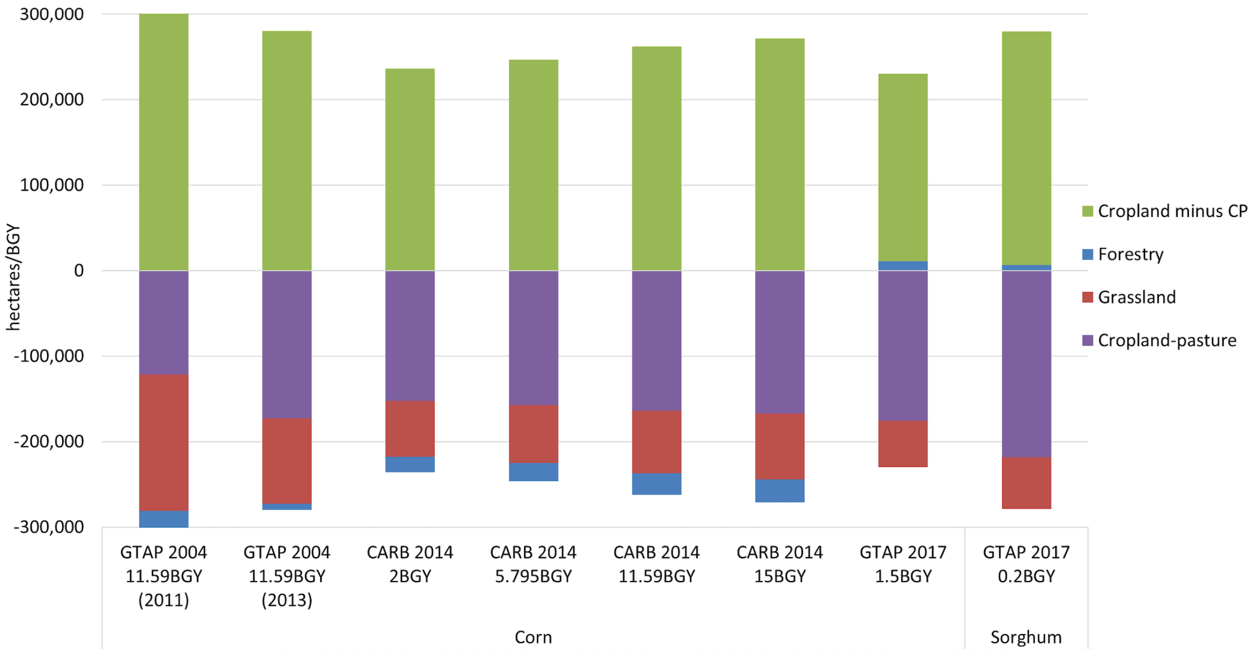

Figure 4.2. Global Land Use Change for Corn And Sorghum Ethanol Across GTAP Models

For sorghum under the 2017 GTAP model, as shown in Figure 4.10, a similar pattern emerges globally, with cropland-pasture contracting as the primary land source and cropland minus cropland-pasture expanding in the United States, Brazil, and Russia, while other regions show comparatively smaller shifts and only limited changes in grassland and forestry.

These patterns reflect the role of land transformation elasticities in GTAP. The Constant Elasticity of Transformation function governs how easily land shifts between uses, with low values limiting forest and pasture conversions and higher values making cropland-pasture the most responsive category. The consistency across GTAP versions, including CARB's 2014 runs and GTAP 2017, underscores how strongly results depend on these elasticity assumptions, which determine which land categories absorb the shock of increased biofuel demand.

4.5.1 Land Transformation Modeling Details

To evaluate claims about the conversion of pastureland to cropland and its associated carbon impacts, it is important to examine actual land transitions recorded in the National Resources Inventory (NRI). Figure 4.3 illustrates the exchanges into and out of the NRI pastureland category across multiple time periods, highlighting the managed and rotational nature of this land type rather than its characterization as natural land (UIC, 2022).

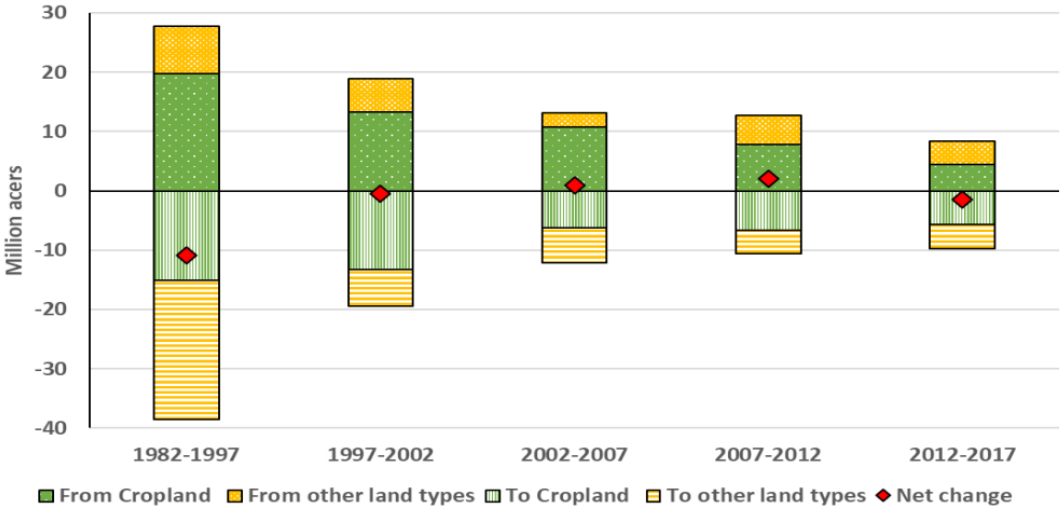

Figure 4.3. Land transitions to and from pasture land from 1982 to 2017.

The data show that between 1982 and 1997, 28 million acres transitioned into pastureland, mostly from cropland, while 38.6 million acres left pastureland for cropland, CRP land, rangeland, forest, or other land uses. In the subsequent five-year period (1997–2002), approximately 19 million acres entered and exited the pastureland category, again primarily involving cropland. This cyclical pattern continued in the three following periods (2002–2007, 2007–2012, 2012–2017), with about 10 million acres shifting in and out of pastureland during each interval.

The cyclical exchange of cropland and pasture observed in the NRI is also evident in modeled outcomes for forest land under GTAP scenarios. The chart displays forest area change per billion gallons of ethanol across multiple biofuel shocks, ranging from 2 to 15 BGY, disaggregated by world region. Most regions show relatively modest decreases in forest area, often under 5,000 hectares per BGY, but larger declines are concentrated in Rest of Asia/Oceania and Sub-Saharan Africa, which together drive the bulk of global forest loss.

