Review of EPA Workshop on Biofuel Greenhouse Gas Modeling

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Terms and Abbreviations

ANL	Argonne National Laboratory
CARB	California Air Resources Board
CH_4	Methane
CI	Carbon intensity
CO_2	Carbon dioxide
EPA	U.S. Environmental Protection Agency
g CO_2e	Grams of carbon dioxide equivalent
GHG	Greenhouse Gas
GREET	The Greenhouse gas, Regulated Emissions, and Energy use in Transportation model
GWP	Global Warming Potential
LCA	Life Cycle Analysis or Life Cycle Assessment
LCFS	Low Carbon Fuel Standard
LHV	Lower Heating Value
N_2O	Nitrous oxide
RIA	Regulatory Impact Analysis
RFS2	Revised Federal Renewable Fuels Standard
VOC	Volatile Organic Compound
WTT	Well-To-Tank
WTW	Well-To-Wheel

1. Summary

EPA's Biofuel Greenhouse Gas Modeling Workshop provided updates on ongoing research related to greenhouse gas (GHG) emissions associated with biofuels. [1] Most of the material covered topics associated with land use conversion and the carbon stocks associated with different land cover types. Many prominent researchers and models were represented at the conference. Representatives of certain other modeling techniques, such as the FAPRI/FASOM model used by EPA in 2010, were notably absent at the workshop. Commentary on the relevance of individual presentations is discussed in the subsequent sections, with a focus on providing EPA feedback on the questions on which it seeks comment regarding sources of data for modeling, best models to use, how to address uncertainty, and how to incorporate best available science.[2]

In general, the presentations kept to the presenter's area of research and did not provide a direct review of the GHG emissions of biofuels in relationship to the EPA's 2010 regulatory impact analysis (RIA) (EPA, 2010) or revised 2022 draft RIA. While reviewing these areas of research in isolation is an interesting exercise that is helpful for furthering the science over the long term, for EPA to "incorporate the best available science into an update of our lifecycle analysis (LCA) of biofuels" EPA will need to consider how to bring these research areas together into a holistic analysis.

The workshop focused primarily on issues related to land use conversion (LUC). Other LCA topics relevant to the analysis of biofuels including reassessment of the 2005 petroleum baseline, petroleum production and its impact on biofuels, natural gas and electric power were not part of the workshop discussion.

The opinions in this report are based on attendance of the workshop as well as extensive prior work on the GHG emissions of biofuels, including a February 2022 Report on *Review of GHG Emissions of Corn Ethanol under the EPA RFS2* submitted as comment to the 2020-2022 RFS Annual Rule. That report reviewed the key factors that affect lifecycle emissions of corn ethanol and the most recent agricultural data available, and found that corn ethanol has about 48% less lifecycle GHG emissions than the appropriate petroleum baseline. By comparing EPA's 2010 predictions from the FASOM/FAPRI models with recent data, the report analyzed which factors the EPA models were able to predict relatively accurately, and which factors had significant deviations from modeled projections. On the whole, EPA's 2010 RIA undervalued the GHG emissions reductions from ethanol largely due to overestimation of the impacts of indirect land use change (iLUC), failure to account for increased soil carbon storage from corn farming, inclusion of deforestation effects that are not tied to ethanol demand, underestimation of the offsetting effects of co-products including distillers' grain solubles (DGS) and corn oil, underestimation of the emissions-reducing effect that efficiency improvements, a cleaner electric grid, and installation of carbon capture technologies would have on ethanol plant

[1] Announcing Upcoming Virtual Meeting on Biofuel Greenhouse Gas Modeling, 86 Fed. Reg. 73,757 (Dec. 28, 2021).
[2] https://www.epa.gov/renewable-fuel-standard-program/workshop-biofuel-greenhouse-gas-modeling.

emissions, and underestimation of the carbon intensity of the 2005 petroleum baseline. Other reviews of the RFS have shown that the GHG emissions from both the petroleum baseline as well as corn ethanol warrant reevaluation (Flugge, 2017; Rosenfeld, 2018; Scully, 2021; Unnasch, 2022). After careful review and consideration of the workshop sessions, nothing in the material presented changes the relevance or validity of the conclusions contained in this February 2022 report.

1.1 Modeling of Land Use Change

Discussions of the following modeling systems were presented.

- Farzad Taheripour, Purdue University - GTAP
- Michael Wang, Argonne National Laboratory – CCLUB (also GREET)
- Page Kyle, Pacific Northwest National Laboratory - PNNL Stefan Frank, International Institute for Applied Systems Analysis - GLOBIOM
- Yongxia Cai, RTI International – ADAGE
- Jennifer Dunn, Northwestern University, Steffen Mueller, University of Illinois, CCLUB

Most notably presentations on the FASOM and FAPRI models used to develop the LUC estimates in the 2010 RIA were absent.

The correlation between LUC and an expansion in biofuel is typically estimated with agro-economic models. Economic models that simulate market behavior (particularly those in the agricultural sector) are often linked to predict the location of land cover change and the emissions associated with conversion of corn to ethanol production based on EPA's 2010 RIA. The iLUC contribution from EPA's analysis is illustrated in Figure 1.1. This prior analysis could have been presented as the background with efforts to examine new information. Instead, much of the material presented during the workshop was on alternative modeling systems.

All of the modeling systems provided estimates of land cover change that could be used to predict iLUC associated with biofuels. The modeling systems use a range of approaches and assumptions. While it is clear that the assessment of iLUC depends on parameters such as price yield elasticity, interactions between cropland and pasture, scenario inputs, impact of trade, and other parameters, none of the presentations compared the inputs and predictions in the original RIA to factors used in alternative models and the effect on land cover predictions.

While more models with similar predictive strategies is interesting, the underlying variability in LUC predictions is associated with the choices and inputs associated with landcover change. For example, EPA's 2010 RIA predicted that international LUC would be the largest effect of the RFS, and this factor remains an area of significant variability across models today. Yet EPA has not conducted a retrospective analysis of land conversion since 2010 as an effort to improve understanding of this critical model input. An efficient way to address this issue is to utilize the CCLUB model which is based on updated iLUC analysis (Taheripour, 2017). This modeling is based on updated economic data and improved estimates of crop intensification.

The U.S. direct land use conversion in Figure 1.1 is the result of the FASOM model which predicts all of the shifts in agriculture in the U.S. based on expansion of corn use and production of distiller's grains. These GHG emissions correspond to a portion of the U.S. emission inventory that is predicted with FASOM. An evaluation of the GHG emissions from current U.S. agriculture and comparison to the predictions made in 2010 would help inform the issue of the direct land use emissions associated with biofuels; however, the CCLUB model includes updated values and is an appropriate model to use for this purpose.

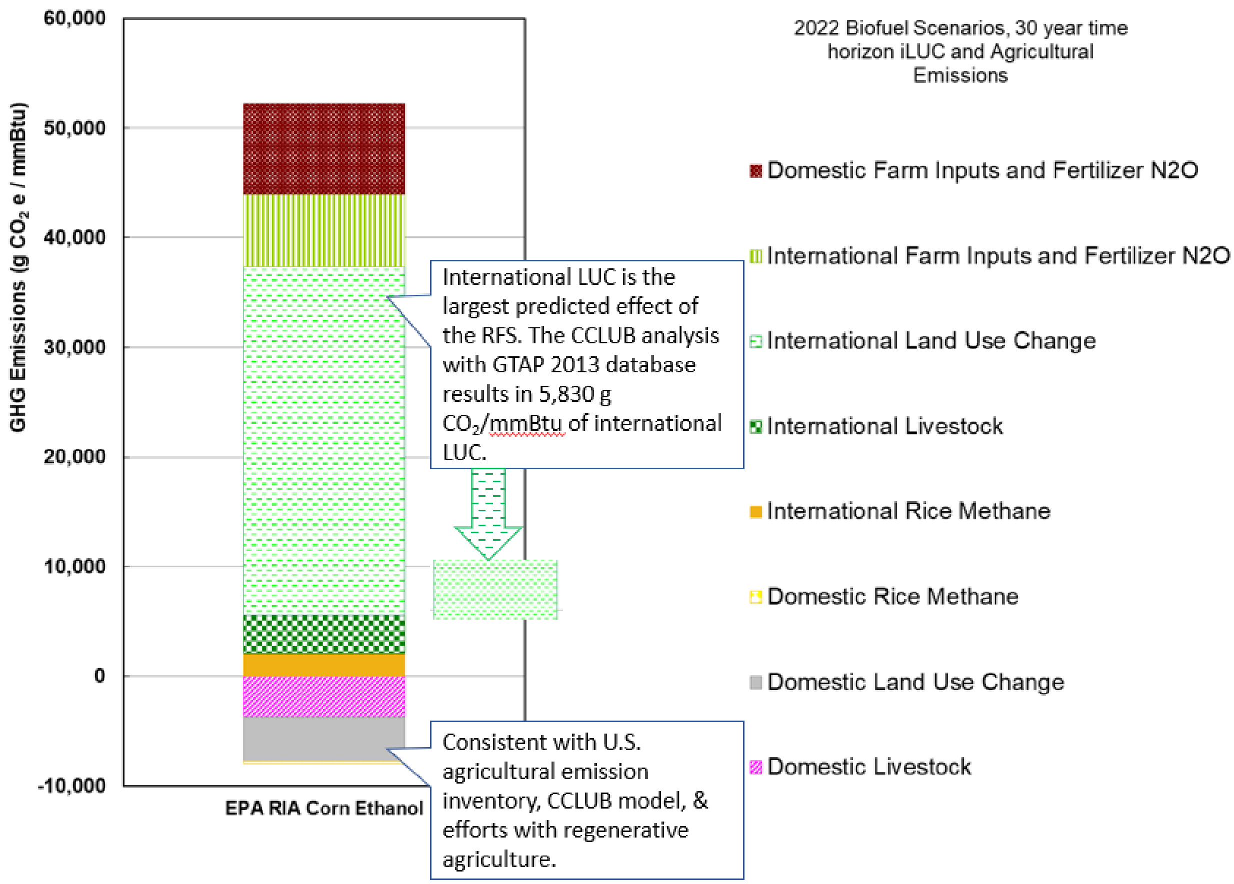


Figure 1.1. Indirect land use effects from EPA 2010 RIA.

1.2 Observations of Land Cover

Observational land cover and land use data impact the assessment of LUC. Recent historical trends in US and global land use change and biofuel feedstock supply were described by the following:

- Dev Shrestha, University of Idaho
- Patrick Flanagan, U.S. Department of Agriculture
- Nancy Harris, World Resources Institute
- Madhu Khanna, University of Illinois, Urbana-Champaign

The presenters described trends in agriculture modeling but provided little tie in to the LUC analysis performed as part of the RIA.

1.3 Model Comparison and Uncertainty

Uncertainty analysis of LCA models provides insight on the likely GHG reductions associated with renewable fuels. Uncertainty analysis based on simulations of LCA models and reviews of model results provided an overview of the ranges in predictions. Three presenters discussed how uncertainty across differing LCA values could be considered in developing biofuels policy.

- Vassilis Daioglou, Utrecht University
- Richard Plevin, Research Consultant
- Nikita Pavlenko, The International Council on Clean Transportation

While uncertainty does exist between different model results, it is important to understand that model inputs are likely more important to a given result than the choice of model. Models which result in a high iLUC value are generally being run with parameters that correspond to high iLUC. Overcoming uncertainty therefore would be better furthered by examining model inputs, including through incorporation of historical data, than by cross-model comparisons that do not account for the importance of the inputted parameters.

1.4 Soil and Biomass Carbon

Several presentations covered quality of biomass and soil carbon stocks and agricultural management practices.

- Seth Spawn-Lee, University of Wisconsin-Madison
- Jane Johnson, U.S. Department of Agriculture
- Stephen Ogle, Colorado State University – DayCent

The presentation from Colorado State is particularly relevant as the DayCent model is an input to the FASOM model which provided the basis for U.S. land use conversion emissions in the 2010 RIA.

2. Domestic and International Land Use Change – Updated Data and Accurate Landcover Characterization

Since EPA's original 2010 RIA established the current LCA values for ethanol, new findings and data on actual deforestation across the globe, crop prices, soil organic carbon stocks, corn and ethanol yields have shown that the 2010 RIA overestimated the contribution of LUC towards the CI of corn ethanol. The 2010 RIA's approach is discussed below including EPA's approach to ILUC modeling followed by modeling options from workshop presenters.

