# Review of GHG Emissions of Corn Ethanol under the EPA RFS2

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# DISCLAIMER



# ACKNOWLEDGEMENT

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# CONTENTS

# Tables

# FIGURES

# Terms and Abbreviations

| | |
|---|---|
| aLCA | Attributional Life Cycle Analysis |
| ANL | Argonne National Laboratory |
| ARB | California Air Resources Board |
| CA | California |
| CA-GREET | The standard GREET model modified for use in CA LCFS |
| $CH_4$ | Methane |
| CI | Carbon intensity |
| cLCA | Consequential Life Cycle Analysis |
| CO | Carbon monoxide |
| $CO_2$ | Carbon dioxide |
| DOE | U.S. Department of Energy |
| 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 |
| HC | Hydrocarbon |
| IPCC | Intergovernmental Panel on Climate Change |
| LCA | Life Cycle Analysis or Life Cycle Assessment |
| LCFS | Low Carbon Fuel Standard |
| LCI | Life Cycle Inventory |
| LCFS | Low Carbon Fuel Standard |
| LHV | Lower Heating Value |
| $N_2O$ | Nitrous oxide |
| NG | Natural Gas |
| RIA | Regulatory Impact Analysis |
| RFS2 | Revised Federal Renewable Fuels Standard |
| UN | United Nations |
| UNFCC | United Nations Framework Convention on Climate Change |
| VOC | Volatile Organic Compound |
| WTT | Well-To-Tank |
| WTW | Well-To-Wheel |

# EXECUTIVE SUMMARY

Twelve years of experience and improved analysis methods have provided new insight into the life cycle greenhouse gas (GHG) emissions from corn ethanol. This study reviews the key factors that affect the life cycle emissions from corn ethanol production as well as the most recent agricultural data. Some of the key factors affecting corn ethanol have evolved as predicted in EPA's 2010 Regulatory Impact Analysis (2010 RIA), while other factors point towards substantially lower life cycle GHG emissions.

EPA developed a consequential LCA approach that estimated the emissions associated with the incremental ethanol capacity induced by the RFS policy as well as the incremental crop production required to make up for the net effect of corn crops diverted to ethanol production and distiller's grains sold as animal feed. The modeling approach involved a combination of the FASOM model that has been used to develop the U.S. inventory for agricultural emissions, the FAPRI model, which estimates the effect of the use of agricultural products on global agricultural production, and the GREET model, which estimates life cycle GHG emissions from the fuel used in ethanol plants. EPA's analysis aligned the economic modeling of the FASOM and FAPRI modeling and calculated emission impacts that are tied to the model predictions including changes in rice and beef consumption as well as deforestation associated with new crop production.

The 2010 RIA overestimated the GHG impact of corn ethanol due largely to overestimating indirect land use conversion (ILUC) emissions as well as numerous small details associated with the life cycle of corn ethanol. EPA's agro-economic models rely on economic projections to attribute land use change to crop production without considering factors such as changes in farming and cattle production practices. Recent data on deforestation has shown that land ownership is much more important in affecting deforesting than the macro-economic pressure or crop prices. Burning in the Amazon has declined and increased due to policies associated with land ownership. A more accurate representation of the effect of crops on pasture conversion is represented in more recent publications based on the GTAP model and EPA would generate similar results if its ILUC modeling tools included an accurate representation of factors such as flexibility in changing cattle stocking rates. The analysis inputs to GTAP modeling would yield similar results in the FASOM/FAPRI modeling system. If EPA continues to use the FAPRI results for its international LUC analysis, the results could be scaled to reflect the values from GTAP that more accurately represent the interaction between pasture and cropland.

Several other factors affecting corn ethanol have also changed since the publication or the 2010 RIA. Corn ethanol uses about 0.7 kWh to produce one gallon of ethanol and the GHG intensity of electric power has declined substantially with increased natural gas production, a reduction in coal-based power, and growth in renewable power. The RIA also underestimated the adoption of low emission technologies that have resulted in lower emissions from ethanol plants and many small details associated with each step of the ethanol life cycle.

More significantly, EPA underestimated the effect of distiller's grains and corn oil. Much of the corn used for ethanol production has resulted in the displacement of soybean production. The same acre of land that was producing soybeans and converted to corn for ethanol produces the same amount of feed via the distiller's grains from the ethanol plant. Therefore, any change in net feed requirements is subtle at best. The GREET model also underestimates the displacement effect of both soybeans and urea that would otherwise be fed to cattle. Even though soybeans fix nitrogen[1], USDA data shows that they have required more nitrogen fertilizer than projected in the RIA. Also, the emissions associated with urea feed in the GREET model omit the displacement of fossil carbon[2] in urea. Corn ethanol plants have produced significant quantities of corn oil as predicted in the 2010 RIA. However, about half of the corn oil is used as biodiesel which corresponds to about 2.5% of the energy output of an ethanol plant. The GHG emissions associated with corn production and any ILUC should be partially assigned to biodiesel.

These factors should be incorporated in EPA's GHG analysis of corn ethanol in this 2020, 2021, 2022 Renewable Volume Obligation (RVO) rulemaking, including the following considerations:

- ILUC and soil carbon storage should reflect the latest research.
  - ANL soil carbon storage modeling (CCLUB) shows increased soil carbon storage with corn farming that was not taken into account in the 2010 RIA.
  - New analysis based on the GTAP shows the effect of pasture intensification which predicts lower rates of forest conversion to agriculture.
  - CARB revised ILUC for LCFS from 30 g $CO_2$e/MJ to 19.8 g $CO_2$e/MJ with the newest GTAP results showing 7.5 g $CO_2$e/MJ.
- The FASOM and FAPRI modeling system predict effects that are not tied to ethanol use and should be corrected.
  - The latest data and science demonstrate that deforestation rates occur due to many factors and the supply and demand of agricultural products has little effect on this phenomenon.
- Co-product credit value of distillers' grain solubles (DGS) is higher than anticipated due to:
  - Greater emissions from the displacement of soybean meal;
  - Higher nitrogen (N) application rate on soybeans than originally anticipated;
  - Displacement of fossil $CO_2$ in urea feed.
- A high adoption rate of corn oil extraction has led to the rapid growth in use of corn oil as biodiesel feedstock.
  - The preferred use of corn oil is biodiesel; so, the appropriate co-product treatment for 50% of the corn oil is as an energy product via allocation.

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[1] Soybeans and other legumes assimilate nitrogen from the atmosphere into organic compounds through a process known as fixation.

[2] The GHG intensity of urea in the GREET model represents the life cycle emissions per ton of urea. The urea molecule includes carbon that is derived from natural gas. When urea is used as fertilizer or animal feed, the carbon is metabolized to produce $CO_2$. GREET counts the field emissions for urea when used as fertilizer but omits the emissions when it is used as a co-produce animal feed.

    - Corn oil when used as a biodiesel feed displaces fats such as soy oil and palm oil which have much higher indirect land use change (ILUC) values than corn oil when treated as DGS mass.
- Ethanol plants produce lower GHG emissions than estimated in the 2010 RIA due to:
    - Elimination of coal for dry mill plants with natural gas;
    - Lower carbon intensity for electric power used by ethanol plants;
    - Use of biogas motivated by California low carbon fuel standard (LCFS) program;
    - Ongoing efficiency improvements from many sources;
    - Utilization of $CO_2$ to displace fossil sources and $CO_2$ sequestration.
- 2005 Petroleum baseline in the 2010 RIA is underestimated because the baseline fails to adequately account for:
    - Higher rates of methane venting and flaring from oil production;
    - Mix of secondary oil recovery technologies and oil sands.

This study found that corn ethanol has resulted in greater GHG emission reductions compared to those originally predicted in the 2010 RIA. The results for dry mill corn ethanol plants from this Study (Figure S.1) are aligned with the approach in the 2010 RIA. The emissions are based on GREET calculations and adjustments to reflect EPA's categories with projections for energy use in 2022 developed in this study. The emissions include allocation of half of the GHG emissions associated with corn oil to biodiesel. Higher nitrogen application rates for soybean farming, which affect the DGS co-product credit as well as fossil carbon displaced in urea feed are also considered in the analysis. The lower carbon intensity of electric power compared to 2010 projections is reflected in fuel production emissions. The small effect on rice methane and livestock emissions is based on the recent study funded by the U.S. Department of Agriculture by ICF (Rosenfeld, 2018). These results compared with appropriate adjustments to EPA's 2005 baseline translate into about a 48% reduction in GHG emissions as shown in Figure S.1.

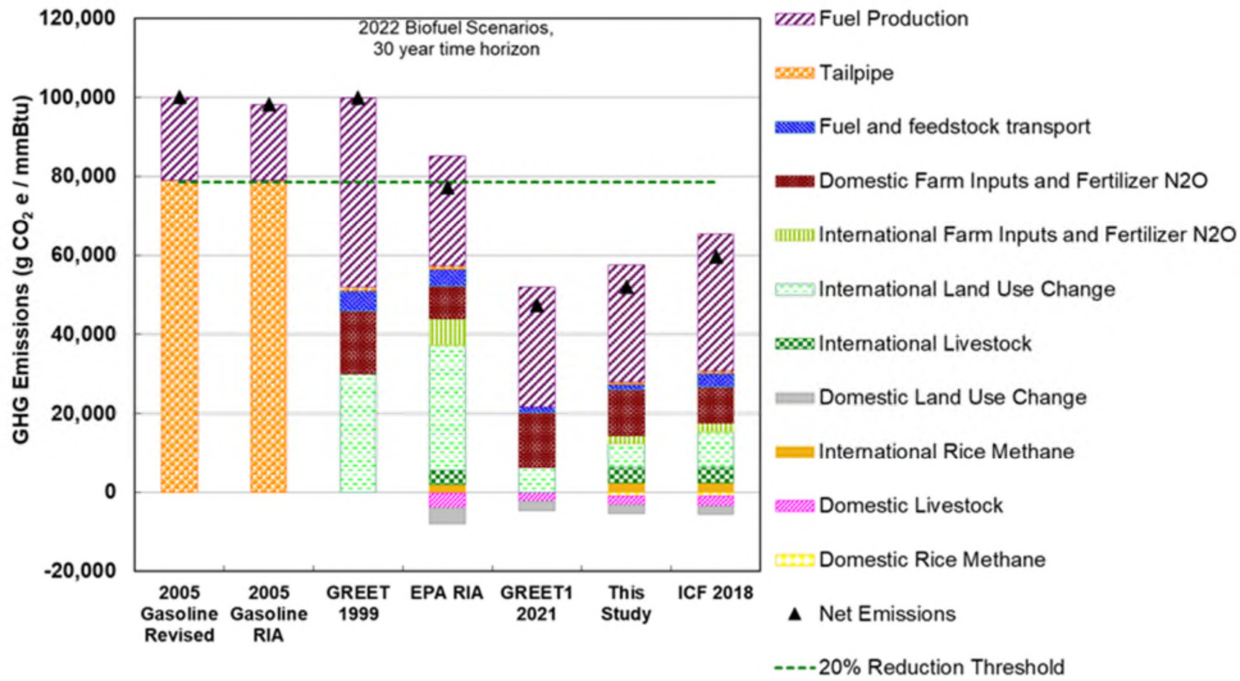


**Figure S.1.** Life Cycle GHG Emissions from Dry Mill Corn Ethanol and 2005 Petroleum Gasoline.

# 1. INTRODUCTION

As part of EPA's 2010 Regulatory Impact Analysis (2010 RIA) of the Renewable Fuel Standard (RFS), it conducted a life cycle assessment (LCA) of the biofuels specified in RFS2 by accounting for direct and indirect emissions for the year 2022. 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 1.1). The highest GHG emissions for corn ethanol correspond to international land use change (LUC) followed by Fuel Production. International LUC corresponds to the change in carbon 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. 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 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.