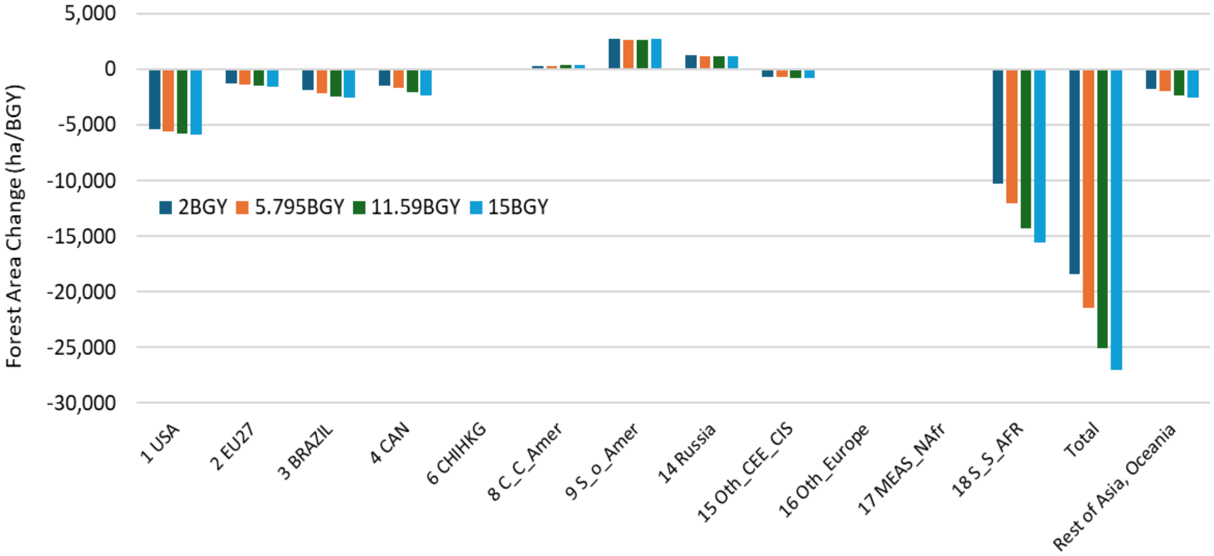

Figure 4.4. Forest Area Change By Region Based on Different Shock Sizes

The chart highlights the scale of forest conversion increases incrementally with larger biofuel shocks, yet the overall spatial distribution remains consistent across scenarios. This pattern reflects GTAP's treatment of land transformation elasticities, where forests are generally less responsive to demand shifts than cropland-pasture but still serve as a marginal source of land in specific regions. The results emphasize that while U.S. and European forestland remain relatively stable, international regions with higher transformation parameters or weaker land protections absorb more of the modeled forest conversion associated with ethanol expansion.

The interaction between forest dynamics and cropland expansion is made clearer when looking at the aggregate land category shifts across GTAP vintages and CARB scenarios. Figure 4.5 shows net land use change in hectares under ethanol shocks, broken out by cropland-pasture, cropland minus cropland-pasture, pasture, and forestry. In the CARB 2014 runs, cropland-pasture consistently contracts by over one million hectares at higher shock levels, while cropland minus cropland-pasture expands by a nearly equivalent amount, reflecting the conversion of idle or low-intensity land into active crop production. Pasture and forestry change only slightly, with relatively small contributions to overall land reallocation.

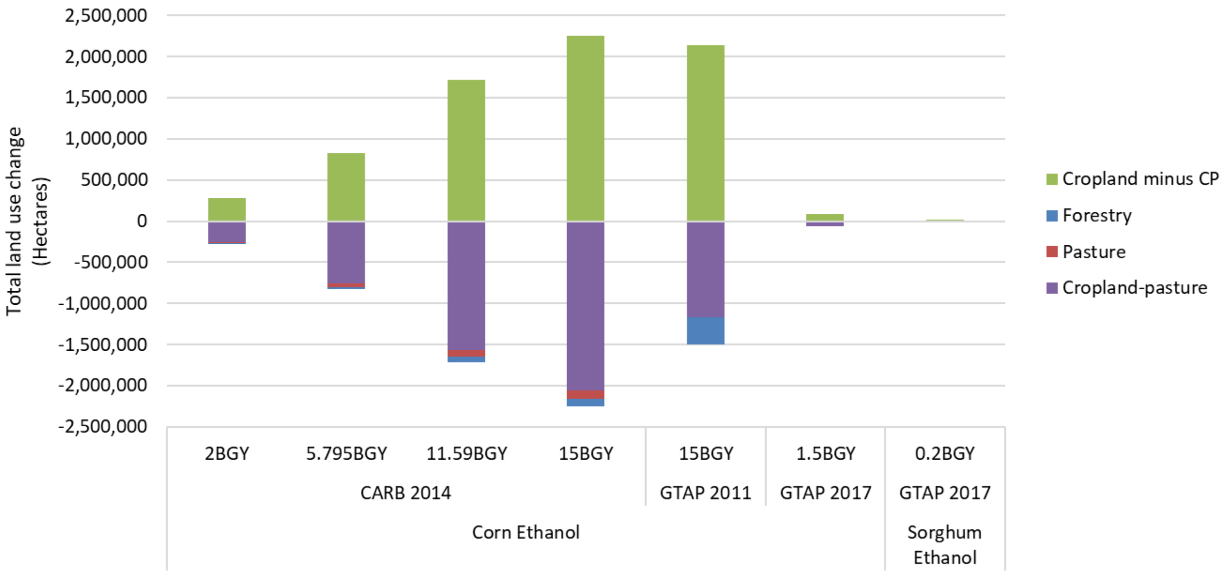

Figure 4.5. U.S. Corn and Sorghum Ethanol Total Land Use Change

The GTAP 2011 15BGY case shows the same general pattern but with greater forestry participation, indicating that higher elasticities in this vintage allowed a portion of cropland demand to be met from modeled forest conversion. By GTAP 2017, the magnitude of shifts per unit of ethanol is smaller, and cropland-pasture remains the dominant source of new cropland, reinforcing its role as the most elastic land category in the model. Together, these results demonstrate that land transformation elasticities channel most of the biofuel-induced adjustment through cropland-pasture, with forests and pasture playing a secondary role depending on parameterization. This technical structure explains why cropland-pasture serves as the balancing category across scenarios, while forestry impacts are limited and region-specific.

The final column of the chart shows land use change for sorghum ethanol under GTAP 2017, modeled at a 0.2 BGY shock. The results indicate near-zero land reallocation across all categories, cropland-pasture, cropland minus cropland-pasture, pasture, and forestry, suggesting that the impact of sorghum ethanol expansion is minimal compared to the much larger shocks applied to corn ethanol. Unlike the corn ethanol cases, which show millions of hectares of cropland-pasture conversion offset by cropland expansion, the sorghum scenario produces negligible changes in global land allocation.

The key reason for this discrepancy lies in both the scale of the shock and the structural assumptions in GTAP 2017. The corn ethanol cases are modeled at shock levels ranging from 1.5 to 15 BGY, while sorghum ethanol is modeled at only 0.2 BGY. Since GTAP operates as a comparative static equilibrium model, the magnitude of the exogenous demand shock is directly proportional to the scale of land use responses. A 0.2 BGY shock is an order of magnitude smaller than the corn ethanol shocks and therefore generates proportionally smaller changes in land reallocation.

Model documentation for GTAP-BIO 2017 further explains that sorghum is treated as a smaller, regionally concentrated crop with limited displacement effects in global feed and fuel markets. The crop substitution elasticities are lower relative to corn, and the trade flows are less significant. This means that incremental sorghum demand for ethanol can be absorbed largely within existing production systems, with minimal pressure on cropland expansion or conversion of pasture and forestry. By contrast, corn is a more widely globally traded, high-volume commodity with stronger linkages to animal feed and biofuel markets, so ethanol shocks generate broad land market responses.

In technical terms, the difference between corn and sorghum reflects a combination of shock size, substitution elasticities, and baseline market shares embedded in GTAP 2017. Corn shocks at the scale of 1.5–15 BGY drive large reallocations from cropland-pasture into active cropland, while the small sorghum shock at 0.2 BGY interacts with weaker elasticities and smaller global market shares to produce near-zero modeled land use change. This highlights both the proportionality of GTAP's equilibrium structure to shock size and the importance of crop-specific market linkages in determining iLUC outcomes. This raises important questions about how much additional corn ethanol volume is attributable to the policy being modeled, as opposed to other factors such as octane enhancement.