Workshop presenters introduced a variety of LUC models; however, greater attention to reducing the variability within model inputs may be a more effective strategy to improving modeling accuracy than the continued introduction of new models. Use of retrospective data acquired over the past 12 years would likely be helpful in reducing this input variability.

Further, accurate landcover characterization remains an important consideration in evaluating the best available LUC information.

2.1 EPA RIA Approach for Land Use Change

The 2010 RIA takes into account the incremental change of diverting corn crops to biofuel production. The modeling attempts to answer the question: what would change if U.S. ethanol use increased to 15 billion-gallon per year[3] while holding constant the consumption of food. Both the incremental farming inputs as well as the incremental effects of land conversion on crops were estimated through macroeconomic modeling.

The 2010 RIA also includes the indirect farming emissions associated with new crops in addition to LUC. This method is intended to represent the make-up crop inputs as well as land use conversion.

[3] EPA 2010 RIA, Section 1.1.1.1

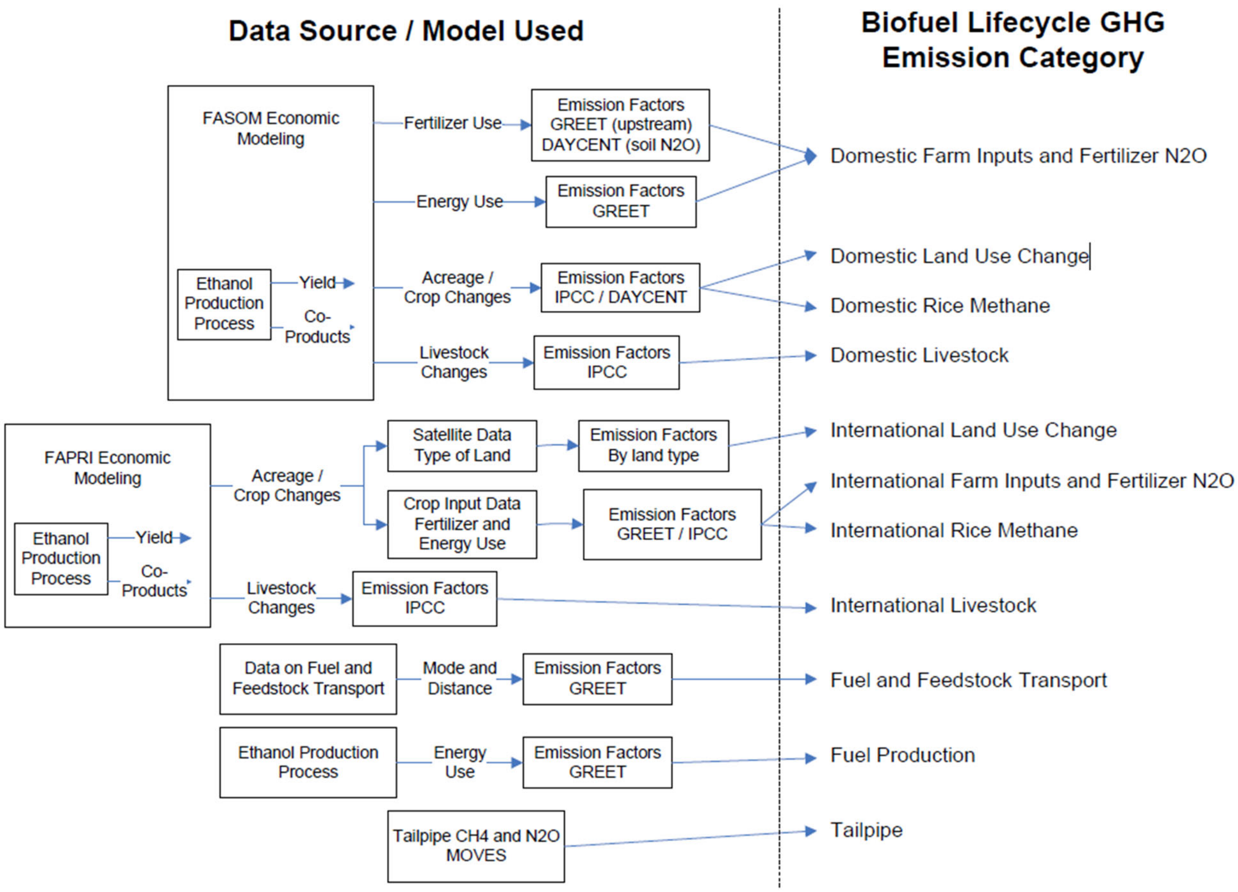


Figure 2.1. System Boundary Used in EPA RIA Study. (EPA, 2010)

The 2010 RIA identified 11 emission sources which capture the full life cycle GHG profile of corn ethanol and compared these emissions with those of gasoline (Figure 2.2). The highest GHG emissions for corn ethanol correspond to international LUC followed by fuel production. International LUC corresponds to the change in carbon emissions associated with the growth of new crops outside the U.S. EPA estimated that these emissions include the release of soil carbon and avoided carbon storage from forest and pastureland when these lands are converted to cropland. The landcover change is predicted with the FAPRI model and is combined with carbon stock factors developed by Winrock International. (The EPA workshop had no review of these emission factors). Fuel production emissions include the emissions associated with natural gas combustion as well as upstream natural gas and electric power. International farm inputs and N_2O correspond to the crop farming activity required to make up for changes in U.S. farm exports. The modeling system estimated the effect of expansion in corn production.

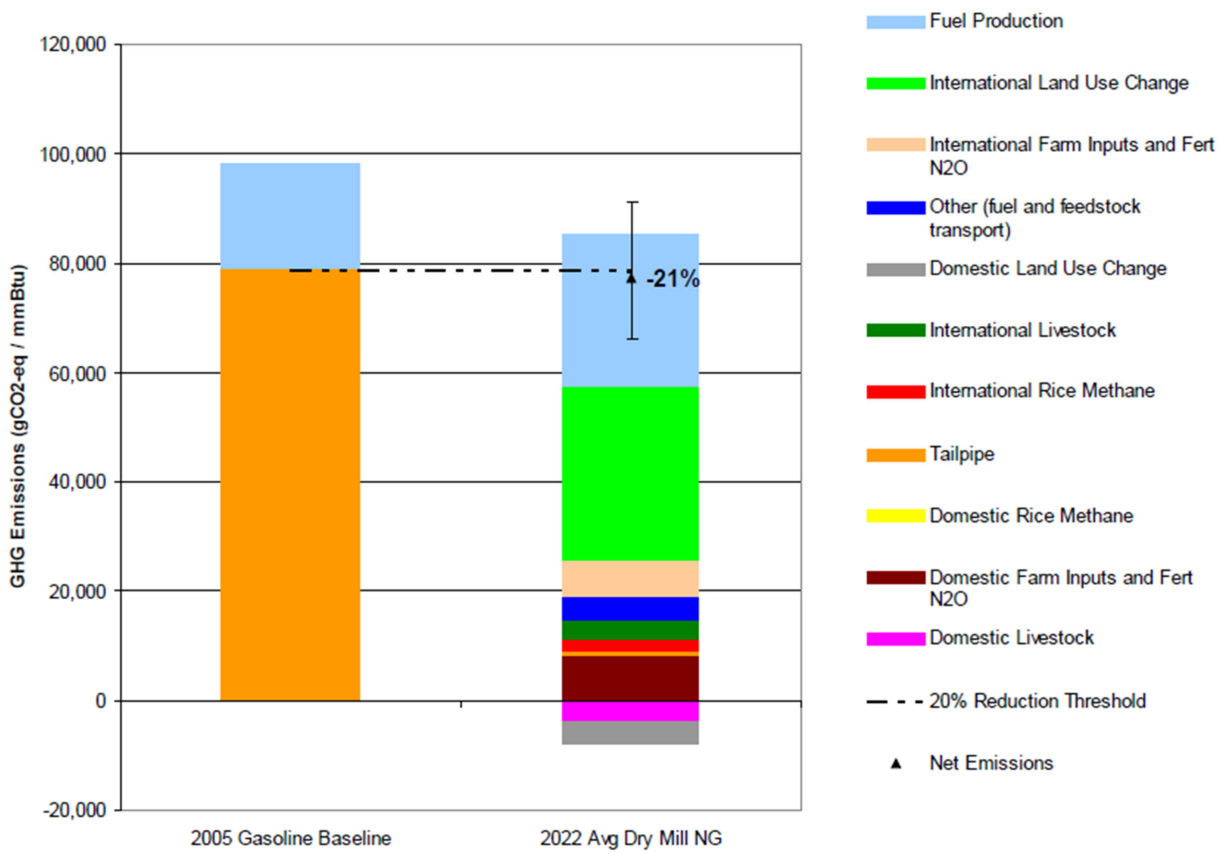


Figure 2.2. EPA's Analysis of Corn Ethanol GHG emissions. (EPA, 2010)

Given EPA's extensive efforts in the 2010 RIA, stakeholders may have anticipated the agency's 2010 analysis to have featured more prominently in the workshop, including through a comparison of:

- What was modeled in 2010.
- How did land use evolve with 12 years of biofuels?
- What was the retrospective value of EPA's analysis?
- What modeling system could improve the iLUC estimates?
- How do the results from new iLUC analyses that take into account more details on pasture intensification, elasticities, and newer economic data?

While the iLUC estimates in the 2010 model are inaccurate and out of date, other portions of the analysis may be a useful baseline for comparison, if the past 12 years of improvements in carbon intensity reductions are taken into account.[4]

[4] *See* Life Cycle Associates, *Review of GHG Emissions of Corn Ethanol under the EPA RFS2* (Feb 4 2022) at p. 48 for a detailed list of factors contributing to the reduction of corn ethanol emissions as compared to 2010 projections.

2.2 LUC Models

LUC models predict land cover, change, changing yields, both to the biofuel crop being examined as well as other crops grown globally. These yield improvements include both projected future improvements due to better farming practices (some of which may have nothing to do with an expansion in biofuels), as well as yield improvements that are due to higher prices sending a signal to the market to incentivize better farming practices, more efficient harvest, and technology improvements. Expanded use of crops for biofuels will also affect feed prices and shift the use of agricultural commodities. The production of DGS from corn affects feed markets. The removal of land from feed production will also result in market shifts due to price mediation. Higher corn prices, for example, could result in a shift from feedlot-fed cattle to other sources of meat that are less feed intensive. The effect of displacement by DGS as well as shifts in crop usage may be the most significant factor. Demand mediation or a reduction in the demand for feed and food also reduces the overall requirement for land. Another key LUC prediction is associated with cattle stocking rates on pasture as well as the selection of forest land, marginal land or grassland. These predictions affect the carbon stock factor for LUC.

The indirect emissions associated with biofuels have been modeled as US emissions from the FASOM model and international land cover change from the FAPRI model. Assessment of the performance of EPA's modeling would reasonably include updates to the inputs to the model, such as price yield elasticity data and other price relationships, improvements in land conversion such as land rents, and relationships between pasture cropland and conservation reserve program and cropland pasture.

Based on the information presented in the workshop and the literature there have been many efforts to address this analytical subject including the updates to several models that predict LUC. EPA summarized the range of GHG emissions from various corn ethanol analyses in Figure 2.3. The largest variability is LUC. Conversion emissions depend on the specific technologies and are less of a source of uncertainty than LUC.

EPA should clearly define its modeling objectives. For example, the agency could refine the original FASOM and FAPRI analysis with new data or it could use a more accessible model such as GTAP to predict iLUC. Given all the information for new modeling systems, EPA could also identify the factors in the models presented in the following subsections and compare these with the inputs to the 2010 RIA.