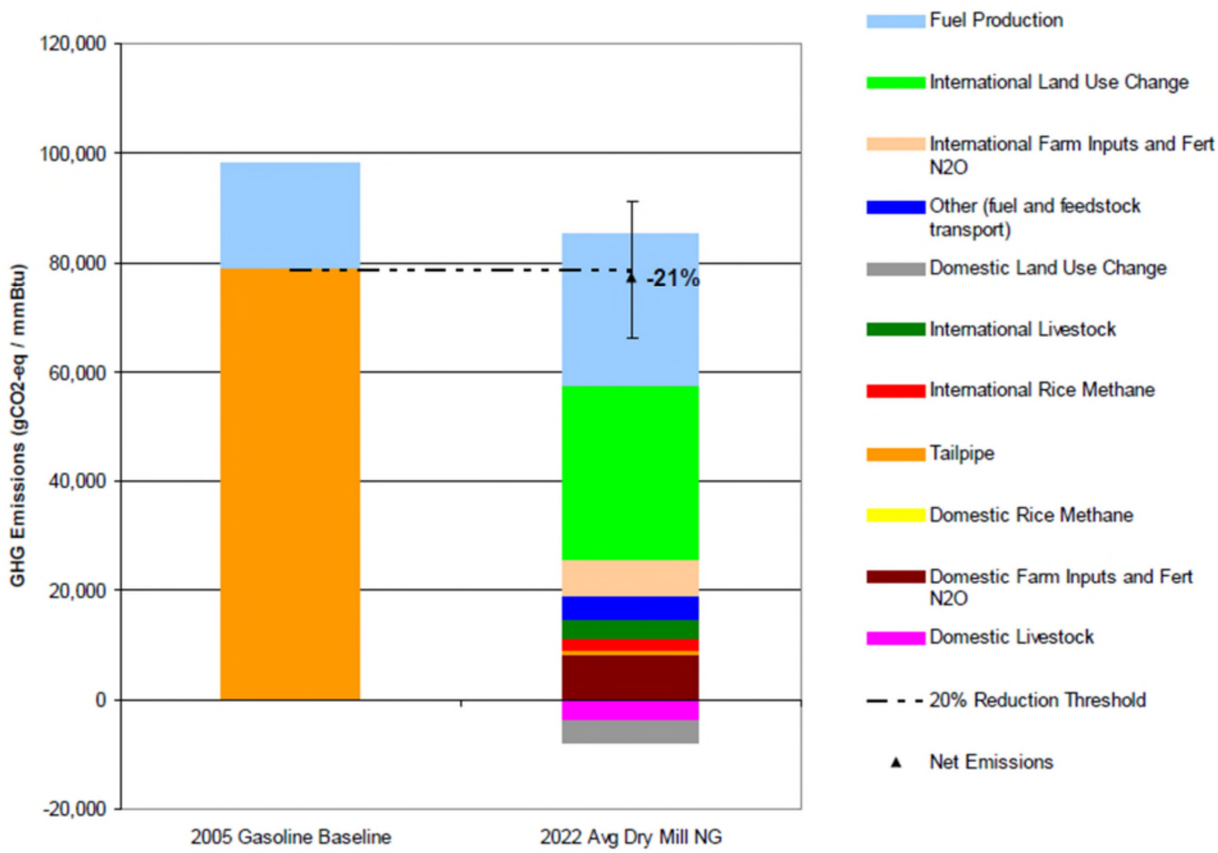


**Figure 1.1.** EPA's Analysis of Corn Ethanol GHG emissions. (EPA, 2010)

The objective of this study is to evaluate EPA's analysis based on the availability of new data and a better understanding of models and assumptions. This study focuses on emission categories with the highest impacts such as international land use change and compares the results of 2010 RIA with the new findings. Another key effect examined in the study is the impact of co-product credits and different methods of allocation. The study includes the following sections.

- Sections 1.1 to 1.4 provides an introduction to corn ethanol life cycle GHG emissions.
- Section 2 presents domestic and international land use change and their impacts on corn ethanol carbon intensity.
- Section 3 discusses farming inputs and the sensitivity analysis.
- Section 4 presents the impact of different co-products and their allocation factors on corn ethanol carbon intensity.
- Section 5 describes technologies used in ethanol production and their advancements.
- Section 6 analyzes the energy sources used in the fuel production stage.
- Section 7 describes the GHG emissions related to various types of extraction of fossil fuels and their projection.
- Section 8 presents the results of this study and compares them with those of other studies and EPA RIA.
- Finally, Section 9 summarizes this Study's conclusions.

## 1.1 Life Cycle GHG Analysis

The RFS2 and other biofuel policies around the world require GHG reduction targets relative to the conventional fossil fuels. The GHG reduction is measured through life cycle assessments (LCAs), which account for cradle-to-grave emissions (and/or other environmental impacts), starting with raw material extraction and ending with fuel consumption. LCA is a technique used to model the environmental impacts associated with the production of materials. LCA models assess environmental impacts over a range of categories, including energy consumption, GHG emissions, criteria air pollution, eutrophication, acidification, water use, land use, and others. The analysis includes a full inventory of all the inputs and outputs involved in a product's life cycle. Determining life cycle emissions for all inputs requires an iterative analysis of these components because some components of the life cycle of fuels depend on inputs that are part of the LCA. The net GHG emissions are converted to a $CO_2$-equivalent basis and then normalized by the energy content of the fuel (e.g. g $CO_2$e/MMBtu). This carbon intensity (CI), when compared with the CI of petroleum fuels, provides a measure of the net GHG reductions of renewable fuels.

In the case of corn ethanol, with the U.S. the largest producer of corn in the world, the hypothesis is that diverting corn to biofuel feedstock reduces the supply of corn in food and feed markets. This effect is realized through increases in the price of corn and other agricultural commodities globally. In order to address the shift in corn supply, farmers across the globe switch from other crops to corn (direct land use change) or convert grasslands, wetlands, or forests which are carbon sinks to crop production. The conversion of land to cropland results in indirect land use change (ILUC) emissions due to the release of carbon in the soil, above ground biomass, and the foregone sequestration of $CO_2$. Two different approaches covering the extent of life cycle impacts are referred to as attributional and consequential LCA. Attributional LCA (aLCA) focuses on the direct processes used to produce and consume a product while consequential LCA (cLCA) examines the consequences of possible (future) changes between alternative product systems (Brander et al., 2009). An aLCA identifies the direct energy inputs and emissions associated with corn farming and ethanol production. A cLCA identifies the net change in global emissions due to induced impacts of corn consumption, energy inputs for ethanol plants, and ethanol use. The 2010 RIA is aimed at calculating cLCA emissions based on the displacement effect of corn diverted to ethanol production.

## 1.2 Land Use Change

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 to crops as illustrated in Figure 1.2

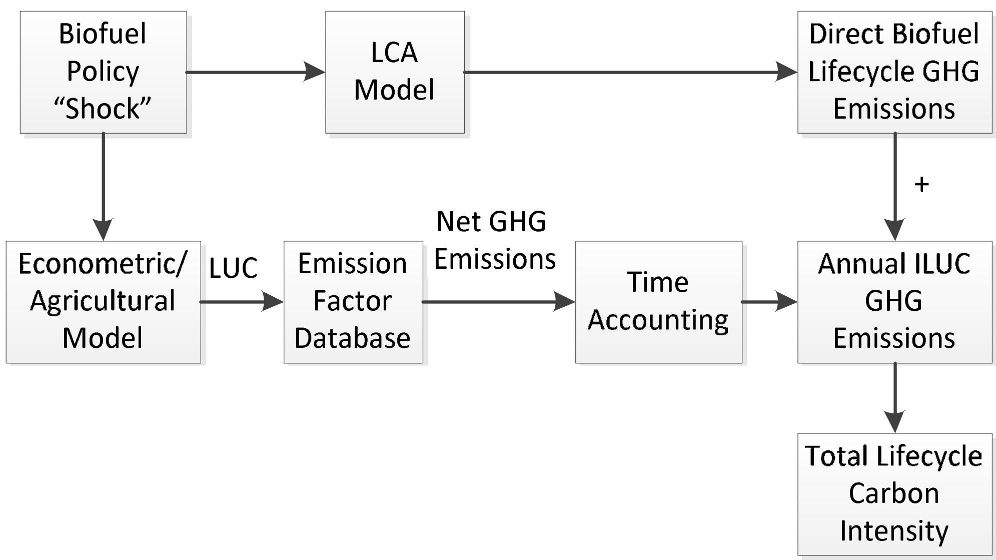


**Figure 1.2.** Modeling Flow for Determination of Total Biofuel Lifecycle Carbon Intensity, Including Both Direct and Indirect Effects.

## 1.3 Modeling Approaches

The system boundary defines the scope of activities and emissions associated with a life cycle analysis. The inputs to the system and emission flows are counted in the analysis are defined in a system boundary diagram (SBD). The system boundary identifies how far emissions are tracked and the treatment of co-products.

### 1.3.1 Approach for Revised GHG Analysis

This study combines new data on corn ethanol production with the methods used by EPA in the RIA to develop a revised estimate of the GHG emissions associated with corn ethanol. Repeating the details of the modeling in the RIA is not practical due to the complexity of the FASOM and FAPRI modeling systems. This study estimated the emission categories within the 2010 RIA methodology based on energy inputs and co-product yields thereby allowing for a comparison with the 2010 RIA results.

The system boundary used in this study is shown in Figure 1.3. Ethanol and corn oil for biodiesel are fuel products. Corn oil is also used as animal feed as modeled in the 2010 RIA but current fuel policies favor the use of corn oil as a biodiesel feedstock. Fermentation $CO_2$ is another coproduct for many ethanol plants. This study compares data on corn production, ethanol inputs and ethanol plant yields with those in the 2010 RIA and then estimates emissions for each of the RIA categories based on the best available data. The effect of each of the co-products on the net life cycle emissions is examined here.