Regional detail reinforces this point, as the chart compares forest area change across GTAP 2004 (2011 and 2013 implementations) and GTAP 2017, as shown in Figure 4.6. While most regions exhibit only minor shifts, large forest losses appear in the United States and Sub-Saharan Africa under earlier GTAP versions, whereas GTAP 2017 shows smaller declines and in some cases gains, particularly in Europe and parts of Asia. The differences highlight how updates to land transformation elasticities and regional parameterization have progressively constrained forest participation in meeting biofuel demand, further concentrating the adjustment on cropland-pasture and reducing the modeled contribution of forests to iLUC.

With the evolution of the GTAP model over the years, the modeled land use changes for a corn ethanol shock have also evolved significantly. The following chart in Figure 4.6, shows the land use changes in hectares per 1 billion gallons per year of corn ethanol shock, categorized by land use type, for various versions of the GTAP model over the years. The land cover predictions vary largely due to modifications to the CET function discussed in Section 2.2.4.

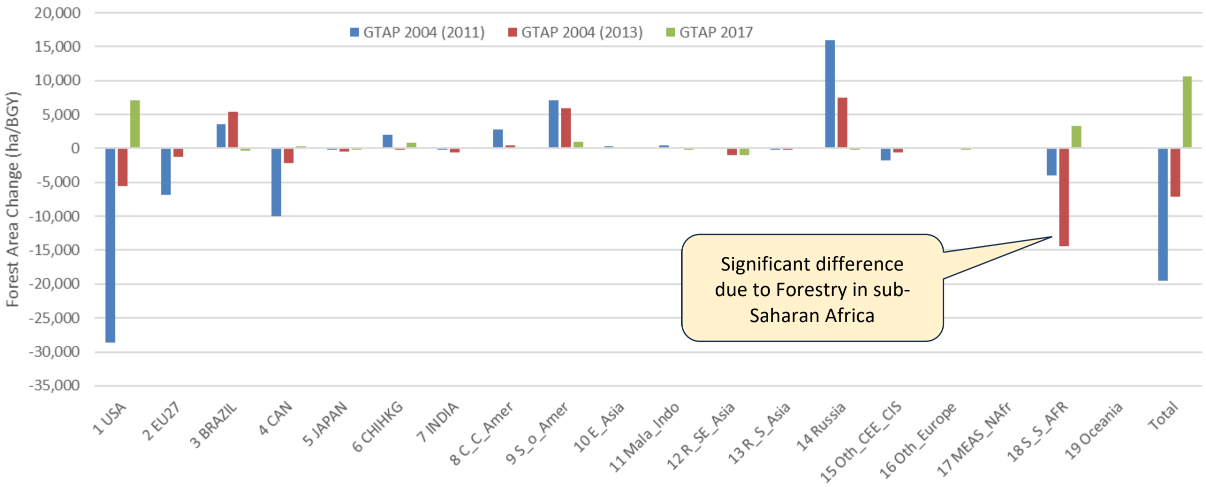

Figure 4.6. Global Forest Area Change for Corn Ethanol

The GTAP 2004 model run from 2011, using AEZ-EF model as implemented in the current CCLUB, shows the largest land use reduction for pastures, followed by cropland-pasture and then forests. All such land use changes combined together result in a net ILUC value of about 14.76 gCO2e/MJ. Despite the smallest share of land use changes for forests, land use change emissions from forests conversion constitute about 75% of the total ILUC value.

In 2013, following some adjustments to the GTAP 2014 model, corn ethanol shock resulted in a smaller pasture conversion, larger cropland-pasture conversion and a much smaller forest conversion. The ILUC emissions also show corresponding changes, resulting in a smaller ILUC of about 10.24 g/MJ. The forest conversion emissions reduced by about 40%, representing the largest change in the net ILUC value.

CARB's September 2014 ILUC assessment utilized the GTAP 2009 model with numerous customizations which has been published by CARB as "ARB1409". We re-ran the ARB1409 GTAP model with multiple ethanol shock sizes to explore the effect of the shock size on the modeled land use changes. By calculating the land use changes per BGY and comparing the same for increasing total shock sizes, we observed slightly more than linear land use change effect per BGY of shock. In other words, a higher total corn ethanol shock led to a higher land use change per BGY, implying that for a higher total ethanol demand shock, even more land conversion per gallon ethanol was needed.

Finally, the latest available GTAP model, GTAP 2017, was reviewed for land use change per BGY. In contrast with all the previous GTAP models, the GTAP 2017 model showed a net increase in forest area, with an even increased reduction in cropland-pasture. This directional reversal in the forest area change dramatically drops the emissions from forest land, about 88% reduction compared to the 2013 run of the GTAP 2004 model, or about 93% compared to the 2011 run of the GTAP 2004 model.

The forest area change moving from -19k ha (per BGY) in GTAP 2004 to +10k ha (per BGY) in GTAP 2017 is the largest driver of the change in ILUC reducing from 14.76 to 4.32 g/MJ.

The GTAP 2017 model results show a larger cropland-pasture area being converted due to biofuel shock compared to GTAP 2004. However, the corresponding increase in ILUC emissions is more than offset by the increase in forest area and its corresponding emissions being much lower than the GTAP 2004 model. The overall effect is a net reduction in the ILUC as estimated using GTAP 2017 compared to the ILUC estimated using GTAP 2004.

Figure 4.7 presents the breakdown of the land use change emissions in Mg C/BGY of corn ethanol for GTAP 2004 (2011 run), GTAP 2014 (2013 run) and the GTAP 2017 model (corn and sorghum), as documented in the current CCLUB model using the AEZ-EF emissions model.

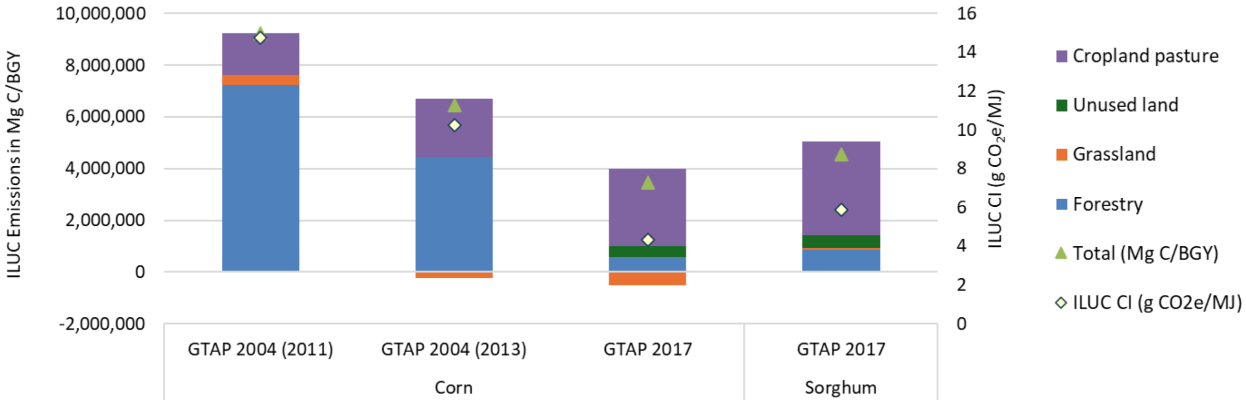

Figure 4.7. Land Use Change Emissions of Ethanol Across GTAP Models

For corn under GTAP 2004 (2011), forestry dominates the emissions profile, contributing the majority of nearly 9 million Mg C/BGY, with additional contributions from cropland-pasture and smaller inputs from grassland and unused land. The associated iLUC CI is approximately 13–14 g CO_2e/MJ. By GTAP 2004 (2013), emissions fall to about 6–7 million Mg C/BGY, with forestry reduced and cropland-pasture emerging as a larger contributor. The carbon intensity also declines, to 10 g CO_2e/MJ. Under GTAP 2017, emissions fall further, to roughly 2–3 million Mg C/BGY, with cropland-pasture dominating and forestry contributing less. The CI drops to around 4–5 g CO_2e/MJ, showing the effect of model updates that shift the burden of land conversion toward cropland-pasture and away from forests.