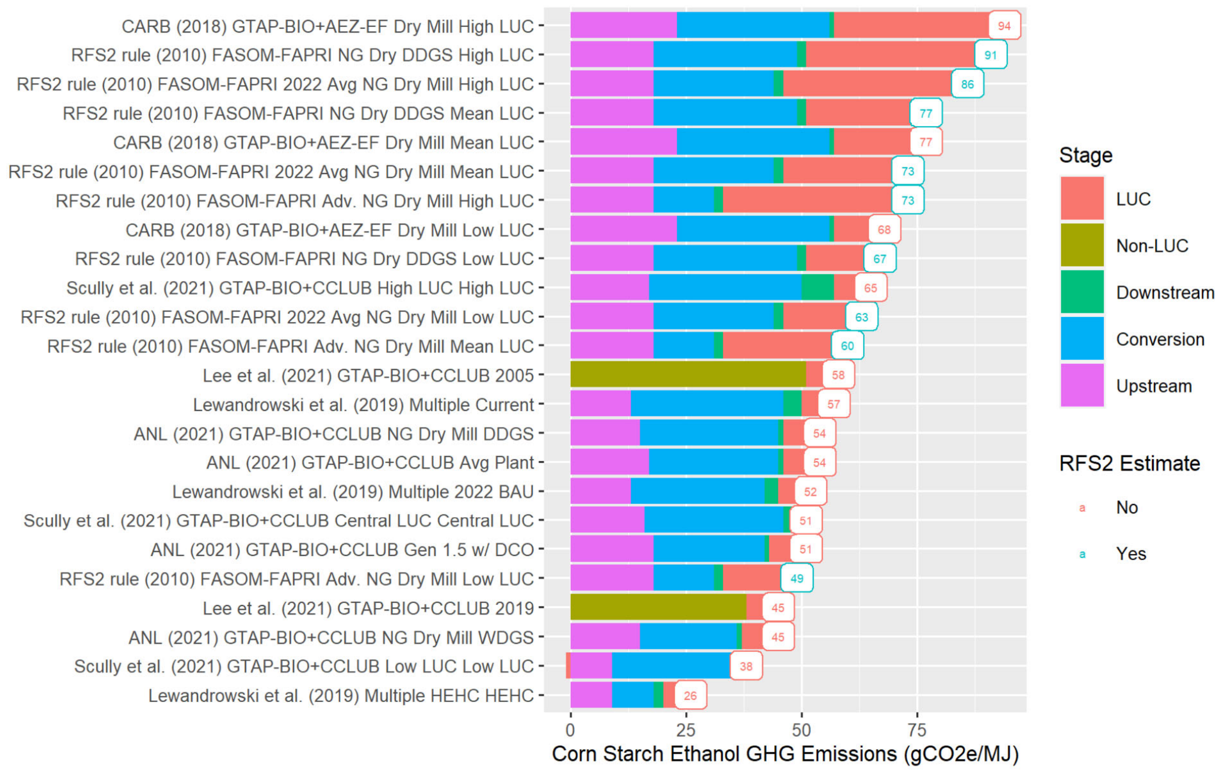


Figure 2.3. Range of GHG Estimates presented by EPA
(Simon, 2022)

Several iLUC modeling systems were presented at the EPA workshop. The models provided new estimates of iLUC with questions remaining about differences in model predictions. A brief description of each model presented at the workshop follows. The presentations did not provide recommendation on how to rectify differing results between models. While proliferation of new models with similar predictive strategies may be an interesting conceptual exercise, it does not address underlying variability within model inputs. Over the past 12 years of U.S. biofuel usage under the RFS, empirical data has developed on real-world landcover change. EPA could implement a retrospective analysis of land conversion since 2010, which would help inform the models and reduce variability. However, such an analysis would be complicated to undertake. The more recent GTAP analysis described below represents the best estimate for the iLUC of corn ethanol and could readily be implemented by EPA.

GTAP

Dr. Taheripour provided an overview of Purdue University's GTAP model.[5] Since 2010, numerous studies have examined the international LUC for corn ethanol and their results showed that the international LUC was significantly lower than the 2010 RIA's estimation. Typically, agro-economic models predict a reduction in U.S. crop exports for both corn and soybean as either corn exports are reduced or corn-soy rotation is converted to continuous corn. The models take into account the price effects of agricultural commodities as well as yield

[5] https://www.gtap.agecon.purdue.edu/

improvements and predict the type of land converted to crop production. A series of peer-reviewed publications have shown that the international LUC is even lower. Publications from Purdue University (Tyner et al., 2010; Taheripour et al., 2017) are based on the GTAP model; which was employed by Argonne National Laboratories and incorporated into GREET (the model used by California Air Resource Board (CARB) and other state Low Carbon Fuel Standards, such as Oregon's Clean Fuels Program). Modeling from GTAP provide the basis for land cover change in Argonne National Laboratory's CCLUB model.

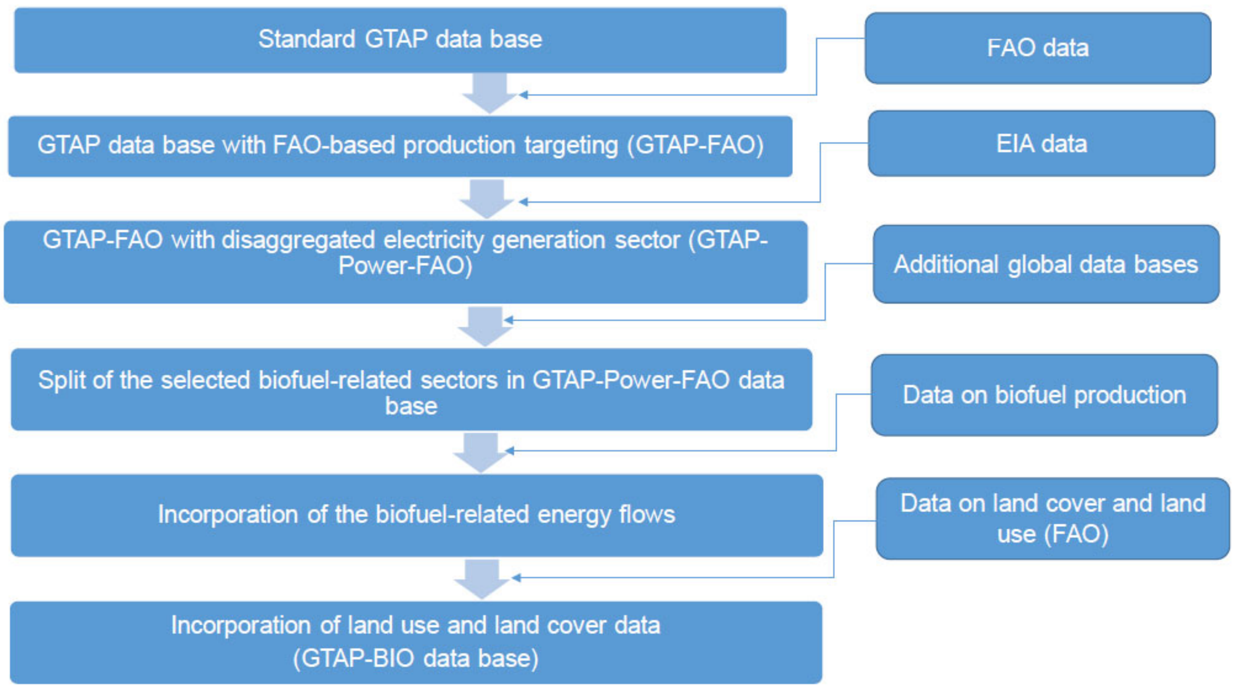


Figure 2.4. GTAP Bio Construction Steps.
(Taheripour, 2022)

Updates to the GTAP model (Taheripour, 2017) include changes in the global economy from 2004 to 2011, changes in crop areas, and yields. The update also includes changes in the mix of GDP globally. The revised model better handles crop intensification and better calibrations of yield price elasticity by region.

The GTAP analysis is reflected in the CCLUB model as shown in **Figure 2.5**

Results

Land Use Change (LUC) GHG Emissions (g CO2e/MJ)

Note: total GHG emissions account for both carbon emissons and N2O emissions

LUC Emissions	Forest	Grassland	Cropland-Pasture	Young Forest-Shrub	Sum
Carbon Emissions					
--Domestic Emissions	0.8	-0.1	-3.0	0.1	-2.3
--International Emissions	0.7	3.1	1.8	0.0	5.5
				Total	3.3
N2O & CH4 Emissions					
--Domestic Emissions	0.0	0.0	0.0	0.0	0.0
--International Emissions	0.2	0.1	0.2	0.0	0.4
				Total	0.5
Total GHG Emissions					
--Domestic Emissions	0.8	-0.1	-3.0	0.1	-2.3
--International Emissions	0.8	3.2	1.9	0.0	6.0
				Total	3.7

Figure 2.5. CCLUB analysis for corn ethanol, GTAP 2013 database. (Dunn, 2014).

GCAM

The Global Change Assessment Model (GCAM) is an integrated assessment model that links the world's energy, agriculture and land use systems with a climate model. The GCAM[6] model provides another integrated system model that predicts LUC. The model includes dynamic time steps to represent changes in technology and related the effect of biofuels on oil consumption due to price effects. The model is designed to assess various climate change policies and technology strategies for the globe over long time scales. GCAM runs in 5-year time steps from 1990 to 2100 and includes 14 geographic regions in the energy/economy module and 151 regions in the agriculture and land use module. GCAM has been updated many times since the early eighties to include additional technology options and more detailed information about agriculture and land use systems. The model has been exercised extensively to explore the effect of technology and policy on climate change and/or the cost of mitigating climate change. More recent applications of the model have begun to explore the role of terrestrial system and its interactions with the energy and climate systems. GCAM is a community model developed and run at the Joint Global Change Research Institute, University of Maryland.

[6] https://cfpub.epa.gov/si/si_public_record_report.cfm?Lab=OAP&dirEntryId=212503

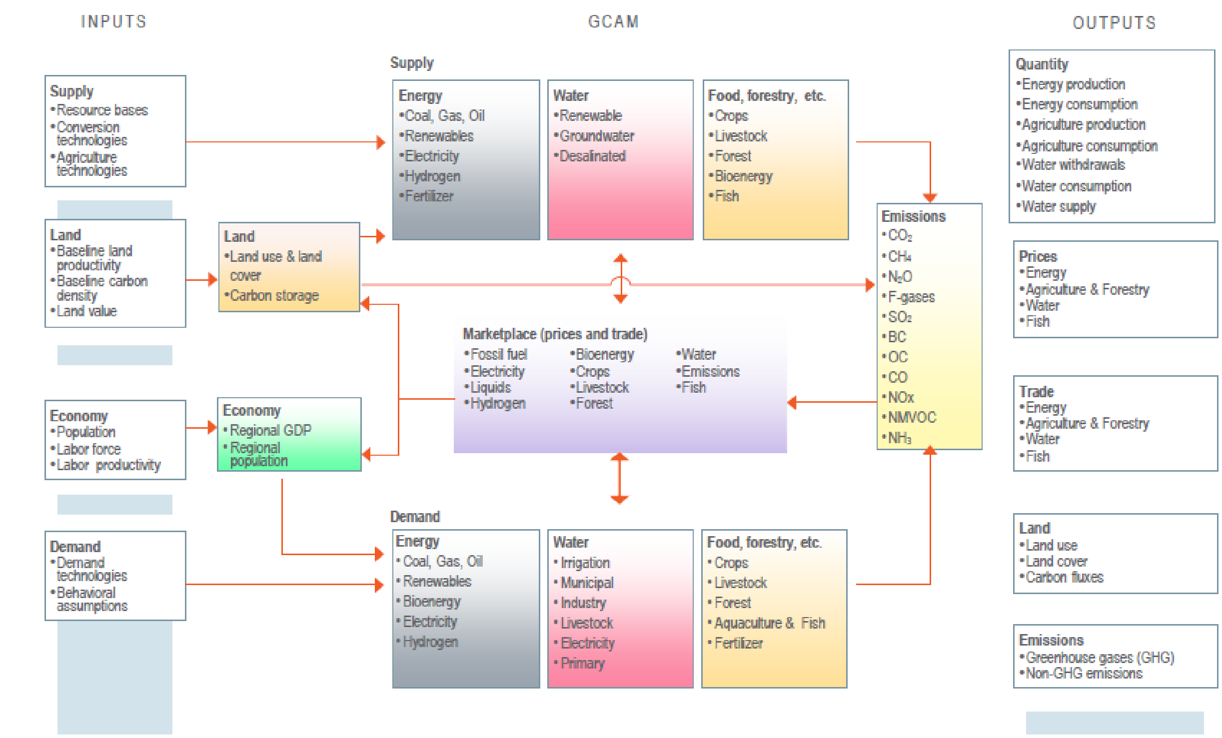


Figure 2.6. GCAM Model inputs and outputs.
(Kyle, 2022)

GLOBIOM

IIASA's Global Biosphere Management Model (GLOBIOM)[7] is used to analyze the competition for land use between agriculture, forestry, and bioenergy, which are the main land-based production sectors. As such, the model can provide scientists and policymakers with the means to assess, on a global basis, the rational production of food, forest fiber, and bioenergy, all of which contribute to human welfare. GLOBIOM has been developed and used by IIASA since the late 2000s. The partial-equilibrium model represents various land use-based activities, including agriculture, forestry and bioenergy sectors. The model is built following a bottom-up setting based on detailed grid-cell information, providing the biophysical and technical cost information. This detailed structure allows a set of environmental parameters to be taken into account. Its spatial equilibrium modelling approach represents bilateral trade based on cost competitiveness. The model was initially developed for impact assessment of climate change mitigation policies in land-based sectors, including biofuels, and nowadays is also increasingly being implemented for agricultural and timber markets foresight, and economic impact analysis of climate change and adaptation, and a wide range of sustainable development goals. The GLOBIOM model has been used in several biofuels assessments including EU ILUC & ILUC2, ICAO CORSIA, and EU Energy & Climate Policies.