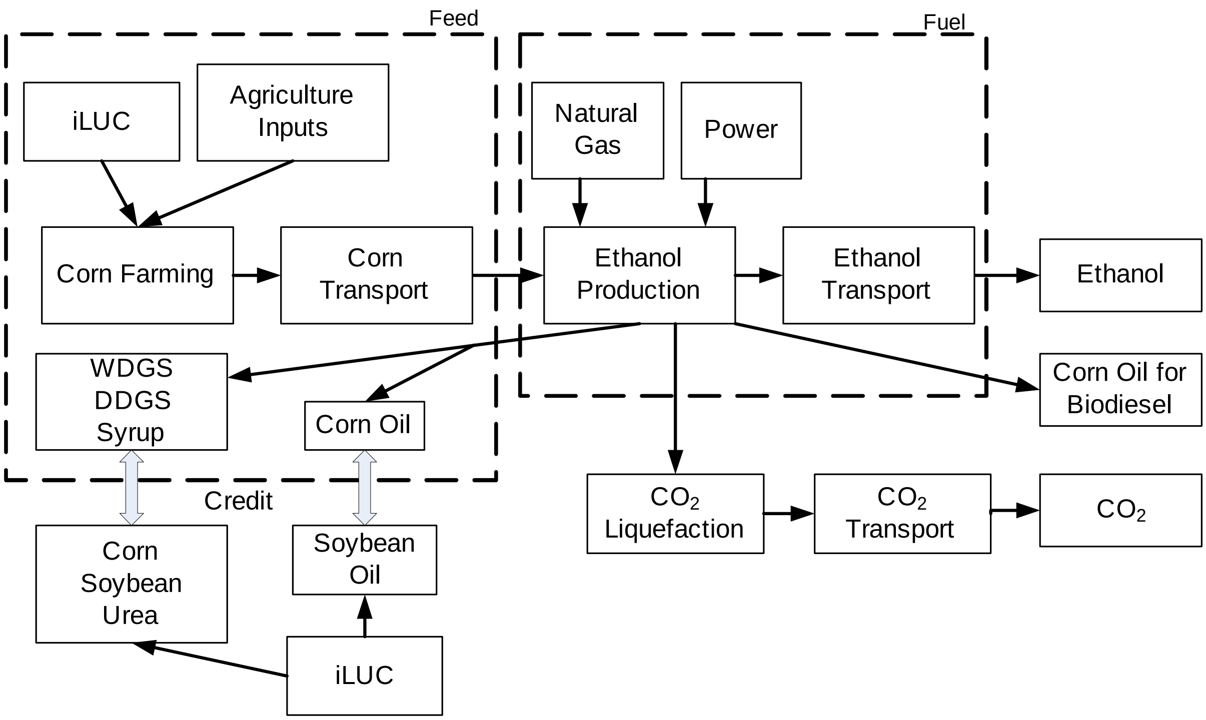


**Figure 1.3.** System Boundary Diagram for Corn Ethanol Production.

## 1.4 Global Warming Potential

The global warming potential (GWP) represents GHG emissions based on their radiative forcing and lifetime in the atmosphere on equivalent units of carbon dioxide ($CO_2$). These factors are estimated by the Intergovernmental Panel on Climate Change (IPCC) and updated in each IPCC Assessment Report (AR). The 2010 RIA used the factors provided by the IPCC's Second

Assessment Report (SAR), however, these factors have been updated since 2010 and the most recent one is the Fifth Assessment Report (AR5) shown in Table 1.1 (IPCC, 2014). This study uses the AR4 factors to calculate the CI of fuels since these values are currently adopted by the EPA for calculations of the national GHG inventory.

**Table 1.1.** Global Warming Potential (100-year time horizon).

| Greenhouse Gas | SAR | AR4 | AR5 |
|---|---|---|---|
| $CO_2$ | 1 | 1 | 1 |
| $CH_4$ | 21 | 25 | 28 |
| $N_2O$ | 310 | 298 | 265 |

# 2. Domestic and International Land Use Change

Since 2010 when EPA conducted the RIA, 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, as well as new studies on LUC, are discussed below. EPA's approach to ILUC modeling, improved ILUC estimates, and the estimates used in this study are discussed.

## 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.

### 2.1.1 EPA Modeling Approach

The system boundary used in 2010 RIA is shown in Figure 2.1. The analysis includes the direct emissions associated with tailpipe emissions, fuel production, fuel and feedstock transport. The carbon in fuel is treated on a carbon neutral basis with zero emissions associated with the short cycle carbon in ethanol and ethanol plant fermentation emissions. The effects of the corn feedstock are analyzed in a cLCA with estimates of the effects of an incremental increase in the use of ethanol and consumption of corn. The modeling takes into account the direct farming emissions in the U.S. and internationally as well as the effect on rice and livestock methane emissions due to shifts in the production of agricultural products. The U.S. emissions are predicted with the FASOM model and the international crop production is predicted with the FAPRI model combined with emission factors for land cover change and agricultural inputs.

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

[3] EPA 2010 RIA, Section 1.1.1.1

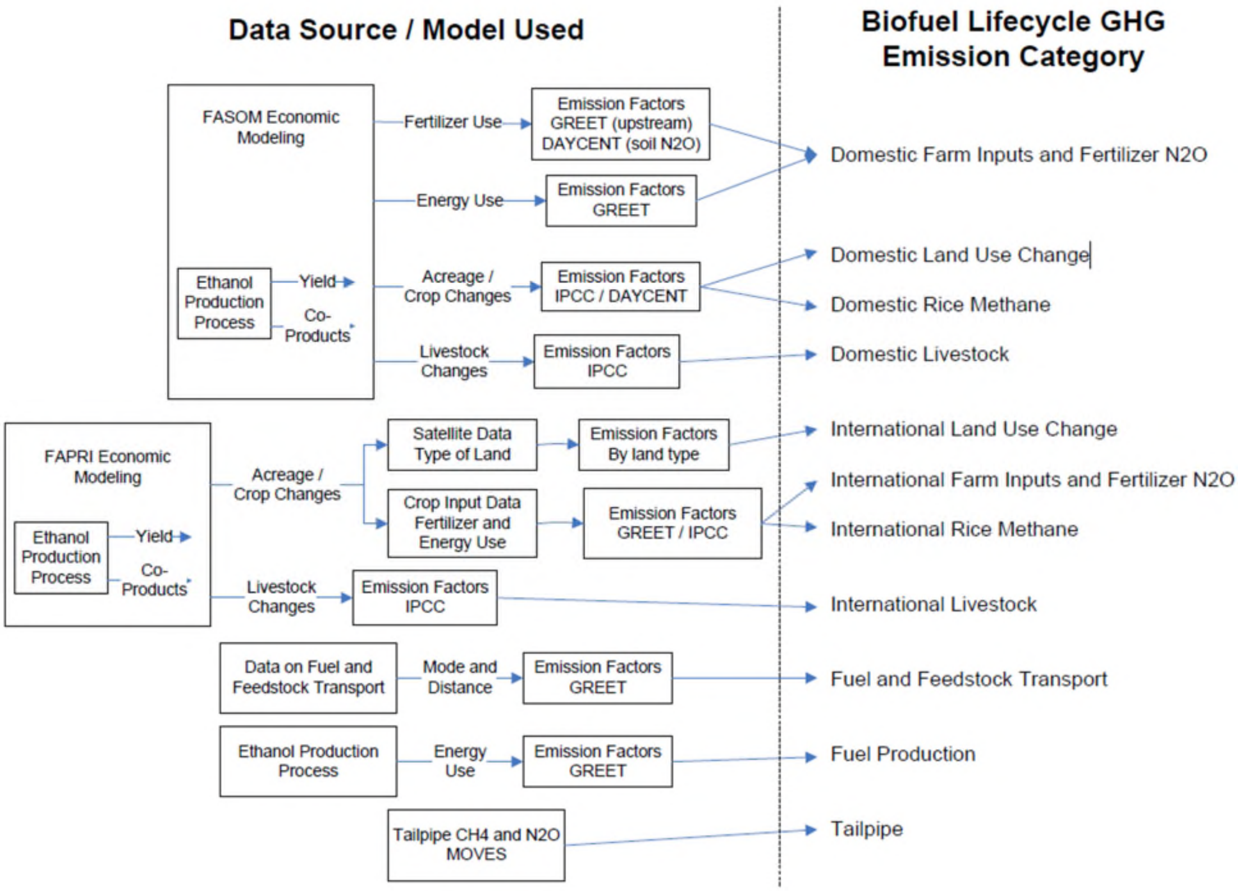


**Figure 2.1.** System Boundary Used in EPA RIA Study. (EPA, 2010)

For the purposes of discussion in this study direct and indirect land use change are described separately.[4] Direct land use change refers to land already used for a specific purpose (e.g. growing food) and whose future use will achieve the same result. For instance, in response to an increase in production of corn ethanol, lands previously used for food production might be converted to corn for fuel. On the other hand, indirect land use change refers to the land whose ultimate purpose is essentially changed from its previous use (Farm Energy, 2019). For instance, converting forests or grasslands to agricultural land is called indirect land use change. The 2010 RIA aggregated the impacts of direct and indirect land use change in the U.S. and called it "domestic land use change." Also, the RIA assumed international land use change occurred as a result of domestic biofuel production expansion.

EPA used the Forestry and Agricultural Sector Optimization Model (FASOM), developed by Texas A&M University and others, to estimate the changes in crop acres resulting from increased biofuel production. FASOM is a partial equilibrium model of the forest, agriculture,

[4] Some argue that all LUC is indirect since corn used for biofuel production is diverted from the overall U.S. corn supply.

and livestock for the United States. The model tracks U.S. cropland by county and estimates emissions associated with the conversion to cropland (i.e. domestic land use change). Within the model, the linked agricultural and forestry sectors compete for a portion of the land within the U.S. Prices for agricultural and forest sector commodities as well as land are endogenously determined given demand functions and supply processes. The FASOM model maximizes the net present value of the sum of consumers' and producers' surpluses (for each sector) with producers' surplus estimated as the net returns from forest and agricultural sector activities. The GHG calculations are based on available data on inputs from crop budgets coupled with estimates from EPA, the IPCC, and the DAYCENT model developed by Colorado State University. The FASOM model also estimates the energy consumption, as well as fertilizer use, of crop production. The projection of farm inputs by FASOM was used in 2010 RIA to calculate the GHG emissions of corn ethanol in 2022. The model takes into account shifts among agricultural production including changes in livestock population due to changes in corn prices. The population provides the basis for estimating livestock methane emissions.

Since FASOM is only applicable for modeling the land use change within the U.S. (domestic LUC), EPA employed the integrated Food and Agricultural Policy and Research Institute international models, as maintained by the Center for Agricultural and Rural Development (FAPRI-CARD) at Iowa State University (as summarized in CRC, 2014), to estimate the changes in crop acres and livestock production by type and by country globally (international LUC) in the 2010 RIA. While FAPRI-CARD models how much cropland will change, it does not predict what type of lands such as forest or pasture will be converted. Therefore, EPA used Winrock International's data to estimate what land types are converted into cropland in each country (EPA, 2010). EPA also used the GTAP model and confirmed that the GTAP results were consistent with outputs of FASOM and FAPRI models. Since then, the GTAP model has undergone several revisions, but EPA has not compared its findings with the new results from the GTAP model.