For sorghum under GTAP 2017, the emissions profile resembles that of corn in the same vintage, with cropland-pasture as the primary contributor and smaller roles for forestry, grassland, and unused land. Total emissions are slightly higher than corn in the 2017 run, producing a CI near 6 g CO_2e/MJ. The comparison across crops and vintages highlights how assumptions about land category responsiveness, carbon stock assignments, and model improvements drive substantial changes in iLUC outcomes, with later GTAP versions yielding lower iLUC intensities as land transformation elasticities and carbon accounting methodologies are updated.

Figure 4.8 illustrates the modeled shifts in land cover globally in response to a corn ethanol demand shock. It shows that cropland pasture contracts sharply, serving as the dominant land source, while pastureland and forest experience smaller reductions. At the same time, active cropland expands modestly to accommodate the additional corn demand. The balance of these land reallocations highlights the GTAP 2017 model's structural change from earlier vintages where forest loss was a larger driver toward a dynamic in which cropland pasture is the primary margin of adjustment for meeting biofuel expansion.

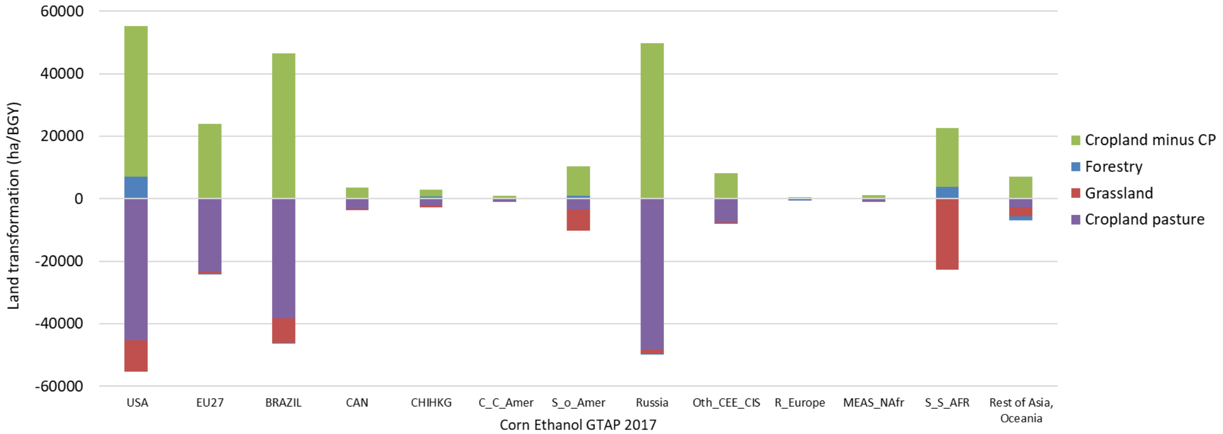

Figure 4.8. Global Land Use Change for 2017 GTAP Model for Corn

Figure 4.9 extends this comparison by showing the regional land use reallocations that underpin the corn ethanol results for GTAP 2017. In terms of total LUC (not per billion gallons per year), the United States dominates the global adjustment, with more than two million hectares of cropland minus cropland-pasture added, offset by a contraction of cropland-pasture exceeding two million hectares. This confirms that cropland-pasture remains the primary land source converted into active production to meet corn ethanol demand. Smaller reductions in U.S. grassland and forestry are also observed but contribute far less to the overall balance.

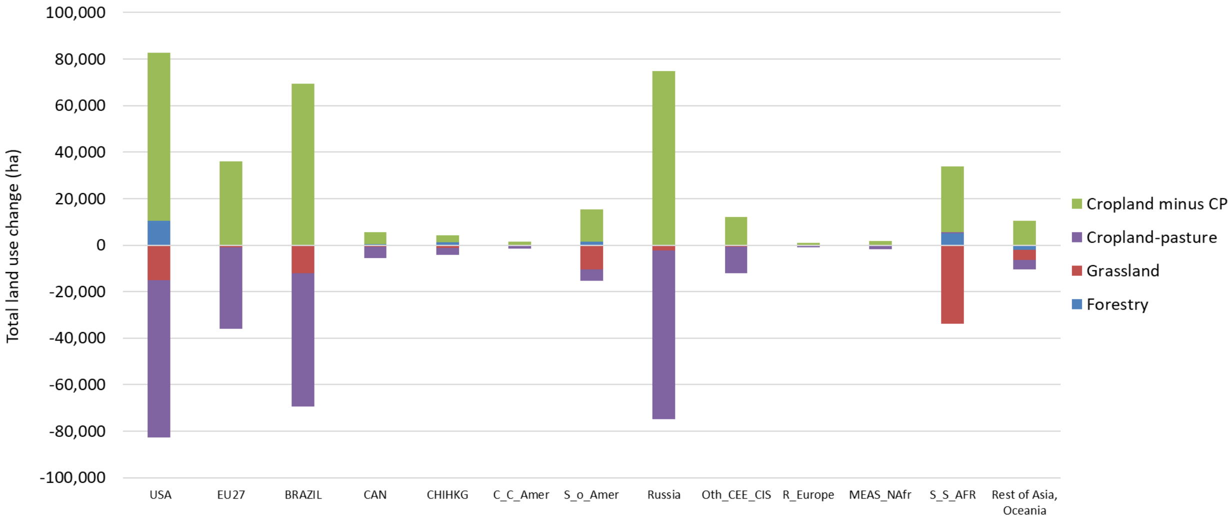

Figure 4.9. Corn Ethanol Land use Conversion for GTAP 2017

Outside the United States, the scale of land conversion is modest but broadly consistent across regions. The EU27, Brazil, and Canada all show moderate expansions of cropland minus cropland-pasture, matched by contractions in cropland-pasture and grassland. Other regions, including Central and South America, Russia, Sub-Saharan Africa, and Rest of Asia/Oceania, display relatively small reallocations, with cropland increases largely balanced by reductions in grassland and cropland-pasture. Taken together, the results illustrate that under GTAP 2017, corn ethanol-driven land conversion is concentrated in the United States, where cropland-pasture provides the dominant adjustment pathway, while contributions from international regions are comparatively minor and distributed across multiple land types.