[7] https://previous.iiasa.ac.at/web/home/research/GLOBIOM/GLOBIOM.html

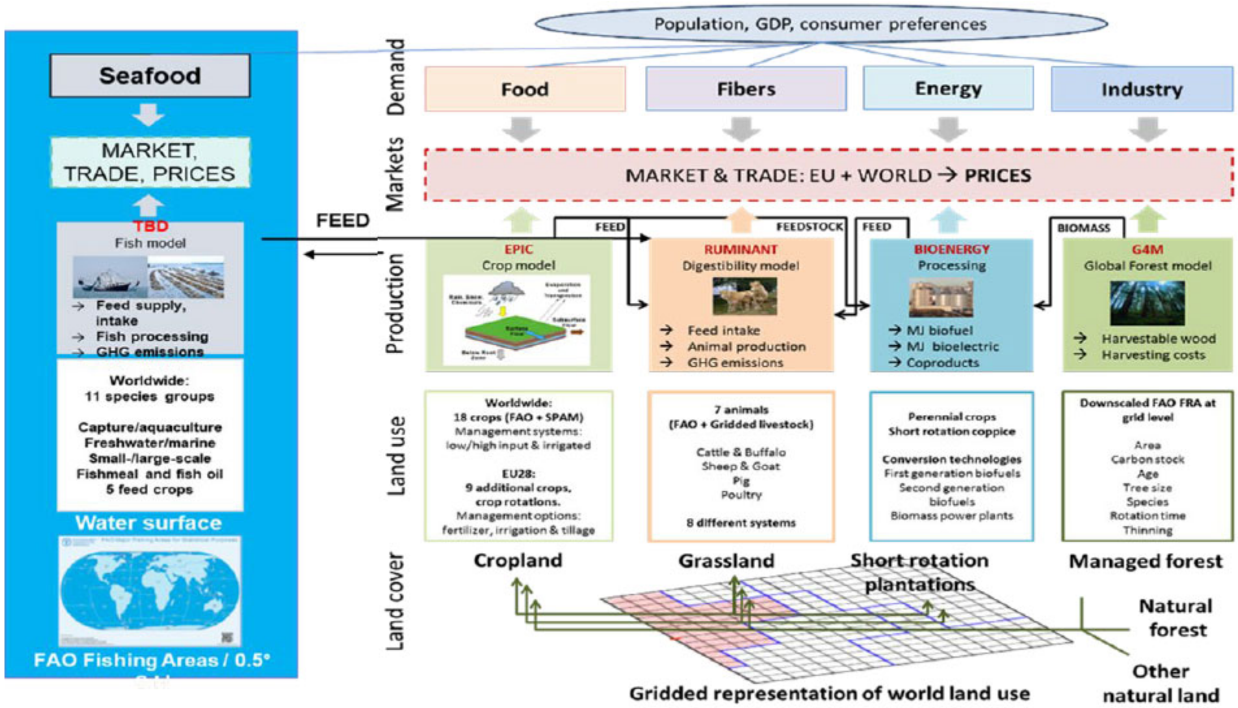


Figure 2.7. GLOBIOM model structure.
(Frank, 2022)

ADAGE

The Applied Dynamic Analysis of the Global Economy (RTI ADAGE)[8]: U.S. Regional Module is a dynamic computable general equilibrium (CGE) model capable of examining a wide range of economic policies and estimating how all parts of an economy will respond over time to policy announcements. Among the feasible set of policies are many types of economic, energy, and environmental policies.

The latest iteration of the U.S. Regional Module includes nine household types, delineated by income, and nine regions for a total of 81 representative households. The income grouping provides a finer level of granularity among lower-income households and extends up to a $150k+ household group at the high end. The groups are based on the IMPLAN economic data that form the model's benchmark dataset. The nine model regions are defined by the U.S. Census bureau's Census Divisions. The production-structure architecture also has an abridged representation of several sectors including electricity generation. Apparently, this modeling system would provide more interactions between farming activity and other economic activities but the benefits of such an approach are unclear.

[8] https://www.rti.org/publication/applied-dynamic-analysis-global-economy-rti-adagetm-model-2013

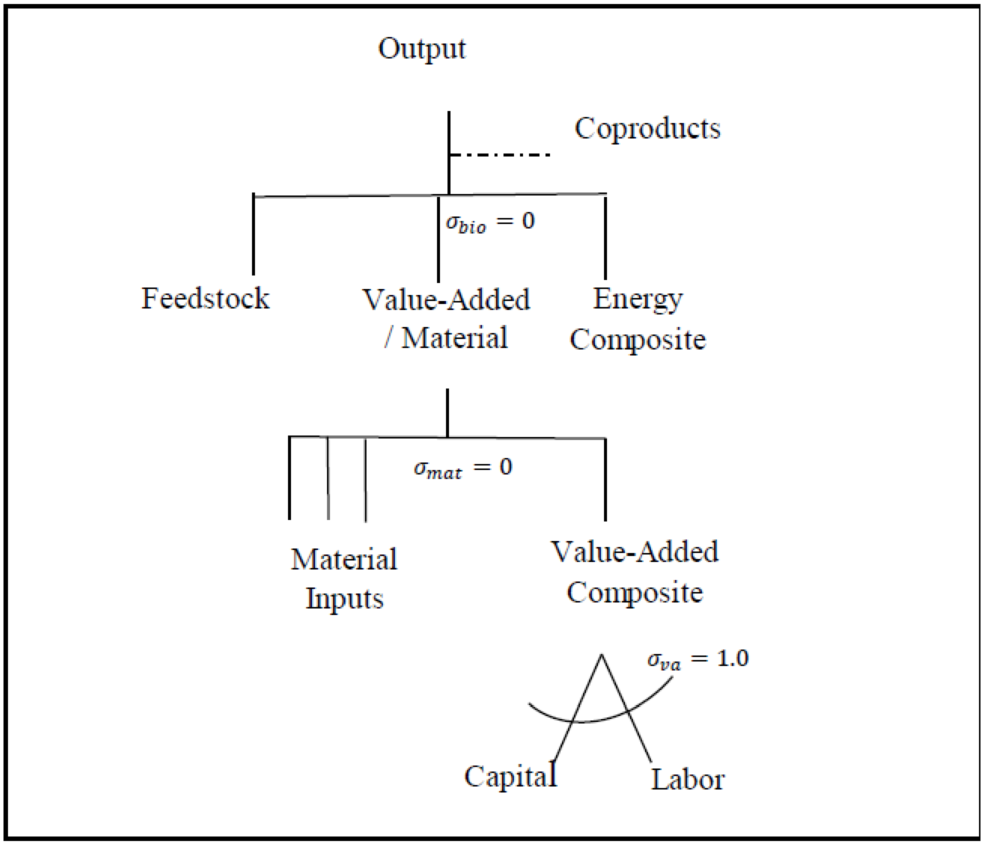


Figure 2.8. ADAGE Model: 1stGeneration Biofuels Supply Production Structure (Cai, 2022)

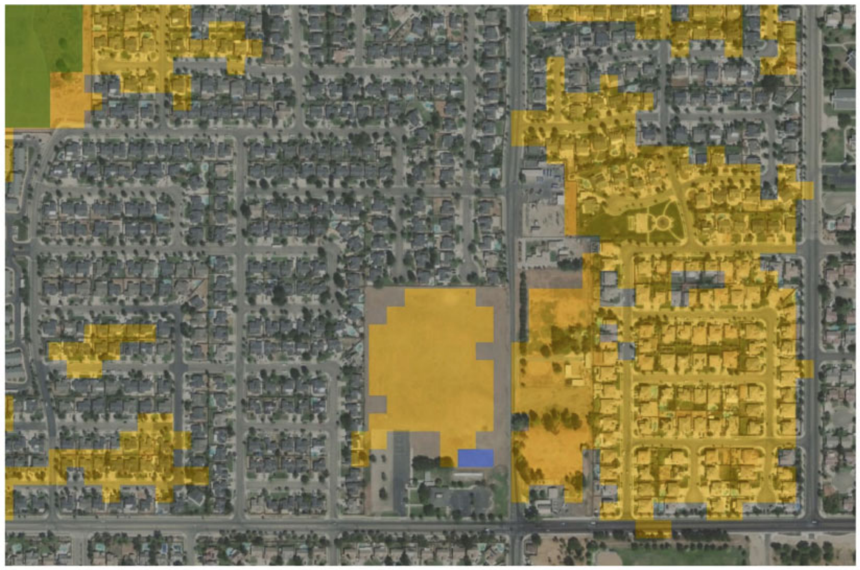
2.3 Land Cover Characterization

The first part of the workshop included presentations on land cover categorization and carbon stocks. The presenters identified issues with categorizing land and conversions among different land types. The takeaway is that land use remains difficult to characterize but methods for land characterization are evolving. Drawing upon work by Dr. Shrestha, and the Argonne National Laboratory/Purdue comments on *Environmental outcomes of the RFS Program* (2022), EPA could examine evolving methods for land characterization and compare these with predictions in the 2010 RIA.

U.S. Cropland Use

Figure 2.10 shows an example of the issues associated with satellite categorization of land cover type.

city of Lemoore, CA



cropland (yellow), open water (blue) and grass/shrub (green)

Figure 2.9. Example of blatant land classification error.
(Shrestha, 2022)

The shifts from among land types represent a relatively small fraction of total agriculture as shown in Figure 2.10.

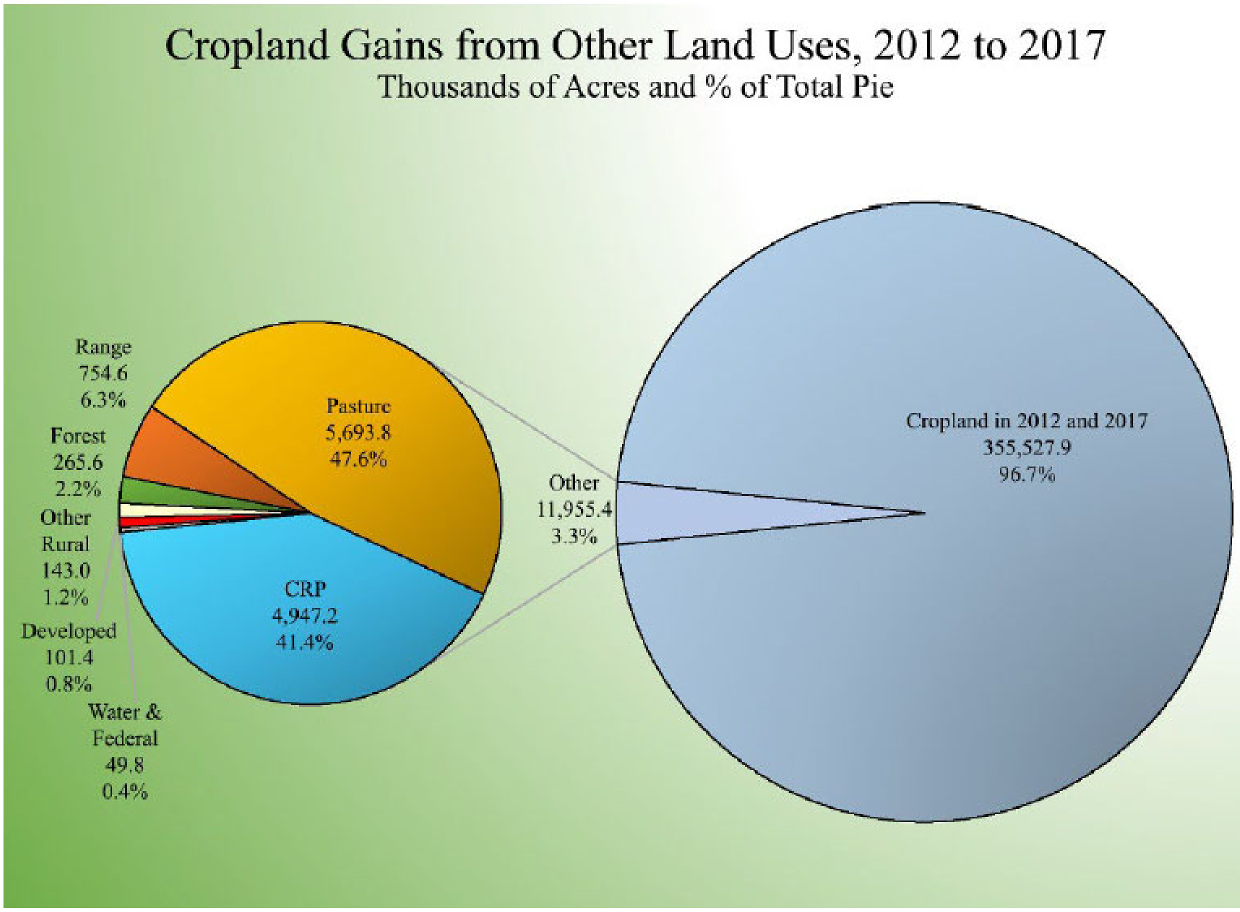


Figure 2.10. Cropland gains from other land uses, 2012 to 2017
In discussion of National Resources Inventory (NRI) (Flanagan, 2022)

The World Resources Institute provided data showing the expansion in oil crops (palm, soy) as well as cattle, cocoa, and coffee in Figure 2.11. U.S. cropland appears stable in this chart and the analysis does not present a relationship between biofuels and cattle expansion.