FASOM also predicted that cultivation of corn increases the soil carbon storage while conversion of cropland pasture and forestland leads to more GHG emissions. Overall, the FASOM results showed that expanding corn cultivation resulted in carbon storage (negative value for domestic LUC). However, the results from FAPRI showed that production of 15 billion gallons of corn ethanol reduced the corn export from the U.S. which causes other countries to allocate more lands to corn cultivation and subsequently convert more pasture and forestland to corn farms which leads to more GHG emissions. Conversion of Brazilian forests to corn farming had the highest share from total emissions associated with international LUC under the methodology used in the 2010 RIA.

### 2.1.2 Challenges with 2010 RIA Land Use Change Analysis

While the direct emissions from ethanol production vary among the studies, the table below shows the large variability in estimates which are largely due to LUC. Early studies employed worldwide agricultural models to estimate emissions from land use change (Searchinger et al.,2008; Searchinger, et al., 2015; Fargione et al., 2008) with higher net GHG emissions for corn ethanol compared to gasoline.

More recent studies, (Hertel et al., 2010) found that the emissions associated with land use change were less than one-third of those projected by Searchinger (2008) and even smaller values of land use change effect were reported by Tyner et al. (2010). The inconsistency in indirect land use change predictions is mainly due to the differences in methods and assumptions. Key factors include elasticity factors that affect the selection of land cover change and carbon stocks. Further, some argue the modeled predictions of indirect land use change are not meaningful because there is not a causal relationship between biofuel use and land conversion (Zilberman et al., 2010). In the 2010 RIA, conversion of Brazilian forestland to corn farm had a significant contribution to the international LUC. However, new studies found that agricultural intensification and governmental policies and regulations have had a great impact on GHG emissions reduction as well as decreasing the deforestation in Brazil (Silva et al., 2018; Garrett et al., 2018). Brazil, for example, is seeking to reduce greenhouse gas (GHG) emissions by 37% below 2005 levels by 2025 and 43% by 2030 through its announced Nationally Determined Contribution (NDC). The role of agricultural intensification in response to increasing commodity prices was not fully considered in the 2010 RIA and therefore international LUC was over-estimated (Rosenfeld et al., 2018).

**Table 2.1.** Addressing Uncertainties in LUC Assessments

| LCA parameter | Uncertainty | Recommendation |
|---|---|---|
| New LUC studies estimate lower emissions associated with international LUC. | LUC estimates vary greatly with model, structure, assumptions and target year. | While it is true that LUC modeling is greatly based on assumptions and model structure, we believe that after 10 years, with the availability of new data, we can see that most of those assumptions were not realistic. The current rate of deforestations, yield price elasticity, type of land being converted, etc. are not close to what EPA projected in 2010. |
| Soil C sequestration of corn is higher than what assumed in 2010 RIA. | The SOC data resulted from recent studies are inconclusive due to variation between studies and dependence on experiment duration. | Recent long-term studies on SOC in Midwest such as Poffenbarger et al. (2017) shows that corn farming results in a significant increase in SOC storage. Various practices such as no-tillage and optimum fertilization increases the SOC storage and more farmers are applying these practices now. |

## 2.2 New Findings on Land Use Change

The emissions associated with LUC include the net accumulation of carbon, taking into account both the carbon release from land conversion and the foregone carbon sequestration. Figure 2.2 shows a simplified breakdown of the factors that affect the LUC presented by the CARB and modeled in GTAP. The significant differences between the GTAP modeling and the FASOM/FAPRI modeling include the carbon stock factors for released carbon as well as the regional detail for crop shifting.  GTAP, for example, takes into account prior trade history between countries. All agro-economic models solve for prices that result in a supply and demand equilibrium. GTAP is a general equilibrium model that includes all sectors of the economy. FASOM and FAPRI are models including only agriculture and, in the case of FASOM, forestry. Those models are more detailed on individual agricultural commodities. All of the models project changes in land cover and predict changes in carbon stock through different carbon accounting mechanisms and carbon stock data sets.  All of the modeling systems need to allocate emissions over time as they are predicting an initial “shock” of biofuel demand that is distributed over a period of biofuel production.

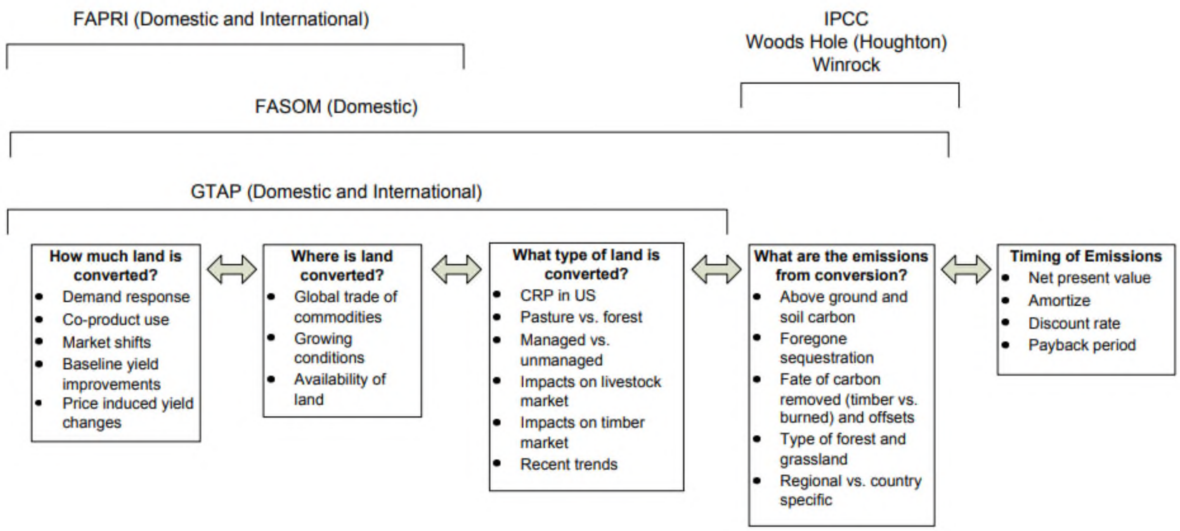


**Figure 2.2.** Approaches to LUC Modeling.
(CARB, 2018)

While the modeling represents the inputs to the GTAP system, the basic principles are the same for all LUC models. Improving crop yields, production of co-products, and high carbon stocks for converted lands reduce LUC emissions. The recent key findings for corn ethanol affecting LUC with GTAP have been:

- Low conversion of land in the U.S.;
- Increase in soil carbon storage due to corn farming practices;
- Overall decline in deforestation rates globally;
- High substitute value of Distillers' grain solubles (DGS) as feed;
- Increased cattle stock rate with pasture intensification;
- Corn oil producing biodiesel increases overall fuel output.

Since an acre of land producing corn for ethanol produces as much animal feed (i.e. DGS) as an acre of soybeans (soybean meal), the net LUC emissions in recent studies by ANL (Dunn, 2017), which are below 10 g $CO_2e$/MJ appear reasonable.

### 2.2.1 CCLUB and GTAP

LUC models also predict 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.

### 2.2.2 Other Corn Ethanol Studies

Two studies conducted by ICF for the U.S. Department of Agriculture (USDA) examined the 2010 RIA. Each study calculated the CI of corn ethanol under different scenarios (Flugge et al., 2017; Rosenfeld et al., 2018). The studies investigated domestic and international land use change based on recent studies and models and concluded that both domestic and international land-use change emissions for corn ethanol are lower than those in the 2010 RIA. Moreover, their estimates of GHG emissions of fuel production stage as well as tailpipe were also lower than those in the RIA.

CARB has revised its estimation of international LUC (CARB, 2015) due mainly to using a newer version of GTAP with an updated database, re-estimating energy sector demand and supply elasticity values, the addition of cropland pasture to the U.S. and Brazil, improved treatment of corn ethanol co-product (DGS), improved treatment of soy meal, soy oil, and soy biodiesel, improved estimation of crop yield across the world, improved estimation of emissions factors, and revision of demand and yield responses to price, among other things. The reduction in estimated forest conversion is an important factor since the GHG emissions associated with conversion of forest is significant.

Argonne National Laboratory (ANL) and California Air Resource Board (CARB) developed GREET and CA-GREET models, respectively, which include the LCA for corn ethanol. CARB's estimates of ILUC have dropped from 30 g $CO_2$e/MJ to 19.8 g $CO_2$e/MJ based on refinements in modeling (Tyner, 2010) and the changing CI of ethanol in Table 2.2 reflects both the ILUC and mix of fuel production technologies. CARB's original modeling with GTAP assumed a 1:1 displacement of DGS with corn, but that has since been revised. Subsequent modeling has also taken into account the displacement of other agricultural products.

**Table 2.2.** Life Cycle Studies Examining Corn Ethanol.

| Year | Study | Model/ Database | ILUC CI ($gCO_2e/MJ$) |
|---|---|---|---|
| 2008 | Searchinger et al. (2008) | FAPRI-CARD/GREET | 100 |
| 2009 | CARB | CA-GREET.8b/GTAP | 30 |
| 2010 | EPA RIA | GREET/FASOM/FAPRI | 28 |
| 2018 | ANL | CCLUB/GTAP/GREET | 3.9 to 7.5 |
| 2017 | Flugge et al. (2017) | FASOM/ FAPRI | 8 to 14 |
| 2018 | Rosenfeld et al. (2018) | GREET/IPCC/GTAP | 7 to 14 |
| 2014 | CARB[a] | CA-GREET2/GTAP | 19.8 |
| 2021 | Scully (2021) | Review of Models | 3.9 |

[a] Average of approved pathways.

These models however, look backward at prior data crop expansion, yield, and land use data. Ten years of increased biofuel production in the United States allows for a revised assessment of the assumptions and results of the 2010 RIA.

### 2.2.3 Empirical Data

Showing the effects of LUC is challenging since the effect occurs even absent biofuel production. No experiment can prove the "counterfactual" effect of land use change absent biofuel production. However, significant empirical data suggests that the relationship between crops used for biofuel production and land use change may not be as significant as predicted in the 2010 RIA. Deforestation rates have declined in the past decade and farming practices continue to store carbon in the soil. In fact, the drivers for deforestation are not directly related to crop production (Zilberman, 2017).

The international LUC effect related to the conversion of Brazil's Amazon region was significant in the 2010 RIA, however, this anticipated relationship was not borne out in reality. When comparing the deforestation in Brazil and corn ethanol production in the U.S. from 2004 to 2015, we can see that not only did U.S. corn ethanol production *not* cause an increase in deforestation in Brazil but annual deforestation rates in Brazil's Amazon region actually *decreased* over 75 percent over that decade (Figure 2.3). These trends in forestry loss are decoupled from biofuel use and this lack of correlation is not, but should be, incorporated into EPA's analysis.