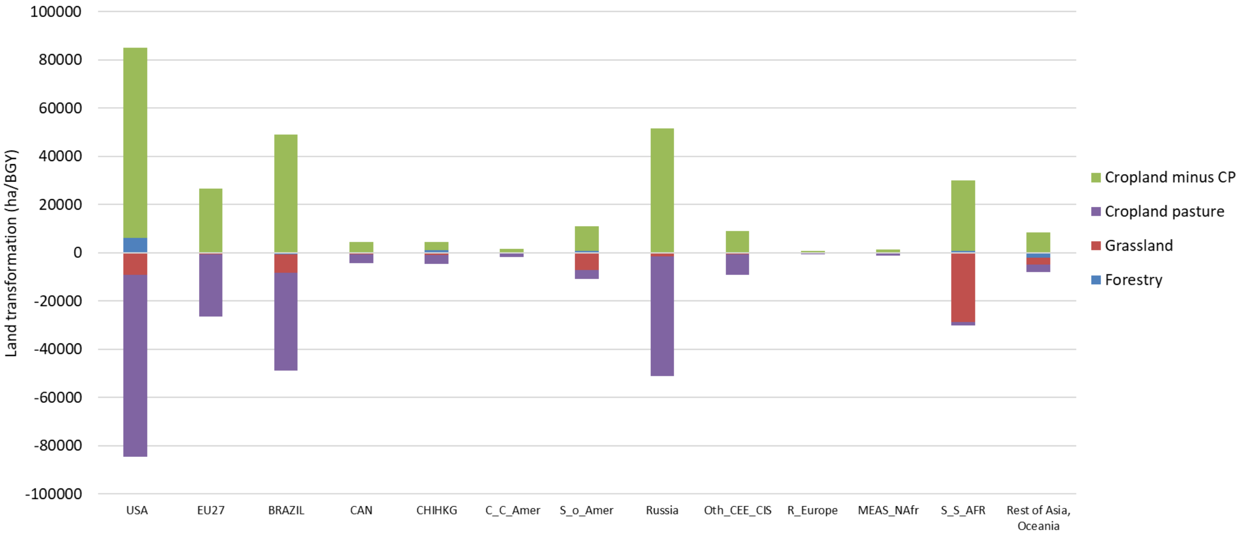

Figure 4.10. Global Land Use Change for 2017 GTAP Model for Sorghum

Figure 4.11 shows the land use reallocations associated with sorghum ethanol under GTAP 2017, highlighting both similarities and distinctions relative to corn. In the United States, cropland minus cropland-pasture expands by roughly 15,000 hectares, while cropland-pasture contracts by nearly 20,000 hectares, confirming that cropland-pasture remains the principal land source converted into active production. Smaller reductions occur in U.S. grassland and forestry, but these play only a minor role in the overall balance.

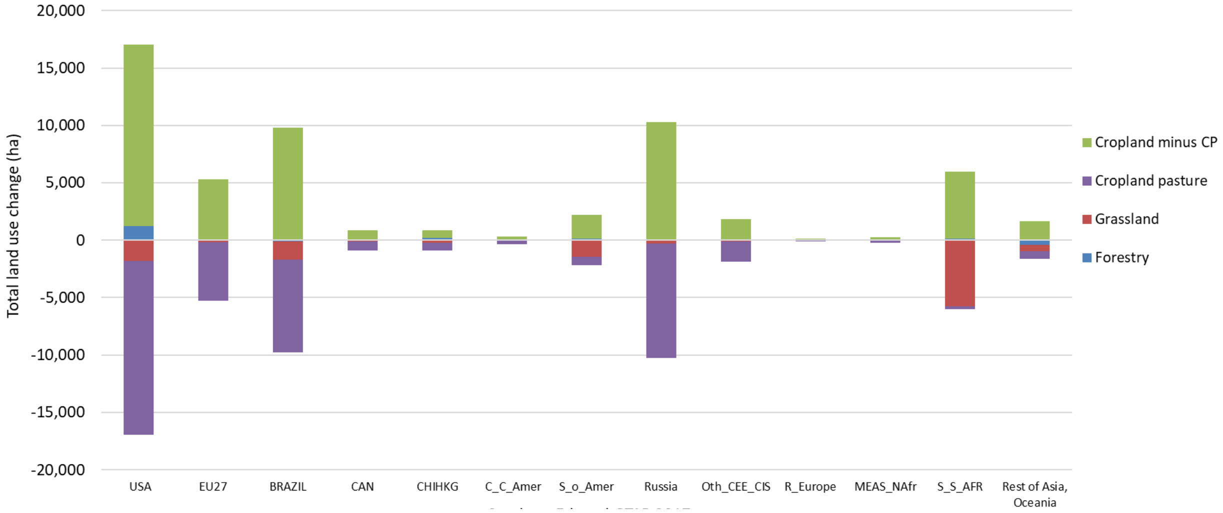

Figure 4.11. Sorghum Ethanol Land use Conversion for GTAP 2017

Internationally, patterns are modest but regionally differentiated. The EU27 and Brazil both exhibit increases in cropland minus cropland-pasture offset by reductions in cropland-pasture and grassland, similar to the corn case but with slightly larger magnitudes. Russia shows a notable expansion of cropland minus cropland-pasture paired with a significant contraction of cropland-pasture, while Sub-Saharan Africa is distinguished by a relatively larger grassland loss. Other regions, including Canada, Central and South America, and Rest of Asia/Oceania, display smaller and more balanced shifts. Collectively, the results indicate that sorghum ethanol land conversion follows the same structural dynamics as corn ethanol, with cropland-pasture serving as the key adjustment mechanism, but regional contributions, particularly from Brazil and Russia, are somewhat more pronounced.

4.6 Range of GHG Emission Results

The 2017 GTAP model provides LUC emissions prediction in the same format as those presented in Section 3. Key differences include a lower rate of forest conversion in sub-Saharan Africa and greater conversion of cropland pasture to cropland in Brazil. This feature is a key parameter that has been debated over the years in CARB workshops. The expansion of cropland into existing pastures in Brazil is a primary response to the demand for crops. Increased cattle stocking rates or pasture intensification allow for the conversion of these lands to crop production.