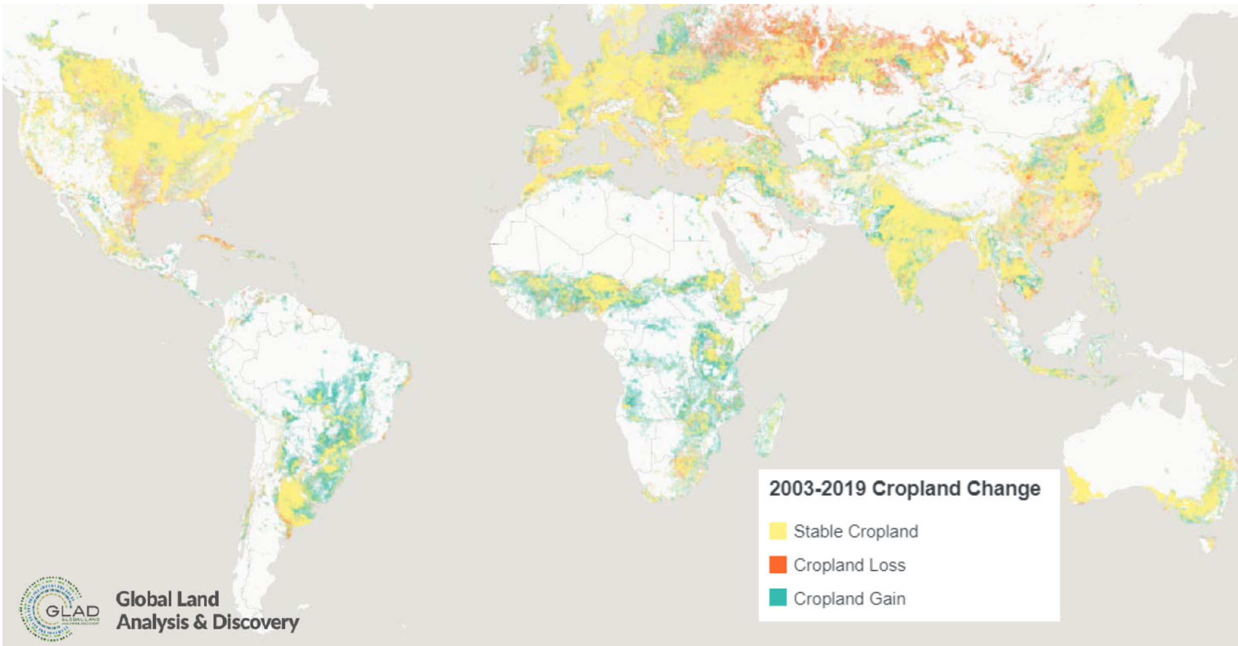


Figure 2.11. Extent and change in global cropland.
(Harris, 2022)

Dr. Jennifer Dunn of Northwestern University presented details related to the challenges in predicting land cover change. For example, grassland area varies greatly between survey and remote sensing-based methods of estimation. Much more land moves in and out of crop activity than permanent change.

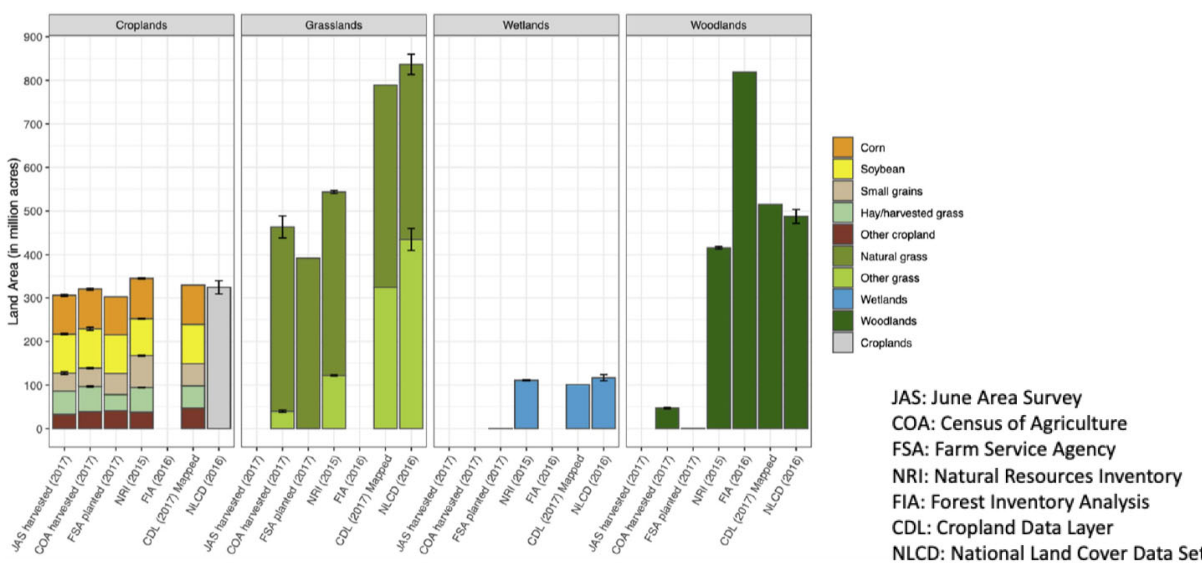


Figure 2.12. Various methods for estimating land cover type.
(Dunn, 2022)

USDA provided information on the changes in cropland for different crop types. The total agricultural land in the U.S. has remained relatively constant with some regional shifts as shown in Figure 2.14.

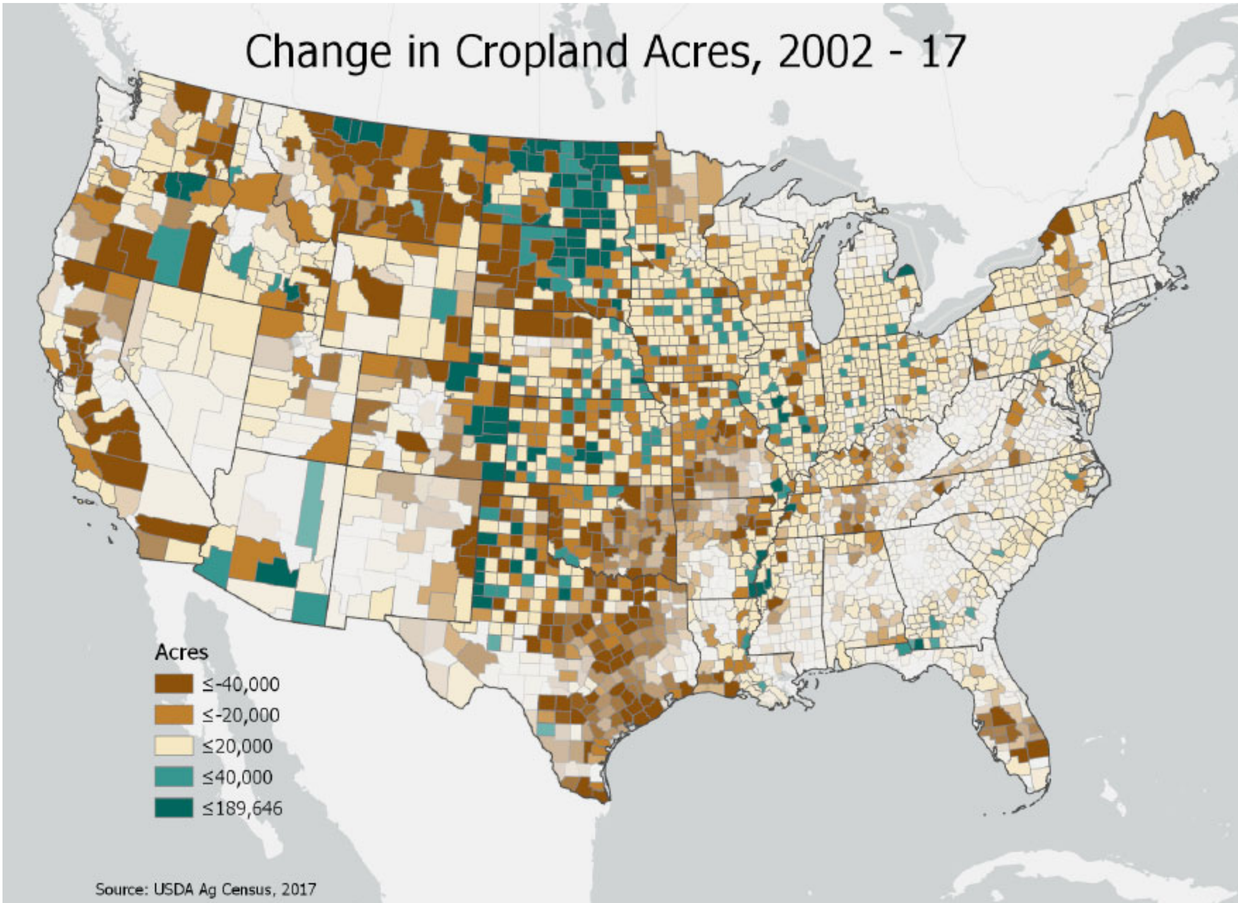


Figure 2.13. Changes in U.S. Cropland:2002 – 2017.
(Hohenstein, 2022)

Further methods of assessing land characterization were presented by the Seth Spawn-Lee of the University of Wisconsin. Expectations of evolving science were that observations would be spatially consistent and continuous and easily updatable with low uncertainty. However, land characterization continues to be data intensive and dependent on the quality of data. Figure 2.14 shows an example of improved soil mapping; however, it is unclear if such improvements also address the agricultural activity deployed on the land.