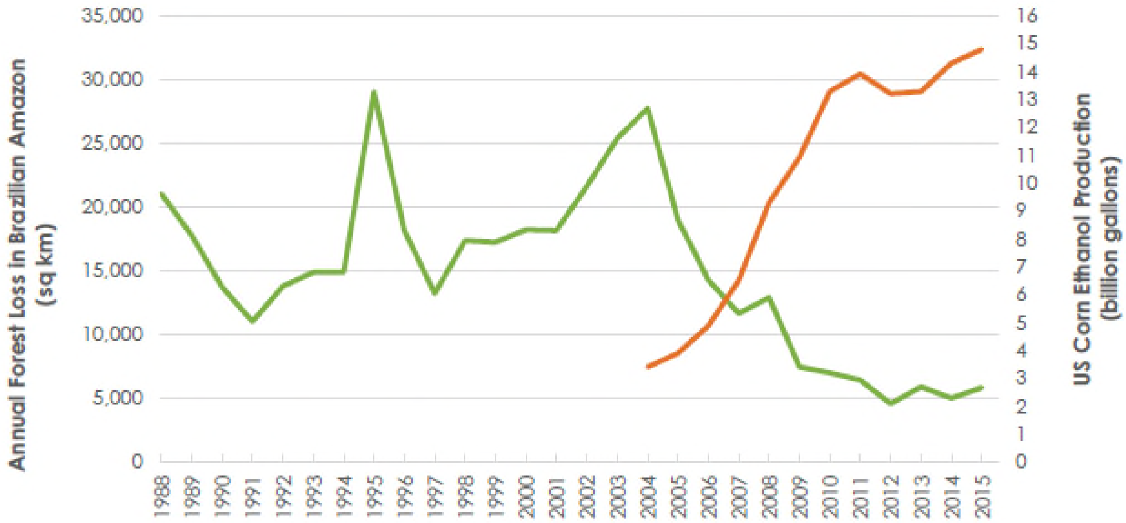


**Figure 2.3.** Comparison of Brazilian Deforestation and U.S. Corn Ethanol Production. (Rosenfeld et al., 2018)

Moreover, 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 2.5 implies that the organic matter content of the soil has improved over time due to corn farming. Part of domestic LUC is the carbon stock change due to crop cultivation and based on Figure 2.5, the carbon stock due to corn cultivation is improving 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.

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 2.4 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.

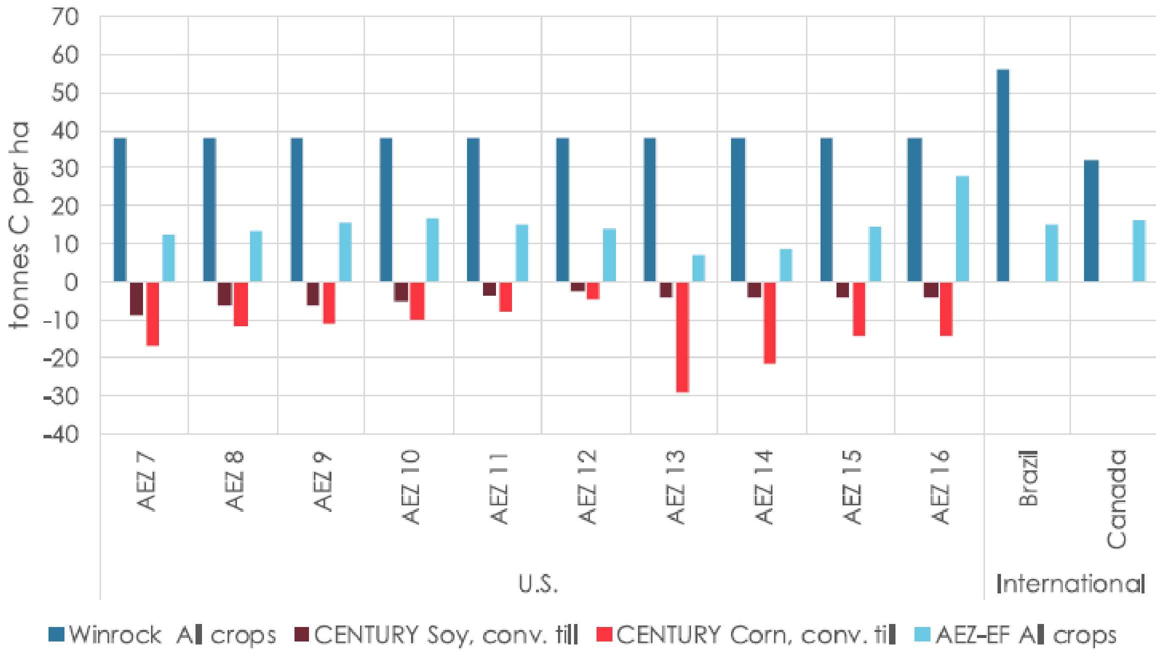


**Figure 2.4.** Carbon loss following cropland pasture conversion using Winrock, CENTURY and AEZ-EF emission factor models. (Malins, et al., 2020).

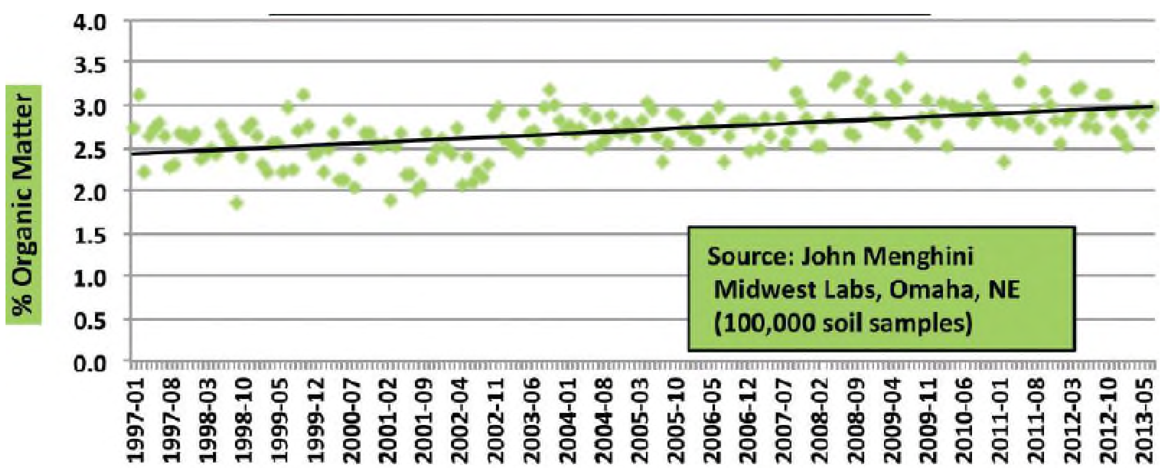


**Figure 2.5.** South Dakota Top Soil Organic Matter. (ACE, 2018)

### 2.2.4 Modeling Results

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 (Figure 2.6). These emissions correspond to the land cover change outside the U.S. induced by a change to corn ethanol. 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 improvements and predict the type of land converted to crop production. The initial ILUC estimate from the California Air Resources Board (CARB, 2009), was a total of 30 g $CO_2$e/MJ of which about half was international LUC (see Figure 2.6). CARB revised its ILUC analysis with a total international component of 15 g $CO_2$e/MJ. These values are roughly comparable to the EPA international LUC result in Figure 2.5 though the 2010 RIA analysis includes additional categories. 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 CARB and other state Low Carbon Fuel Standards, such as Oregon's Clean Fuels Program).

As discussed earlier, several studies based on GTAP evaluated biofuels induced land use changes and GHG emissions. Tyner et al. (2010) estimated the land use change and emissions associated with corn ethanol production using GTAP in support of the LCFS with the newer analysis resulting in lower ILUC emissions. A more recent study (Taheripour et al., 2017) incorporated a newer database (2011 database instead of 2004 database), added an intensification option to the model, and updated the yield price elasticity based on new data from the Food and Agriculture Organization (FAO). As Taheripour et al. (2017) stated, the previous versions of the GTAP model did not account for the intensification of pasture and assumed that a change in the harvested area equals a change in land cover, thus overestimating the emissions associated with ILUC.

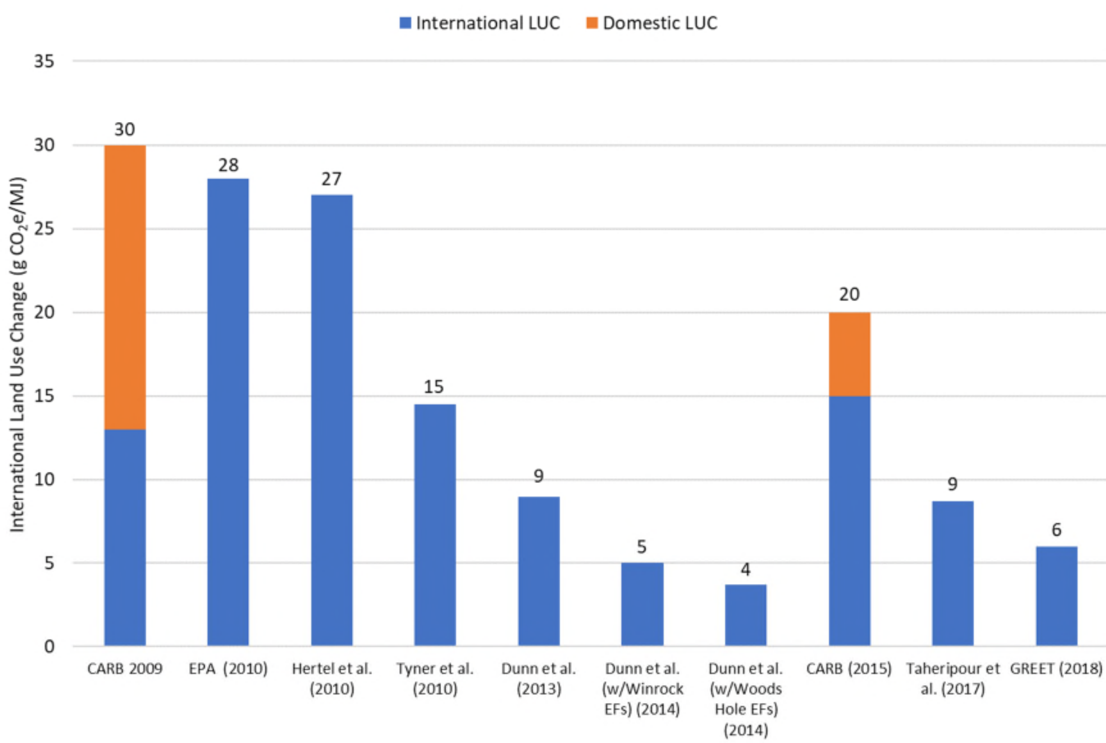


**Figure 2.6.** International Land Use Change Estimated by Several Studies. (Rosenfeld et al., 2018; ANL, 2018)

### 2.2.5 Summary of LUC Effects

International LUC for corn ethanol CI was overestimated in the 2010 RIA as shown by recent studies, availability of more recent data, and more realistic assumptions. Any estimation of LUC involves significant uncertainty with the largest uncertainties associated with the yield predictions on new and marginal land as well as the selection of land cover type. Shifts among agricultural commodities further complicates the analysis and adds a level of opacity to the modeling (CRC, 2014). While the results of LUC modeling are intrinsically uncertain, improvements in models such as those documented in recent GTAP studies indicate that EPA's assessment of both international LUC as well as U.S. LUC are overstated. In fact, soil carbon storage effects from corn farming should lead to a negative LUC in the U.S.