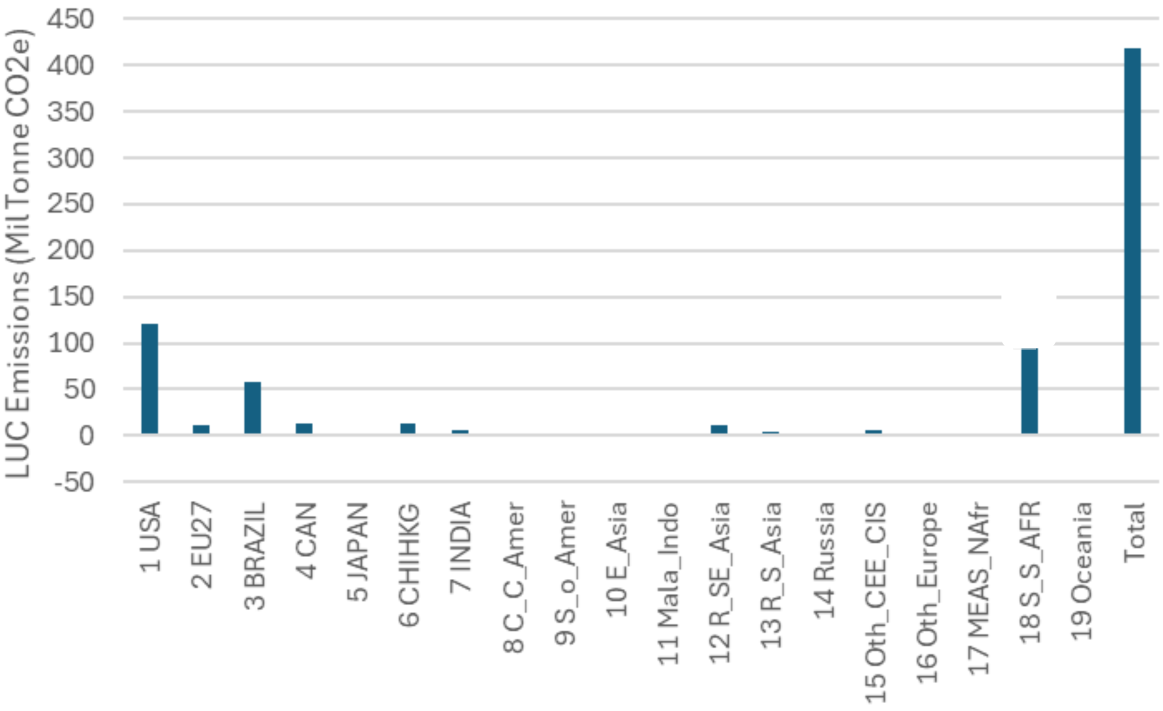

Figure 4.12. Corn Ethanol GTAP 2017, AEZ-EF54, 1.5 BG shock

4.7 Results Comparison

Greenhouse gas emissions from land use change can vary widely depending on the carbon stock dataset used, even when paired with the same GTAP 2017 modeling framework. Comparing domestic U.S. outcomes with international results reveals important differences in both magnitude and direction of emissions, particularly for forest, grassland, and cropland-pasture conversions. By evaluating results across DayCent, AEZ-EF, Century, Woods Hole, and Winrock, the analysis highlights how assumptions about land categories and carbon pools drive divergent iLUC estimates and underscores the greater scale of impacts observed in global contexts relative to domestic land transitions.

Figure 4.13 shows greenhouse gas emissions associated with U.S. land conversions under the 2017 GTAP analysis when paired with different carbon stock datasets and models: DayCent, AEZ-EF, Century, Woods Hole, and Winrock. The results are expressed as positive or negative emissions depending on whether land conversion releases or sequesters carbon.

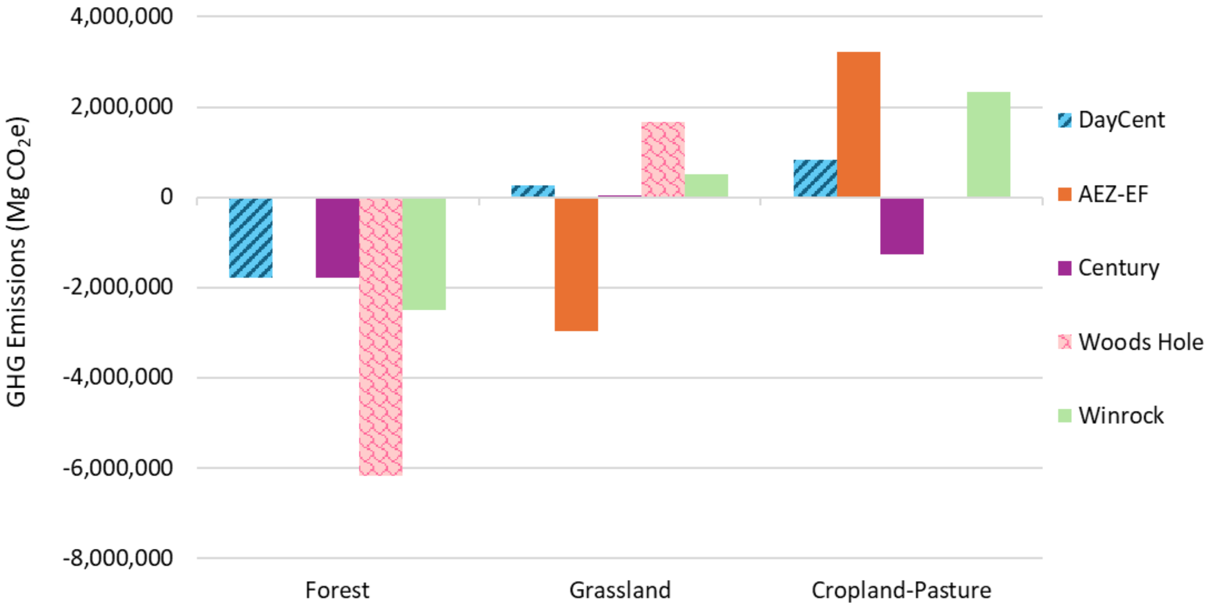

Figure 4.13. GTAP 2017 Domestic GHG Initial Shock, 1.5 BGY Corn Ethanol

For forest land, most datasets show negative values, indicating net carbon sequestration or lower emissions, with Woods Hole showing the largest reduction at nearly 6 million metric tons of CO_2. Grassland results are mixed, with AEZ-EF projecting a large negative value while Woods Hole and some others show small positive emissions. Cropland-pasture conversions generally lean positive, with AEZ-EF and Winrock showing emissions exceeding 2 million metric tons of CO_2, while Century and Woods Hole suggest slight carbon gains.

Overall, the figure illustrates how the 2017 domestic GTAP iLUC results are highly sensitive to the choice of carbon stock model. Some models suggest significant carbon savings from certain land transitions, while others show moderate emissions. The wide range reflects differences in how each dataset defines land categories and characterizes soil and biomass carbon stocks, reinforcing the uncertainty in assigning GHG impacts to specific U.S. land use changes.

Figure 4.14 shows greenhouse gas emissions from U.S. land use change across different datasets, disaggregated into forest, grassland, unused land, and cropland-pasture for sorghum ethanol. Results vary substantially by dataset: forests generally register negative emissions, with Woods Hole reporting the largest sequestration of nearly 800,000 Mg CO_2e, while DayCent and Winrock show more moderate reductions. Grassland outcomes are mixed, with Woods Hole showing positive emissions while AEZ-EF projects a significant net sink. Unused land contributes relatively small positive emissions across all datasets. Cropland-pasture is the most consistent source of emissions, with AEZ-EF estimating the highest values above 700,000 Mg CO_2e, followed by Winrock and DayCent. Overall, the figure highlights that under sorghum ethanol shocks, cropland-pasture dominates domestic iLUC emissions, while forests and grasslands contribute variably depending on carbon stock assumptions.

Figure 4.14. GTAP 2017 Domestic GHG Initial Shock, 0.2 BGY Sorghum Ethanol

Figure 4.15 provides a global comparison to the previous figure which showed domestic U.S. results. While the domestic chart emphasized relatively modest positive and negative emissions from U.S. forest, grassland, and cropland-pasture transitions depending on the dataset, the international results highlight much larger and more consistently positive emissions, especially from cropland-pasture expansion. This underscores that when the GTAP model is extended globally, the scale and direction of GHG emissions from land conversion become more pronounced due to higher carbon stock losses in certain international regions.