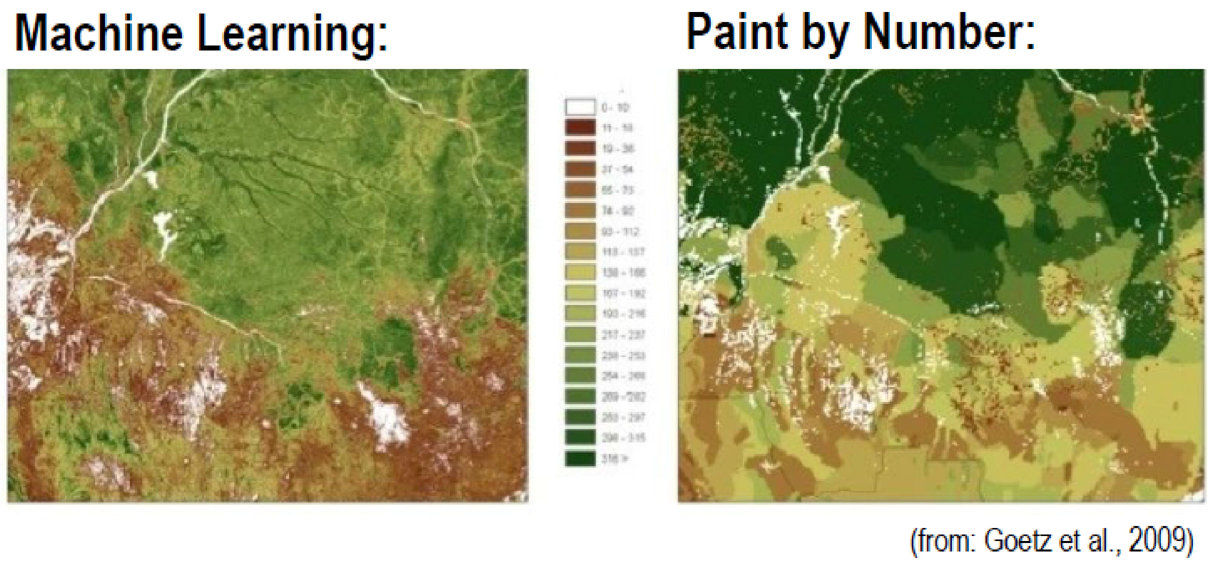


Figure 2.14. Approaches to soil mapping.
(Spawn-Lee, 2022)

While evolving methods to characterize land conversion provide an interesting area of research, land conversion continues to be mischaracterized in analyses of biofuels. For example, a review from Purdue University and Argonne National Laboratory (Taheripour, 2022) accessed the land conversion data layers in an assessment of RFS land cover change (Lark, 2022). They processed the data to see if they could produce results similar to those of Lark, 2022. Figure 2.15 shows substantial conversions to cropland in Lark, 2022. The National Agriculture Imagery Program (NAIP) imagery for each available year from 2003 onward was analyzed to assess the land cover. The analysis shows the Normalized Difference Vegetation Index (NDVI) for each polygon from 1984 to 2021. The Purdue team found that cropland typically has a sharp increase in NDVI from spring to summer, and then a sharp decline from summer to fall. Grassland or fallow land has higher NDVI values in the spring and fall, but lower summer values. Their comparison showed that fields that are identified by Lark, 2022 as expansion to cropland may often be short-term fallow/idle lands (less than 10 years). These estimations would "likely result in a systemic overestimation of SOC changes for these parcels".

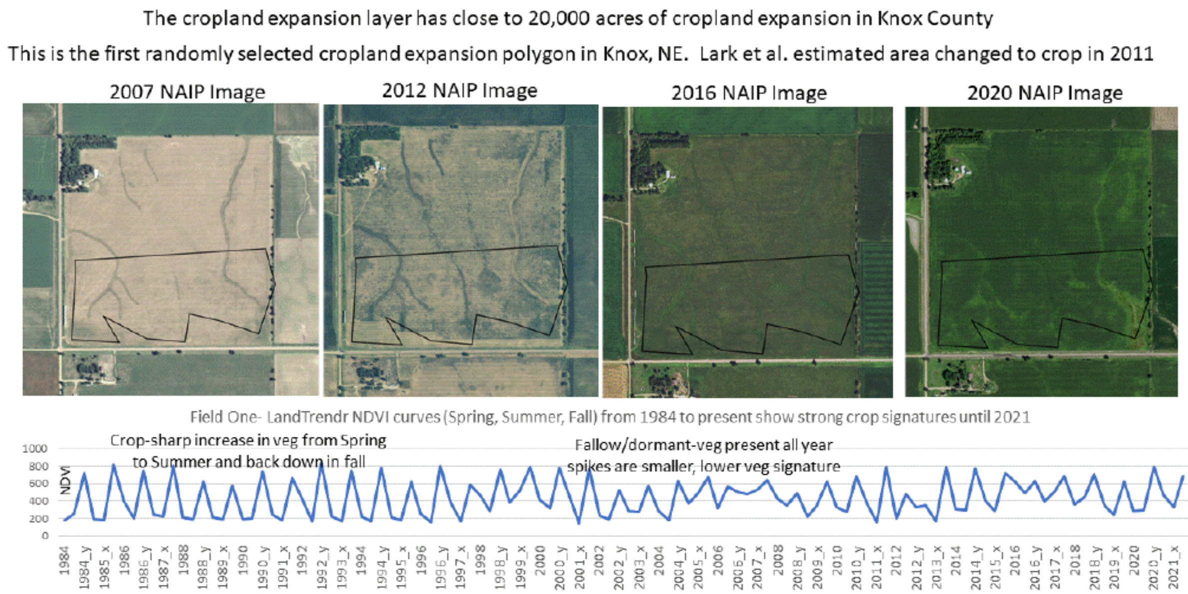


Figure 2.15. Examples of fields identified as crop and expansion (Lark, 2022) were actually fallow based on the Normalized Difference Vegetation Index.
(Taheripour, 2022)

3. Model Comparison and Uncertainty

Three presenters examined sources of uncertainty in biofuel LCA. Key charts from the presentation, which are shown below, show a range of GHG predictions for ILUC for different modeling systems and different feed stock fuel combinations. The presenters identify different categories of uncertainty (aleatory = randomness, epistemic = data and knowledge gaps).

The uncertainty analysis, when viewed without an understanding of the analysis, provides the impression that ILUC could be very high because some modeling systems and scenarios generate high ILUC results. However, this impression would be a misinterpretation that fails to adequately consider the effect of model inputs on the model results.

The high ILUC values cited in these presentations are the results of clearly identifiable modeling inputs. The analyses would be more enlightening if they identified the factors that result in high and low iLUC. Clearly low elasticity factors result in more land conversion and restricting interactions among uses of feed also results in higher iLUC emissions. An assessment of the basis for the elasticity factors would provide more insight into the iLUC of biofuels than simply showing the results for a range of scenario inputs.

Figure 3.1 shows the range of uncertainty values with the GLOBIOM model, which illustrates the challenge with this analysis approach. If the models are being run with parameters that correspond to high iLUC, the models will predict high iLUC. **The choice of model is likely not as important as the inputs.** Emphasis on understanding the inputs and relating historical data to the model inputs would be beneficial to reducing the uncertainty and variability across LUC estimates. To efficiently and accurately update LCA values for biofuels, EPA would be best suited to devote its resources to analysis of model inputs, rather than the development of additional models.

Model inputs which should be analyzed include:

- Biofuel shock
- Elasticities including: yield response, crop shifting, feed shifting, trade activity, shifts among pasture and cropland
- Co-product yields
- Implications of CRP program
- Carbon stock predictions (compare land cover changes, U.S. emission inventory, changes in crop patterns).

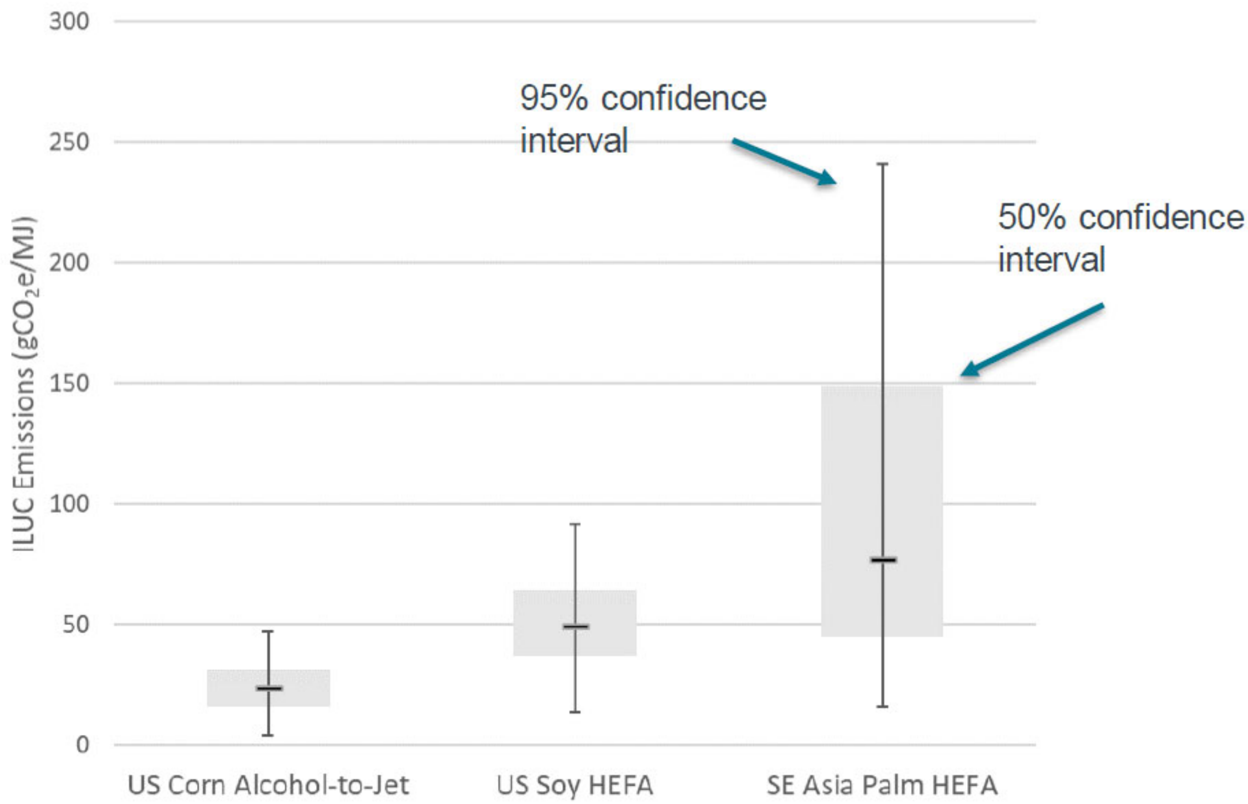


Figure 3.1. GLOBIOM ILUC Sensitivity Analysis Adapted from ICAO CORSIA LCA Methodology. (Pavlenko, 2022)

Similar results are obtained by exercising the range of model inputs to GTAP in Figure 3.2 and with a range of modeling approaches in Figure 3.3.

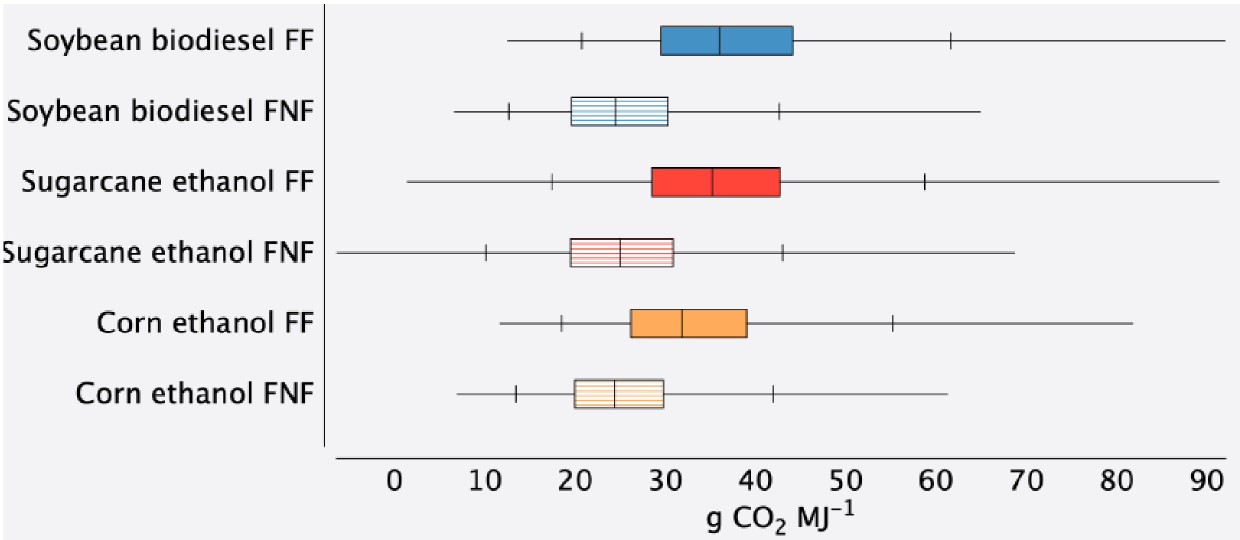


Figure 3.2. ILUC analysis with GTAP BIO and AEZ EF models
FF: food consumption fixed, FNF: food consumption not fixed (Plevin, 2022)