While the study by Searchinger et al. (2008) was the basis of international LUC calculation in the 2010 RIA, Zilberman (2017) has recently evaluated the assumptions made by Searchinger et al. (2008) and concluded that "Searchinger et al. (2008) results may now be seen as fundamentally flawed not just because the ILUC is uncertain and estimates vary considerably, but also because it fails to capture the basic features of agricultural industries and land resources." Dumortier et al. (2011) employed the same model used by Searchinger et al. (2008), but used more realistic assumptions and obtained completely different results (lower emissions). Rosenfeld et al. (2018) used the simulation results of the 2013 GTAP-BIO model available in ANL's CCLUB tool to calculate the impact of international LUC on corn ethanol CI under several scenarios and reported that the emissions associated with international LUC ranged from 1.3 to 16.9 g $CO_2e$/MJ. These findings that elasticity factors and other contributors to ILUC were overstated by the 2010 RIA were confirmed in a recent paper by Scully, et al. (2021). Finally, studies that compare ILUC modeling place a strong emphasis on Winrock land use conversion factors where a critical assumption is that crop land pasture emission rates are half those of pasture conversion (Malins, 2020). These same studies criticize the overestimation of soil carbon storage from ongoing corn farming practices predicted by CENTURY. However, the studies fail to recognize the merits of FASOM's analysis as used in the U.S. emission inventory that reflects real-world soil carbon storage effects.

#### *Modeling Approach for This Study*

This study combines the elements of several approaches to provide an updated assessment of the GHG intensity of corn ethanol. Repeating the steps in the 2010 RIA is a challenging process and EPA acknowledges this issue in the 2021 draft RIA; however, there are reasonable ways to update corn ethanol's CI without undertaking the extensive modeling effort completed in 2010. Here, domestic and international LUC were calculated based on the GREET (2021) model adjusted for the corn oil to biodiesel yield as shown in Table 2.3. The domestic and international ILUC emissions are multiplied by an allocation factor that assigns half of the emissions associated with corn oil production to biodiesel. The GREET model uses CCLUB (Dunn et al., 2017) to estimate the soil organic carbon storage as well as land conversion and associated emissions in response to biofuel expansion. Domestic LUC is based on average tillage practice in the U.S.; however, the more no-tillage practice is used by corn farmers, the more carbon will be stored in the soil and thus the impact of LUC will reduce.

**Table 2.3.** Change in GHG Emissions Due to Land Use Change (g $CO_2$e/MMBtu).

| Study | Domestic | International |
|---|---|---|
| EPA 2010 RIA | -4,033 | 31,797 |
| Rosenfeld et al. (2018) | -2,038 | 9,082 |
| GREET1_2020 | -2,314 | 6,300 |
| GREET1_ 2020, allocated to corn oil | -2,199 | 5,986 |

The following calculation approach was used in this study. It allows for the assessment of the newest corn farming data, addition of the GTAP analysis for ILUC, and inclusion of the original 2010 RIA emission categories.

<u>Emissions Allocated to Corn Ethanol and Corn Oil by Energy Content</u>
Domestic ILUC: CCLUB
International ILUC: CCLUB
Domestic Rice Methane: ICF 2018
Domestic Farm Inputs: GREET minus international fertilizer
International fertilizer: ICF 2018 (to align with RFS categories, subtracted from domestic farm
International Rice Methane: ICF 2018

<u>Emissions Assigned to Corn Ethanol</u>
Tailpipe: ICF 2018
Fuel Production: GREET

# 3. Corn Farming

The consumption of farming inputs such as fertilizers, pesticides, and energy such as diesel and LPG affect the GHG intensity of corn or crops that are grown to make up for corn used for biofuel production. Crop yields yield affect both the land required for crop production and LUC. This section includes new data on corn yield as well as crop inputs. This section also reviews recent data on farming and aligns it with the estimates in the 2010 RIA and the current GREET model.

## 3.1 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 3.1. 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.

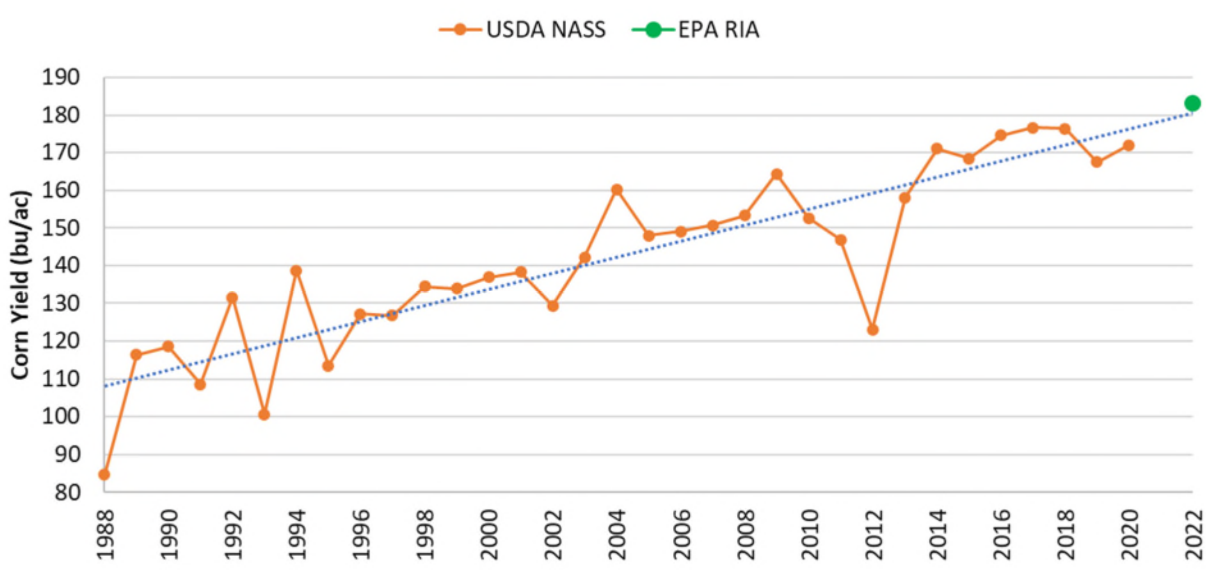


**Figure 3.1.** Corn Yield Over Time. (USDA NASS, 2020)

Management practices such as tillage, and nitrogen (N) application rate affect the GHG intensity of crops. In order to decrease the environmental footprint and lower production costs, farmers have started using new technologies such as precision agriculture to manage their fertilizer consumption. Reduced tillage has become a common practice across the U.S. farms, reduces soil emissions during the farming stage (Figure 3.2). Nitrogen inhibitors reduce the requirement for nitrogen and also reduce the formation of $N_2O$. Precision farming and guidance methods also allow for the more efficient application of nitrogen. The combination of all of these methods results in increased yield per acre and reduced nitrogen per bushel.

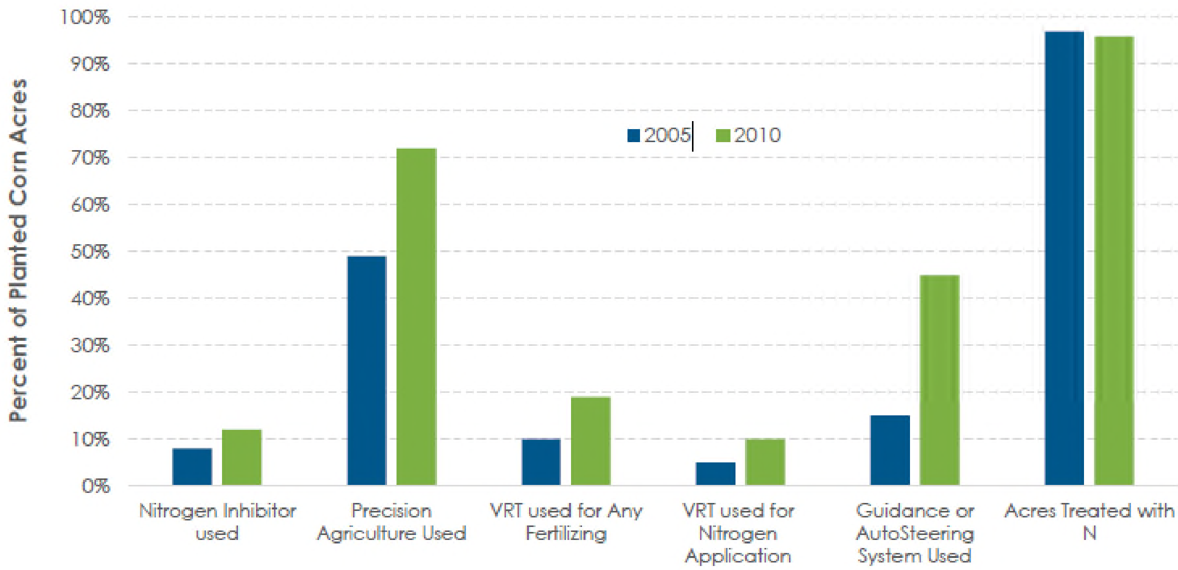


**Figure 3.2.** Changes in Corn Production Practices from 2005 to 2010. (Rosenfeld et al., 2018)

The leading corn farming states in the U.S. produce most of the ethanol in the country as shown in Figure 3.3. The location of ethanol plants is not surprisingly coincident with corn production. This co-location reduces corn transport distance and growth in corn production is occurring in the states with the highest yield per acre, which is shown in Figure 3.4.