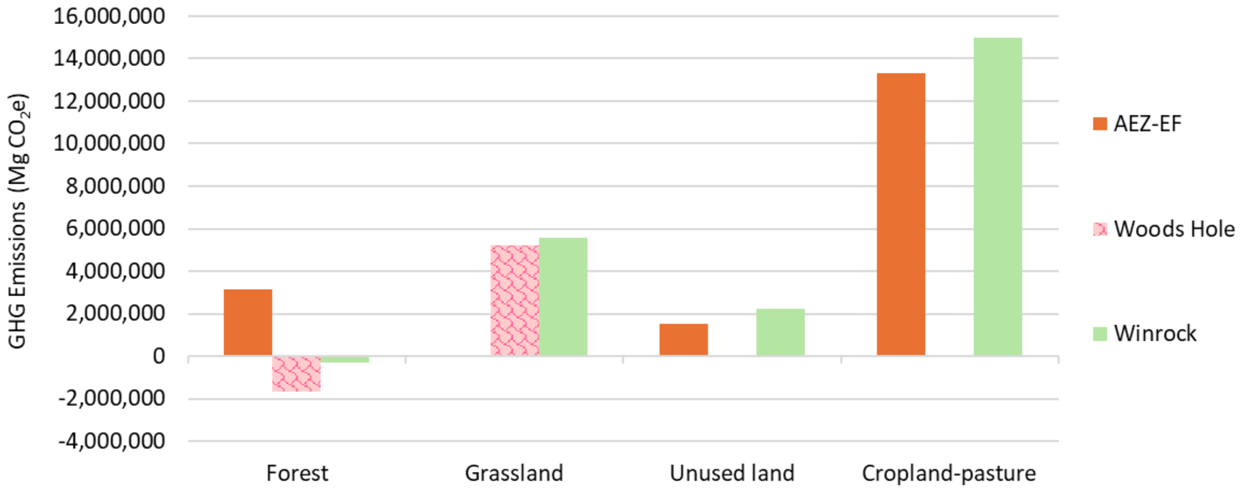

Figure 4.15. GTAP 2017 International GHG Initial Shock, 1.5 BGY Corn Ethanol

Looking across the datasets, AEZ-EF, Woods Hole, and Winrock show very different distributions of emissions by land type. For forests, AEZ-EF projects moderate positive emissions, while Woods Hole shows net sequestration, and Winrock lies near zero. Grassland results vary, with Woods

Hole projecting strong emissions, AEZ-EF showing moderate emissions, and Winrock falling in between. Unused land conversions are consistently small but positive across datasets. The largest impact comes from cropland-pasture, where both AEZ-EF and Winrock exceed 14 million metric tons of CO_2, far higher than any other land type, while Woods Hole also shows substantial emissions but at a lower level.

The chart demonstrates that the choice of carbon stock dataset drives significant differences in international iLUC outcomes, just as it does for the U.S., but the scale of impacts is considerably larger when global land conversions are considered. Cropland-pasture expansion emerges as the dominant source of modeled emissions in the international context, in contrast to the more mixed picture seen in the domestic U.S. analysis.

Figure 4.16 reports greenhouse gas emissions from international land conversions associated with sorghum ethanol expansion, using three alternative carbon stock datasets: AEZ-EF, Woods Hole, and Winrock. Emissions are disaggregated into forest, grassland, and cropland-pasture categories, expressed in megagrams of CO_2e.

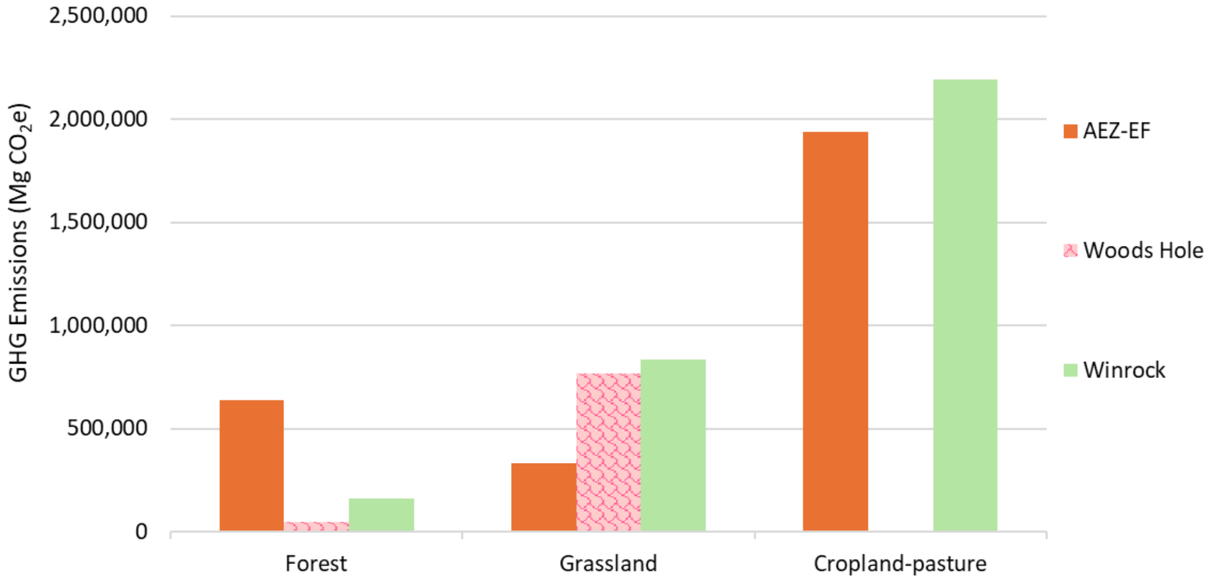

Figure 4.16. GTAP 2017 International GHG Initial Shock, 0.2 BGY Sorghum Ethanol

Across all datasets, cropland-pasture emerges as the dominant source of emissions. Winrock projects the highest cropland-pasture emissions at over 2.2 million Mg CO_2e, followed closely by AEZ-EF at nearly 2 million Mg CO_2e, while Woods Hole does not report values for this category. Grassland emissions vary more widely: Woods Hole and Winrock both estimate substantial positive emissions, ranging from about 0.8 to 0.9 million Mg CO_2e, whereas AEZ-EF projects a more moderate value closer to 0.4 million Mg CO_2e. Forest emissions are comparatively smaller but still significant, with AEZ-EF showing the largest contribution of roughly 0.6 million Mg CO_2e, Winrock projecting a smaller positive value, and Woods Hole estimating only minimal impact.

These results highlight the sensitivity of international iLUC estimates for corn and sorghum ethanol to the choice of carbon stock dataset. While all three approaches agree that cropland-pasture is the most significant emissions source, the magnitude of emissions from grassland and forest conversion differs substantially, reflecting differences in how each dataset defines biomass and soil carbon pools. The AEZ-EF model integrates spatially explicit soil and biomass carbon stock data with GTAP land-use outputs to produce region-specific emission factors that capture the heterogeneity of U.S. agricultural landscapes. More recent literature reaffirms that variation in iLUC results is driven primarily by carbon stock assumptions rather than by the economic structure of GTAP itself, and that AEZ-EF and the most recent version 54 with updated IPCC factors, provides a transparent and reproducible linkage between land-use modeling and life-cycle greenhouse gas accounting making it well positioned as the framework of choice for assessing corn and sorghum ethanol iLUC emissions (Taharipour, 2024).

5. CONCLUSIONS AND RECOMMENDATIONS

Since the California ARB first developed its land use conversion analysis in 2009, the methodology and underlying data have evolved significantly. The initial analysis, and the subsequent 2014 study based on the GTAP 2011 database, provided early estimates of iLUC emissions from biofuel policies. Over time, further analyses have added detail to the model, including:

- More granular categories of land transfer and transformation,
- Improved representation of land used for grazing,
- Updated emission factors for different types of land conversion

.

These improvements have allowed for a more nuanced and accurate assessment of how modeled biofuel shocks in response to different policies affect land use and associated GHG emissions. A key outcome of these analysis efforts is a reduction in predicted GHG emissions from LUC associated with corn ethanol.

GTAP database updates include more recent and accurate data on crop yields, land use, and trade. The interaction of distillers grains co-products with the global demand for animal feed and shifts in protein production reducing net land demand. Updated emission factors reflect new research from the IPCC. On balance the model provides a more realistic simulation of how global markets adjust to increased biofuel demand. A major advance in recent GTAP modeling is the better integration of the model with global energy systems. This integration is crucial because:
It allows the model to account for substitution not only among agricultural products but also among other goods and services in the global economy. It provides a more realistic simulation of how energy policy changes, like increased biofuel use, ripple through the economy and affect land use decisions.