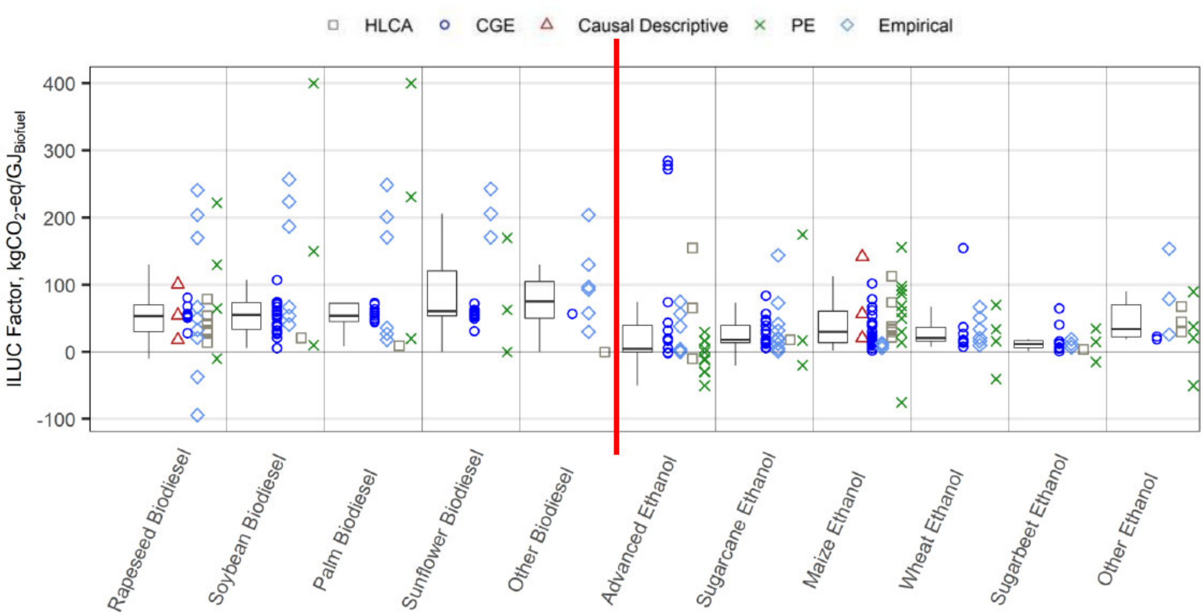


Figure 3.3. Distribution Ranges of Results across feedstocks and methodologies (Vassilis Daioglou, 2022)

4. Corn Farming and Soil Carbon Stocks

4.1 Corn Farming

Historical data on corn yield indicates that the yield has increased steadily over time, from 85 bu/ac in 1988 to 172 bu/ac in 2020 as shown in Figure 4.1. The adoption of double-cross hybrid corn, continued improvement in crop genetics, adoption of N fertilizer and pesticides, and agricultural mechanization resulted in a steady increase of corn yield in the U.S. (Nielsen, 2017). Aside from the steady increase of corn yield, the harvested area of corn has increased over time. Due to the continuous improvement of corn yield, the production quantity has an upward trend (USDA NASS, 2018). The 2010 RIA estimated the corn yield for 2022 as 185 bu/ac, based on past 30 years of corn yields from USDA database. EPA's projection of corn yield for 2022 is consistent with the trendline of current data in Figure 3.1. The USDA data presented here are consistent with global trends presented at the workshop and shown in Figure 3.2. Yields have improved both in the U.S. and globally. While EPA's projection of U.S. corn yields appear close to the outcome, an evaluation of yield in response to price would help inform the iLUC modeling.

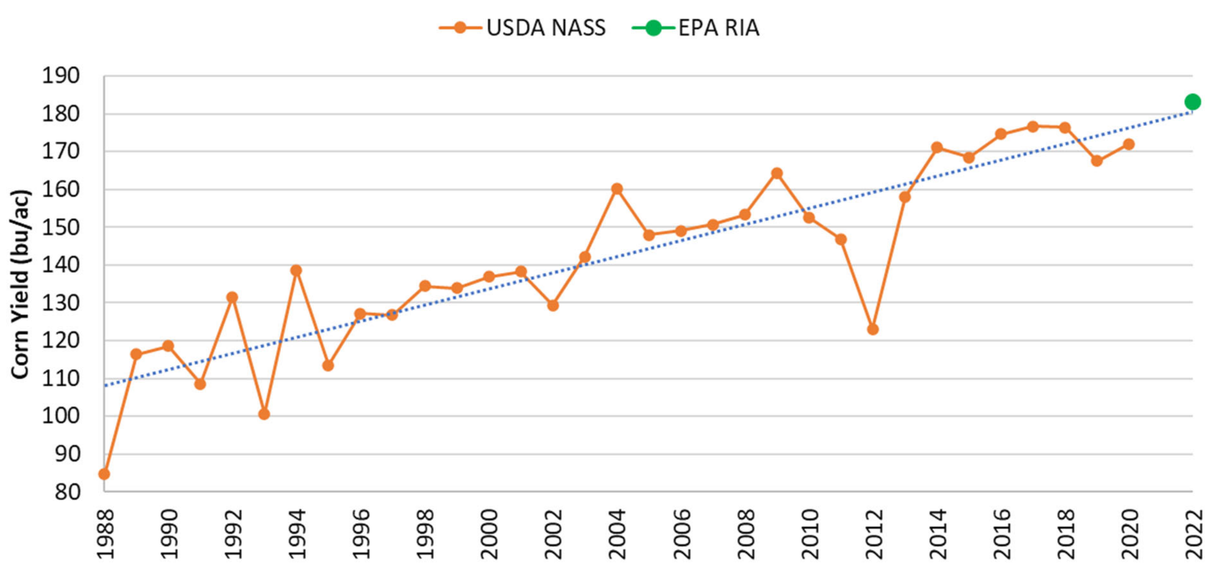


Figure 4.1. Corn Yield Over Time.

(USDA NASS, 2020)

Figure 4.2. Changes in corn yield over time for select countries.

(Hohenstein, 2022)

4.2 Emission Changes in Agriculture

Confirmation of Soil Carbon Savings in U.S.

Several studies have shown that corn crops produce large amounts of high carbon root and residue and this has a major positive impact on soil carbon stocks (ACE, 2018). Figure 4.3 implies that the organic matter content of the soil has improved over time due to corn farming. Part of domestic LUC shown in Figure 1.1 is the carbon stock change due to crop cultivation and the carbon stock due to corn cultivation, which leads to more GHG emissions saving and lower impact of domestic LUC. Clay et al. (2012) studied the impact of corn yield on soil carbon sequestration and reported that in many regions, surface soils are carbon sinks when seeded with corn.

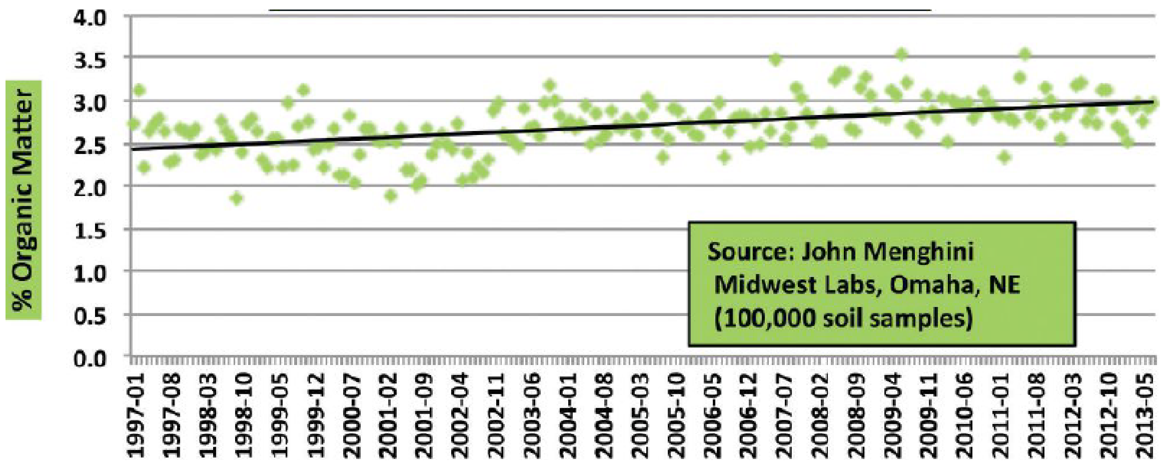


Figure 4.3. South Dakota Top Soil Organic Matter. (ACE, 2018)

The issue of soil carbon storage is illustrated in comments in the literature regarding LUC modeling. The authors of critiques of CCLUB, which represents the newest iLUC analysis from GTAP, (Malins, 2020) argue that the Winrock data for domestic crop conversion is more accurate (which is an option to utilize in GTAP). This is not a defensible position. Much of the debate around LUC estimates as presented in GTAP pertains to the use of emission factors associated with soil carbon release. CCLUB uses the CENTURY emission factors as defaults with Winrock data used by default for international emissions. Figure 4.4 shows the comparison of different emission factors, which support the argument that the higher Winrock emission factors for domestic ILUC would be an appropriate estimate; however, this argument is inconsistent with EPA's GHG accounting as used in the U.S. GHG inventory, which uses FASOM. Shifting to greater corn production from other crops along with the deployment of low carbon farming practices stores carbon, as reflected in FASOM and CCLUB. Accordingly, criticisms of the more recent versions of GTAP are misplaced; the LUC emissions in the U.S. should be negative as shown in the 2010 RIA (which utilizes FASOM) and in CCLUB.

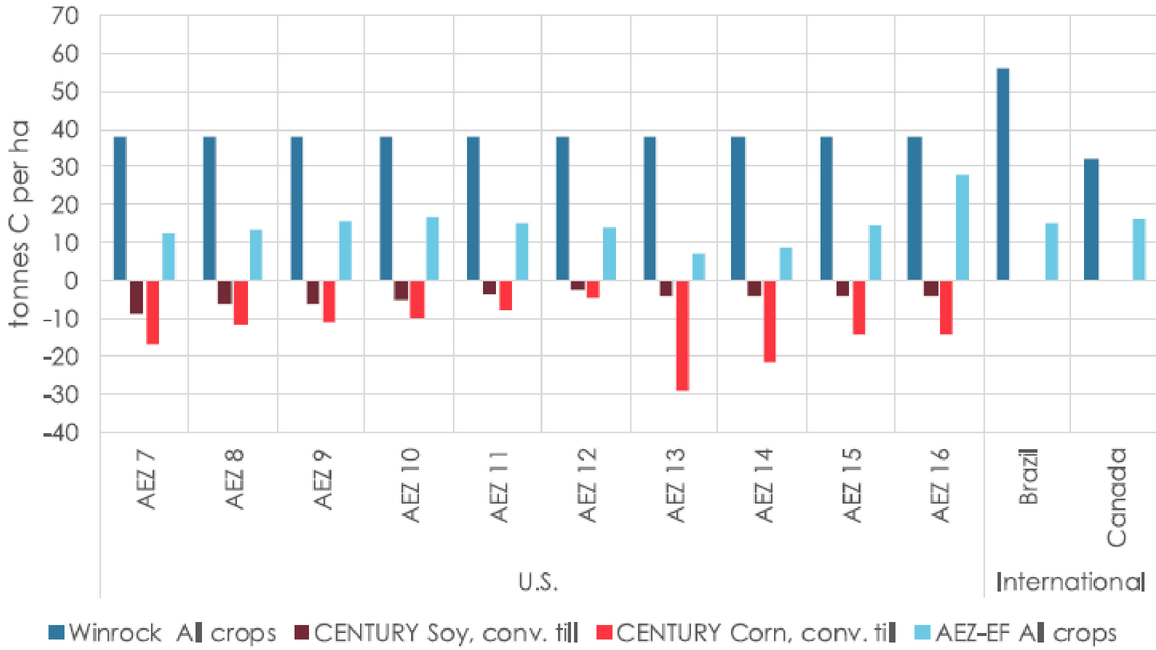


Figure 4.4. Carbon loss following cropland pasture conversion using Winrock, CENTURY and AEZ-EF emission factor models. (Malins, et al., 2020).

A significant outcome of the workshop were presentations that discussed the potential for soil carbon accumulation in the U.S. Figure 4.5 shows that land sinks for carbon, which can be enhanced through climate-smart agricultural practices, are a significant part of the U.S. GHG reduction strategy. Presentations at the workshop are consistent with this expectation.