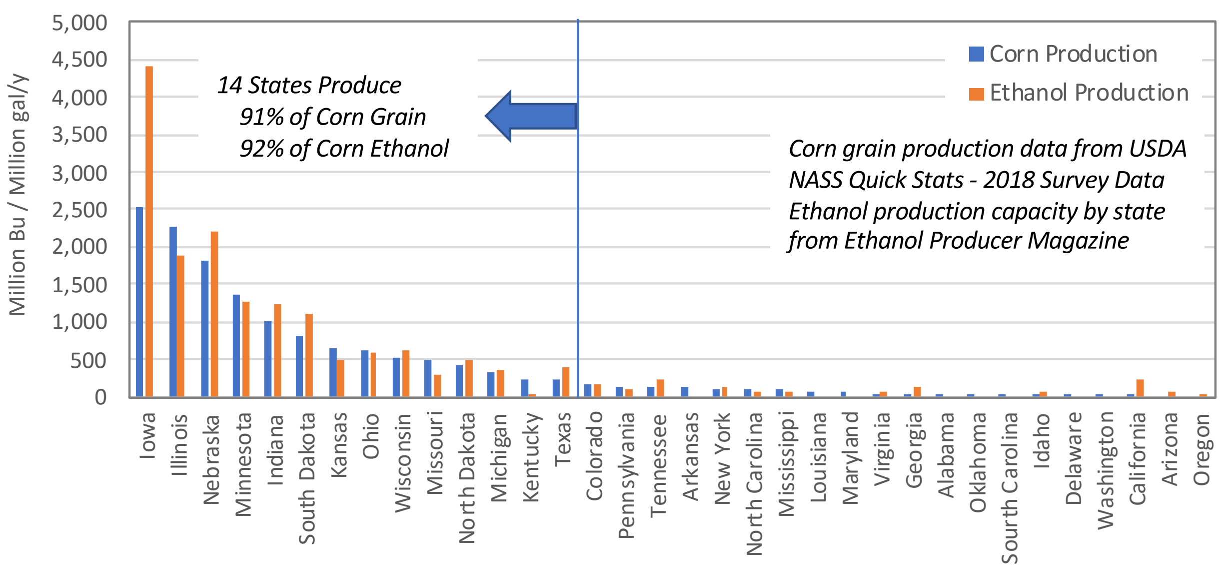


**Figure 3.3.** Corn Ethanol Production by State. (USDA NASS, 2018)

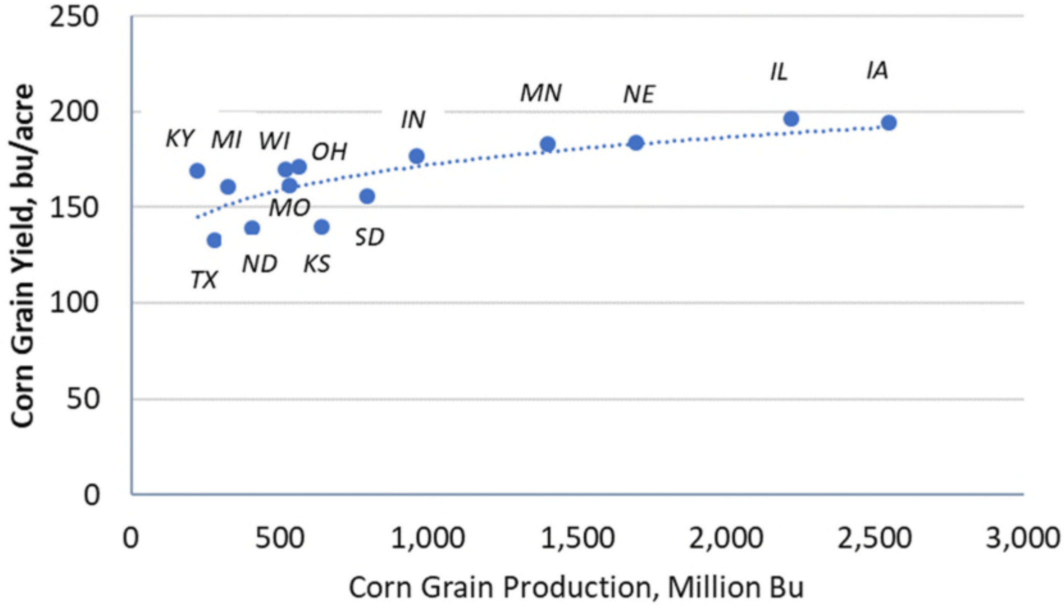


**Figure 3.4.** Average Corn Grain Yield vs. Production for 14 States.
(2014-2018 Weighted Average) (USDA NASS, 2018)

Iowa, Illinois, and Nebraska are the three states with the highest corn production in the U.S. An analysis of NASS data for applied nitrogen and corn yield shows consistent reduction in the nitrogen application rate per bushel of corn (Figure 3.5). The reduction in nitrogen application rate is consistent with the 2010 RIA estimate discussed below.

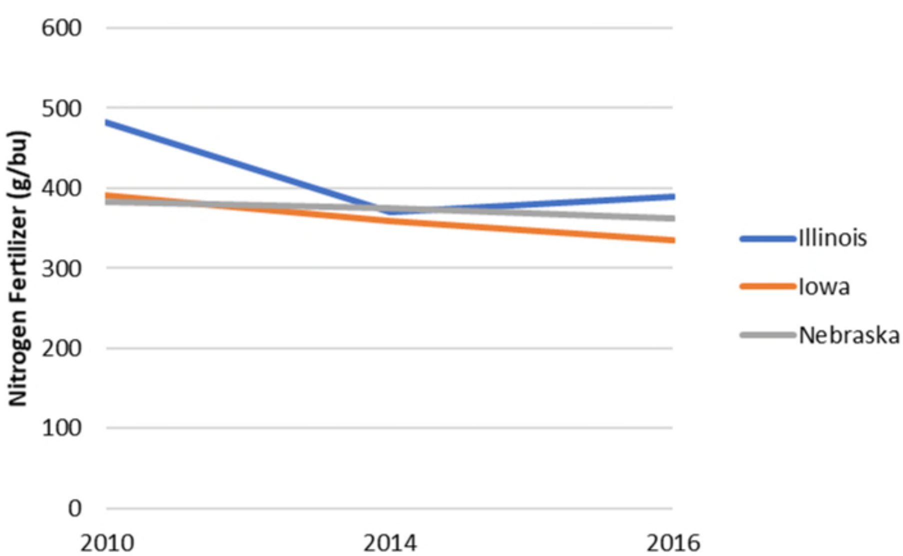


**Figure 3.5.** Nitrogen Fertilizer Use Rate in the Three Largest Corn Producer States.
(USDA NASS, 2018)

Domestic agricultural use of fertilizers, pesticides, and energy was projected by FASOM in the 2010 RIA. The 2022 projections are compared to several evaluations of NASS data in Table 3.1. The 2010 RIA used the GREET interim emission results to calculate the upstream emissions associated with agricultural inputs. The 2022 projections for farming inputs in the RIA reflect improved yields and advancements in farming techniques, which, in some cases, may not have yet been achieved. Overall, this comprises a small portion of ethanol's CI relative to the LUC portion discussed above.

**Table 3.1.** Farming Inputs of Corn in the U.S.

| Input | Unit | GREET (2021) | Rosenfeld et al. (2018) | USDA NASS (2018) | EPA RIA[d] |
|---|---|---|---|---|---|
| Analysis Year | | 2020 | 2015 | 2016 | 2022 |
| N | g/bu | 401.5 | 373 | 380 | 344 |
| $P_2O_5$ | g/bu | 150.6 | 128 | 165 | 79 |
| $K_2O$ | g/bu | 152.3 | 130 | 193 | 98 |
| Lime | g/bu | 1,457 | 1,150 | N/A[c] | 260 |
| Herbicide | g/bu | 6 | 6 | 3 | 5 |
| Pesticide | g/bu | 0.01 | 0.1 | N/A | 1 |
| Diesel | Btu/bu | 5,200 | 4,730[b] | 6,388 | 9967 |
| Gasoline | Btu/bu | 802 | 1,413 | 774 | 1042 |
| Electricity | Btu/bu | 1,326 | 441 | 1,089 | 19 |
| Natural Gas | Btu/bu | 479 | 1,301 | 1,212 | 1283 |
| LPG[a] | Btu/bu | 1,026 | 1,723 | 1,297 | - |

[a] Liquified Petroleum Gas

[b] The energy usage of corn ethanol was not mentioned in Rosenfeld et al. (2018), however they mentioned that they obtained the data from GREET (2015). To make it comparable, the energy usage data for Rosenfeld et al. (2018) were obtained directly from GREET (2015).

[C] Data was not available.

[d] From EPA RIA, Table 2.4-5. The values are listed per MMBtu of ethanol which appear to incorrectly labeled and not possible. If for example, the N fertilizer of 138.8 lb/MMBtu are taken as lb/acre yield and combined with a corn yield of 183 bu/ac from the RIA the N rate is 344 g/bu.

GREET1_2021 is the study input

## 3.2 Sensitivity Analysis of Farm Inputs

A sensitivity analysis was conducted to investigate the impact of each input on overall CI of corn and the results are shown in Figure 3.6. Fertilizer application rates, farm yields, transport distances to ethanol plants, and $N_2O$ production rates were examined for 12 corn farming states using the GNOC model,[5] which provides an easy-to-use assessment tool with global applicability. Uncertainty distribution functions were developed based on the standard deviation of historical data and other variability factors to provide inputs for a Crystal Ball™ simulation of the GHG intensity of corn. The analysis shows that nitrogen fertilizer and $N_2O$

[5] http://gnoc.jrc.ec.europa.eu/

emission are the most sensitive inputs, implying that a reduction in nitrogen fertilizer application rate significantly decreases the GHG intensity of corn and the CI of corn ethanol.

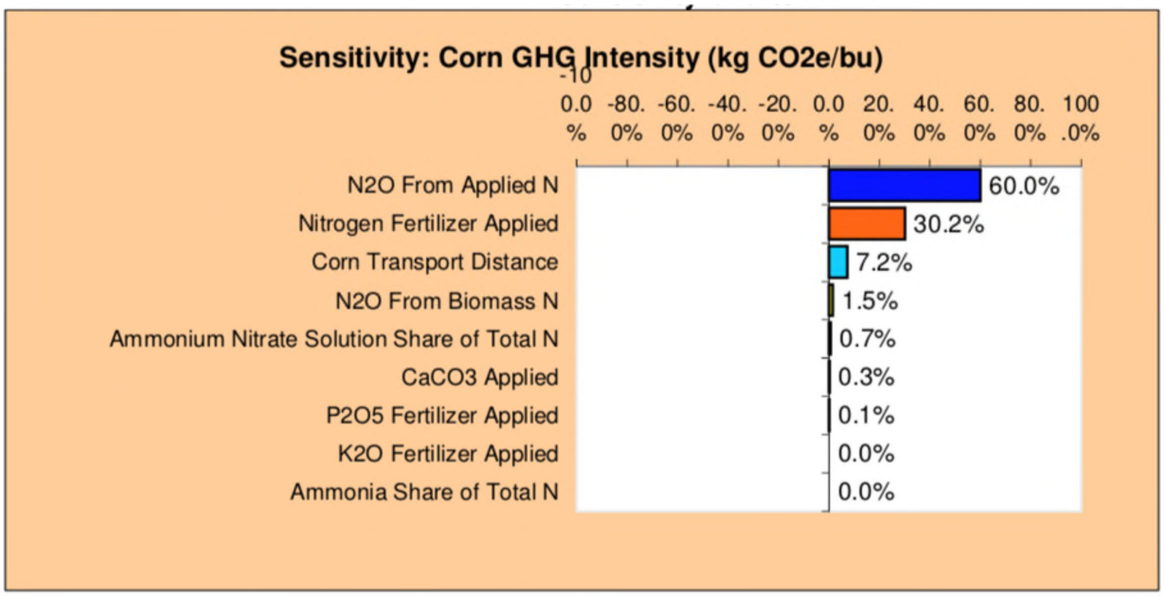


**Figure 3.6.** Sensitivity Analysis of Farm Inputs.

# 4. Impact of Co-Products on corn ethanol CI

The corn farming system and ethanol production generate several co-products that were considered in the 2010 RIA. These include DGS, Corn Distillers' Oil (CDO), and stover that is harvested with corn. Stover was considered as a fuel feedstock and not animal feed co-product. The effect of these co-products on GHG emissions is discussed in the following sections. Some ethanol plants also capture fermentation $CO_2$.