Factors with a Less Extensive Impact on iLUC

The analysis identifies several factors that, despite frequent discussion, have a lower impact on the overall outcome of land use emissions modeling:

- Shock size resulted in a limited variability in LUC emission. A 5 billion-gallon ethanol increase does not significantly alter the qualitative findings compared to a 2 billion or 13 billion gallon shock.
- Soil Carbon Emission Factors: Variations in these factors have a minor effect on total emissions estimates.
- Static vs. Dynamic Models: Dynamic modeling systems would add more assumptions and uncertainty to the analysis.

Recommendations

The recommendation for future land use emissions analysis using GTAP includes:

- Model Version: Use the GTAP 2017 model, which incorporates the latest data and methodological improvements.

- Shock Size: Apply a 600 million gallon shock size to reflect the transition from E10 to E15 ethanol blends in California. This simulates the real-world policy scenario of increasing ethanol content in gasoline and its implications for land use and emissions
- AEZ 54: Focus on AEZ 54, a specific Agro-Ecological Zone within the GTAP framework. AEZs allow for more precise modeling of land use change and emissions by accounting for differences in climate, soil, and growing period. AEZ 54 is significant because it likely represents a productive region, like the U.S. Midwest, where much of the land use change for biofuel feedstocks would occur, and its carbon stock characteristics are critical for accurate emissions estimates.

6. APPENDIX

IPCC data is a primary input into the AEZ-EF model, originally based on 2006 data. In 2019, IPCC significantly updated many factors based on the most up to date academic literature and more accurate reflections of production practices. The updates to the IPCC data include other factors than land use (F_{LU}), including inputs (F_i) manure and farm management practices (F_{MG}) such as tilling. These stock change factors are multipliers that adjust the reference SOC based on land use.

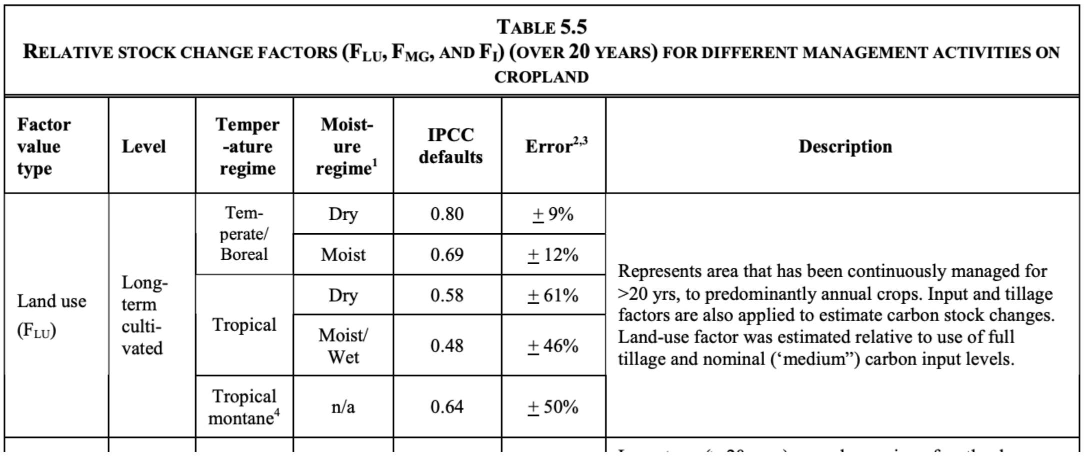

TABLE 5.5
RELATIVE STOCK CHANGE FACTORS (F_{LU}, F_{MG}, AND F_I) (OVER 20 YEARS) FOR DIFFERENT MANAGEMENT ACTIVITIES ON CROPLAND

Factor value type	Level	Temperature regime	Moisture regime[1]	IPCC defaults	Error[2,3]	Description
Land use (F_{LU})	Long-term cultivated	Temperate/ Boreal	Dry	0.80	± 9%	Represents area that has been continuously managed for >20 yrs, to predominantly annual crops. Input and tillage factors are also applied to estimate carbon stock changes. Land-use factor was estimated relative to use of full tillage and nominal ('medium") carbon input levels.
			Moist	0.69	± 12%	
		Tropical	Dry	0.58	± 61%	
			Moist/ Wet	0.48	± 46%	
		Tropical montane[4]	n/a	0.64	± 50%	

Figure 7: 2006 IPCC Land Use Factors, AEZ-EF model inputs

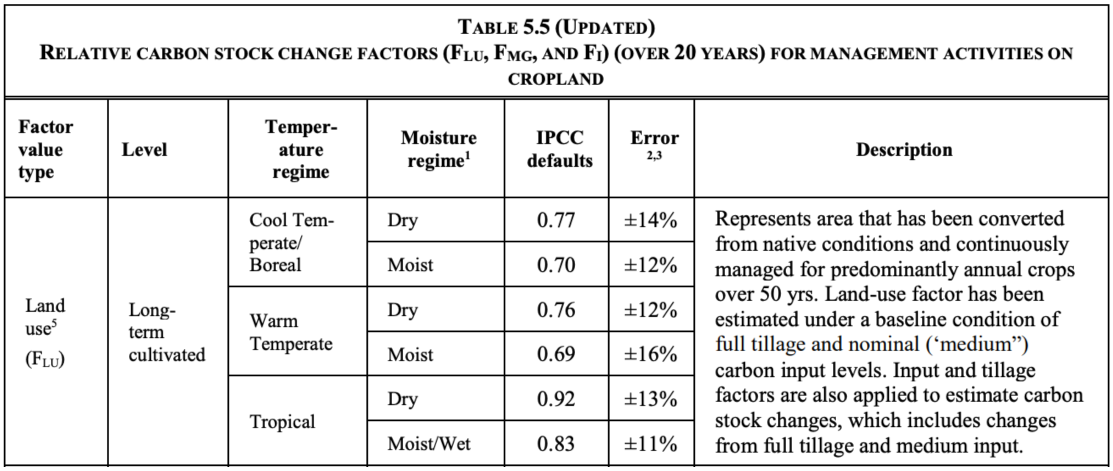

TABLE 5.5 (UPDATED)
RELATIVE CARBON STOCK CHANGE FACTORS (F_{LU}, F_{MG}, AND F_I) (OVER 20 YEARS) FOR MANAGEMENT ACTIVITIES ON CROPLAND

Factor value type	Level	Temperature regime	Moisture regime[1]	IPCC defaults	Error[2,3]	Description
Land use[5] (F_{LU})	Long-term cultivated	Cool Temperate/ Boreal	Dry	0.77	±14%	Represents area that has been converted from native conditions and continuously managed for predominantly annual crops over 50 yrs. Land-use factor has been estimated under a baseline condition of full tillage and nominal ('medium") carbon input levels. Input and tillage factors are also applied to estimate carbon stock changes, which includes changes from full tillage and medium input.
			Moist	0.70	±12%	
		Warm Temperate	Dry	0.76	±12%	
			Moist	0.69	±16%	
		Tropical	Dry	0.92	±13%	
			Moist/Wet	0.83	±11%	

Figure 8: 2019 Updated Land Use Factors, AEZ-EF model inputs

Adjusting the various aforementioned factors within the AEZ-EF model creates a range of ILUC changes modelled under the various SOC assumptions. The largest overall change is associated with the updating of the IPCC land use input factors from the 2006 to 2019 values. The resulting changes caused a slight increase in associated emissions for temperate climates, which includes the United States.

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