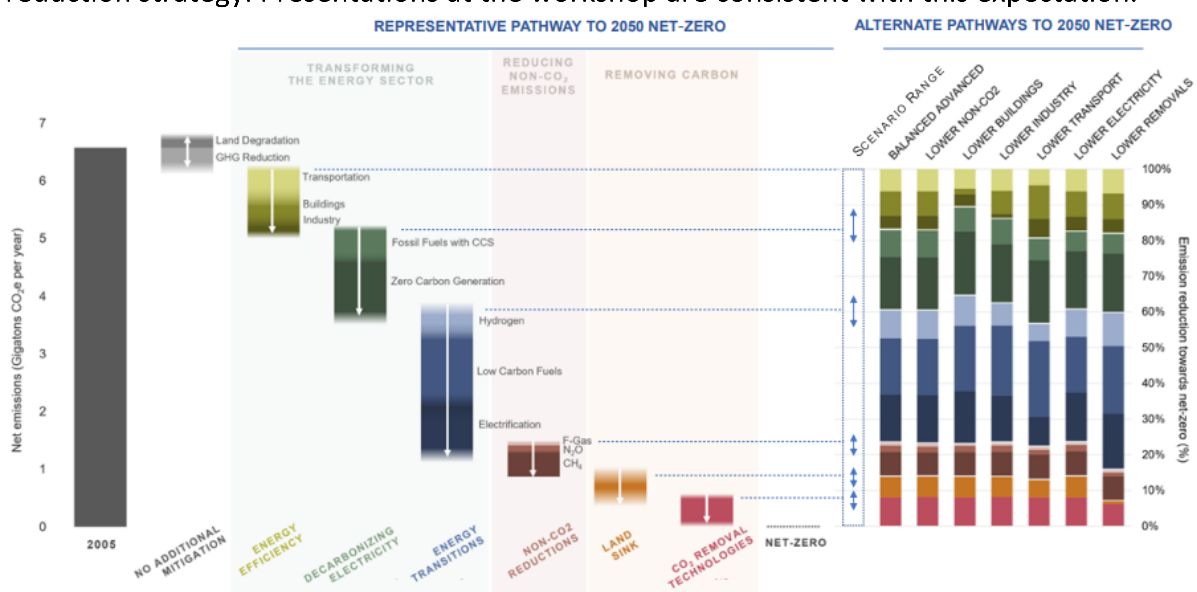


Figure 4.5. U.S. State Department includes emission reductions based on FASOM in projections to achieve 2050 Net-Zero in the United States.
(U.S. State Department, 2021)

The following figures show the trends for improved tillage activity in the U.S. as well as Colorado State's DayCent analysis for GHG predictions. The DayCent analysis is consistent with the CENTURY data used in the FASOM model that predicted a negative U.S. soil carbon change (carbon storage, see Figure 1.1). The relationship between this important prediction in the 2010 RIA and ongoing research was not covered in the workshop. The relationship between EPA's FASOM modeling, the U.S. agriculture inventory, and all of the estimates used to determine GHG reductions associated with regenerative agriculture are closely linked. EPA could perform a side-by-side comparison of soil carbon estimations among the modeling systems currently deployed for U.S. GHG accounting and compare those to the predictions in the 2010 RIA; however, this may be a challenging exercise. The latest Purdue analysis provides a revised estimate of iLUC as described in Section 2.2

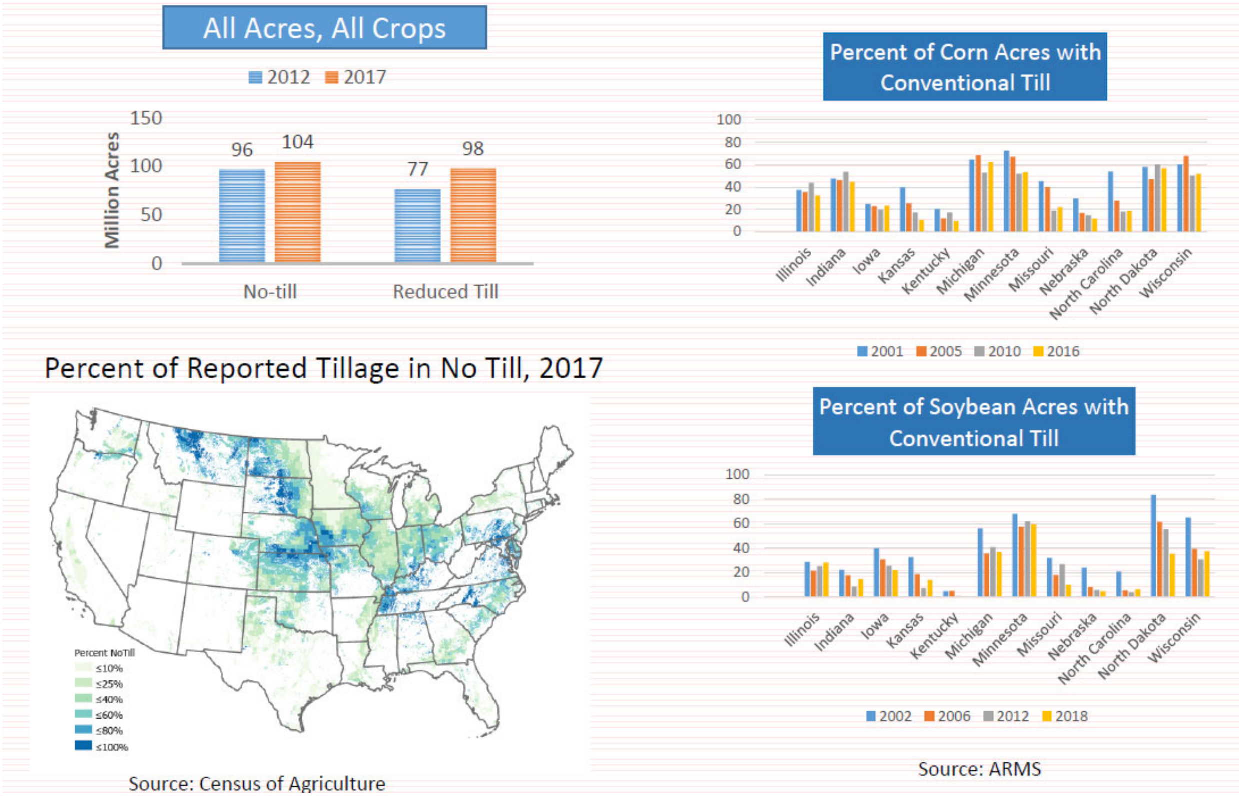


Figure 4.6. USDA data shows a trend for an increase in no till agriculture.
(Hohenstein, 2022)

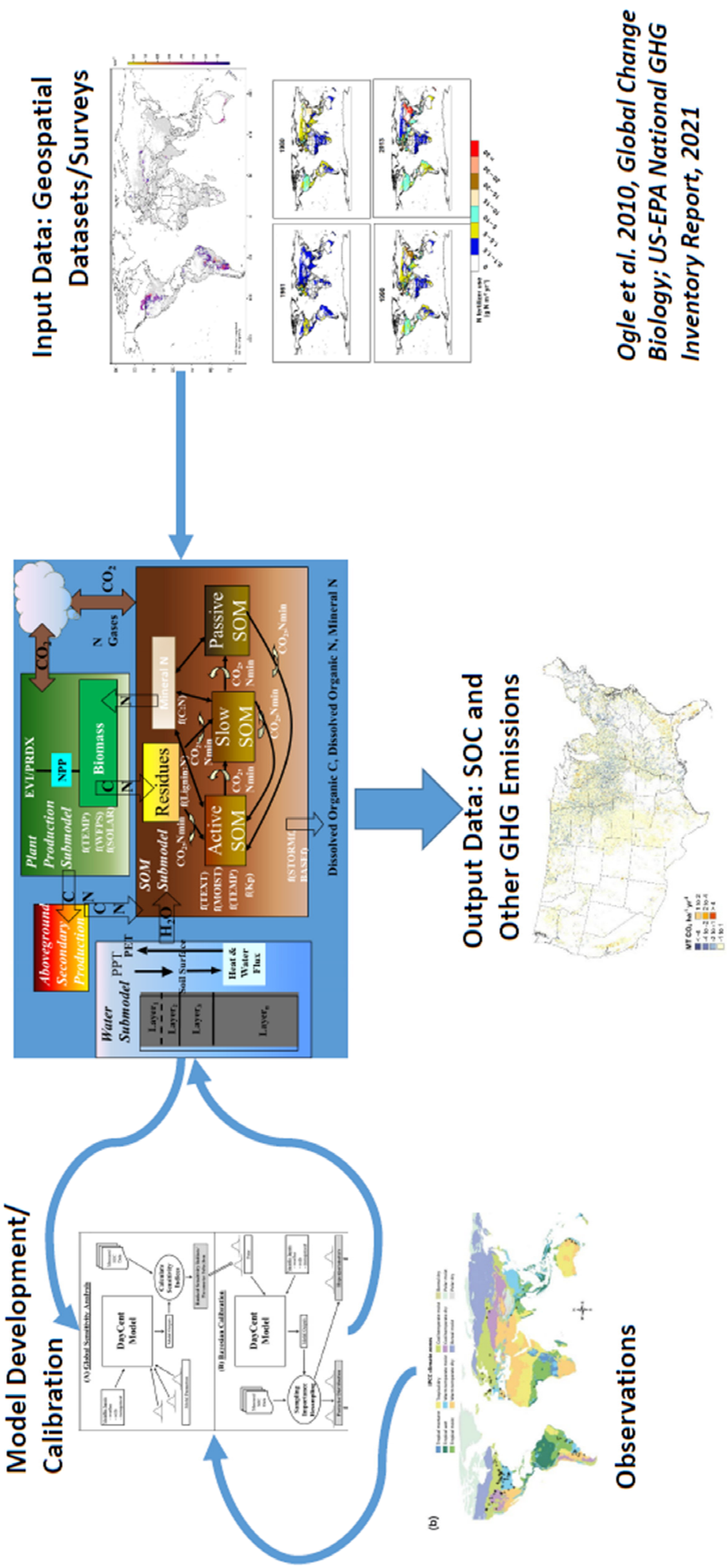
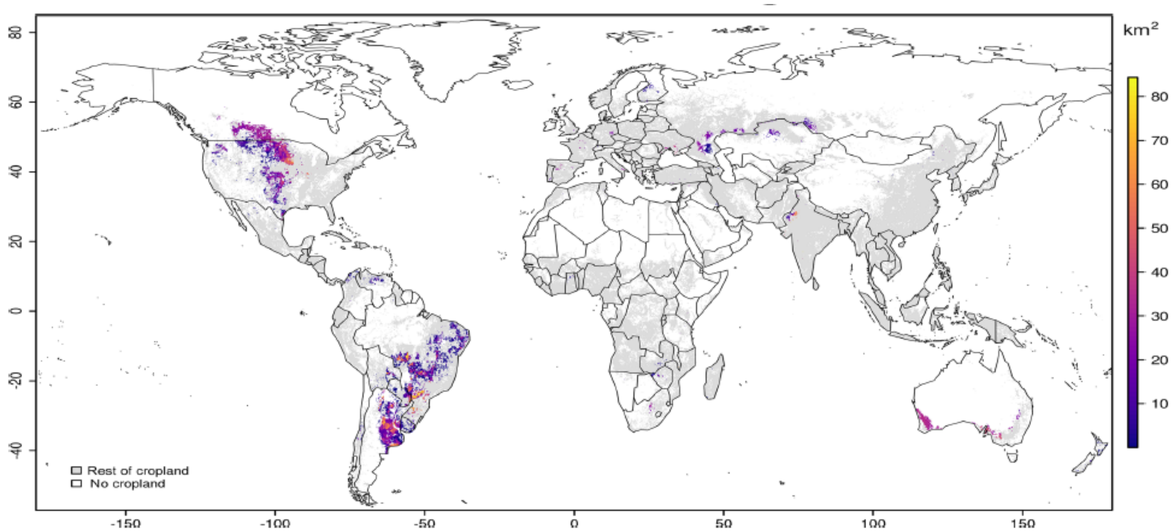


Figure 4.7. DayCent ecosystem modeling platform. (Ogle, 2022)



Porwollik et al. 2019, Earth Syst. Sci. Data

Figure 4.8. Global Implementation of conservation tillage.
(Ogle, 2022)

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