The 2010 RIA also used the study published by Argonne National Laboratory to estimate the DGS replacement rates for corn and soybean meal in animal feed. Production of DGS effectively results in a credit since DGS is a suitable source of animal feed and displaces agricultural crops like corn and soybean meal. However, since FASOM takes the production and use of DGS into account, no further allocation (displacement) was conducted in the 2010 RIA.

## 4.1 DGS Co-Product

Distiller's grains are the nutrient-rich co-product of the ethanol production process and provide an alternative to corn and soybean meal feed. Wet distiller's grains are sold to local markets due to their high moisture content and low shelf life. But generally, the distiller's grains are dried to increase the shelf life and facilitate transportation over longer distances. The product is referred to as Distiller's Dried Grains with Solubles (DDGS) (Iowa Corn, 2019). In the U.S., ethanol plants have the capacity to produce substantially more than 15 billion gallons of ethanol and 44 million metric tonnes of DDGS (U.S. Grain Council, 2018). This effect is significant since an acre of land producing ethanol for corn produces as much feed as an acre of soybeans. Due to its nutritional value, DDGS is considered a good substitute for soybean and canola meal. A recent study has investigated the effect of DDGS vs. soybean meal and canola cake on feed intake, milk production, and milk quality in dairy cows and concluded that DDGS can substitute for a soybean-canola mixture without affecting feed intake, milk yield, and quality, or sensory quality (Gaillard et al., 2017).

Figure 4.1 shows the prices of DDGS and soybean meal over time with a correlation in price activity. Rises in soybean meal prices are followed by rises with DDGS prices supporting the substitution effect. The replacement value of DGS was less well-understood in 2010 when corn ethanol was a less mature technology. While the overall substitution effects are more complicated, DDGS that displaces soybean meal results in the avoidance of emissions from soybean farming.

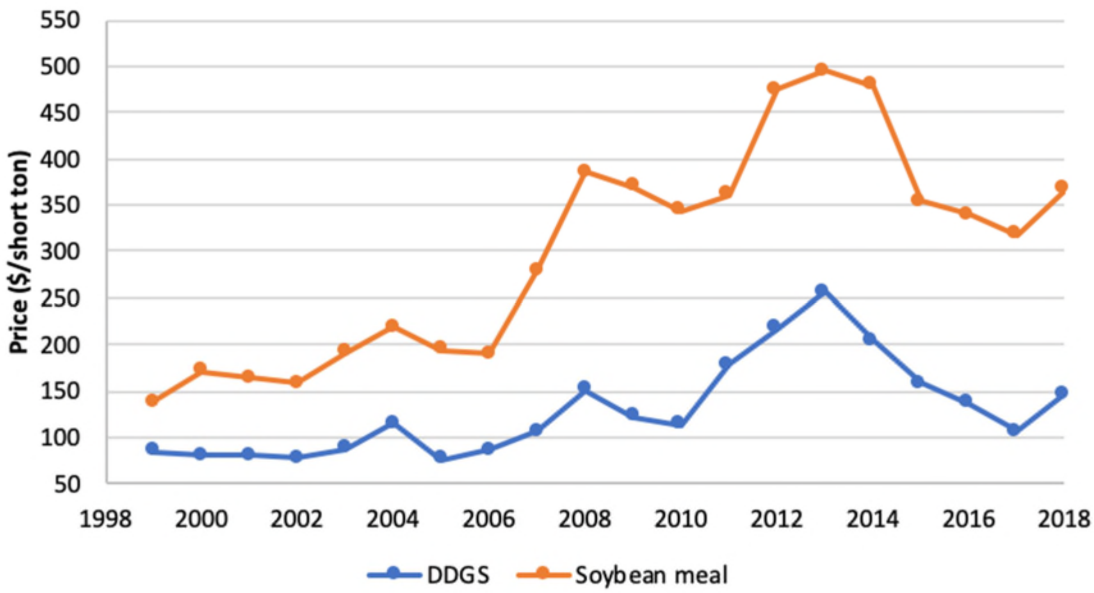


**Figure 4.1.** Historical Prices of DDGS and Soybean Meal. (USDA ERS, 2018; World Bank, 2018)

Soybeans as legumes fix nitrogen in the soil, which provides nitrogen for soybean crop and the following crop which is typically corn. Thus, the application of nitrogen fertilizer is not required for soybean farming. However, without N fertilizer, the soybean yield is limited to 50 to 60 bu/ac. In order to achieve higher yields, 30 to 60 lb/ac of nitrogen fertilizer is required (Schmidt, 2016). In recent years, more fertilizers, especially nitrogen fertilizer, have been used in soybean farming to increase yields (McGrath et al., 2013) (Schmidt, 2016). The GREET model input for soybean farming (ANL, 2018) is 48 g/bu of nitrogen fertilizer, which is based on a 2008 study (Huo et al., 2008). However, recent USDA data indicates that the consumption of nitrogen fertilizer in soybean is 18 lb/ac which translates to 166 g/bu (USDA NASS, 2018). The application of nitrogen fertilizer on soybean crop is triple the GREET input, which directly affects the emissions related to soybean production.

Since DDGS is a substitute for soybean meal, the avoided emissions are substantially higher than originally anticipated. Correcting the nitrogen fertilizer use for soybeans allows for a better estimate of the displacement value of DDGS with corn ethanol production. The FASOM model estimate for nitrogen usage in soybean farming in 2022 in the 2010 RIA appears to be less than 10 lb/ac (Figure A.**1**) with a projected soybean yield as 50 bu/ac in 2022. These parameters correspond to a nitrogen application rate of 64 g/bu, which is much lower than current nitrogen fertilizer use rate reported by USDA NASS (2018) (166 g/bu). (See Appendix A for a discussion of nitrogen application)

By comparing the nutritional value and moisture content, one lb of DGS is equivalent to 0.781 lb and 0.307 lb of feed corn and soybean meal, respectively. Therefore, one lb of DGS production results in the displacement of 118 g $CO_2$e plus 96 g $CO_2$e if replaced for soybean meal and corn (Table 4.1).

**Table 4.1.** The CI of DGS Using Displacement Method.

| Feed Material | Soybean Meal[a] | Corn | Total |
|---|---|---|---|
| CI (g $CO_2$e/g) | | | |
| Production | 0.53 | 0.24 | |
| ILUC | 0.32 | 0.03 | |
| Total | 0.85 | 0.27 | |
| Displacement Ratio | 0.307 | 0.781 | |
| g $CO_2$e/lb DGS | 118.4 | 95.7 | 214.1 |
| g $CO_2$e/MMBtu EtOH | 7,694 | 6,216 | 13,910 |

[a]The co-product credit for DGS depends on the crops that it displaces. In order to assess ILUC based on Figure 1.3, the displacement effect of corn to DGS is already taking into account in ILUC modeling in GREET with 5.0 lb DGS, dry basis per gal ethanol. However, the higher ILUC of soybean meal has not been fully taking into account due to the new market introduction of DGS. The displacement effect of urea feed is now shown here.

## 4.2 Corn Distillers Oil

Another important co-product of the ethanol plant is corn distillers' oil (CDO). Since 2010, corn oil extraction has become a common practice in bioethanol plants due to technological advancements, although it requires additional investment (Batres-Marquez, 2018). In the U.S., almost 85% of dry grind ethanol plants extracted corn oil in 2015, producing about 1.22 million metric tons of CDO (Veljković et al., 2018), and the extraction of CDO has continued to grow (Figure 4.2), which is consistent with the projections in the 2010 RIA. Several studies have shown that CDO has comparable properties to diesel and is used for biodiesel production (Balamurugan et al., 2018; Kumar and Kumar, 2013).

In the U.S., CDO represented the fastest expanding oily feedstock for biodiesel production in 2013 (Grooms, 2014). The California LCFS originally had a very favorable CI for biodiesel produced using CDO as feedstock.[6] This drove increased use of CDO as feedstock. In 2018, about 2,060 million lb of CDO, or 50% or production, was used from biodiesel production based on EIA statistics.

[6] The LCFS CI was 4 g $CO_2$e/MJ of biodiesel for several years. This value has since been raised to about 22 g $CO_2$e/MJ, but the low initial value provided an incentive to use CDO as a biodiesel feedstock.

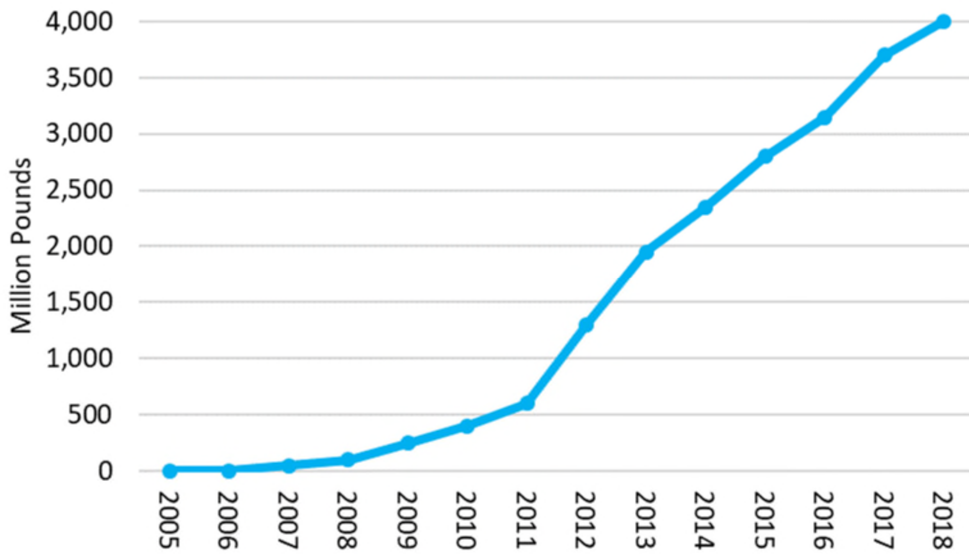


**Figure 4.2.** Corn Distillers' Oil Production in the U.S. (USDA NASS, 2018; RFA, 2019)

### 4.2.1 Corn Oil as Coproduct of Ethanol Production in EPA RIA

EPA estimated that by 2022, 70% of dry mill ethanol plants will conduct extraction, 20% will conduct fractionation, and 10% will not extract CDO. These estimates were incorporated into the FASOM and FAPRI/CARD models to account for extracted corn oil as biodiesel feedstock. The 2010 RIA projected that by 2022, 680 Mgal or 4000 million lb of CDO is produced as a by-product of corn ethanol production and used to produce biodiesel. The RIA analyzed the displacement of CDO with other agricultural products such as soy oil in the FASOM model. If CDO were treated as a fuel product, it would receive a greater share of the ethanol plant emissions and the ethanol plant emissions would be reduced. In practice, about half the CDO is used as biodiesel; which means that a corn ethanol biorefinery produces two energy products and the emissions and ILUC should be allocated between ethanol and CDO for biodiesel.

### 4.2.2 CDO Under Various Allocation Methods

Since CDO is a co-product of ethanol production, emissions from corn farming and ethanol production should be allocated to CDO or treated as a displacement credit. Several allocation methods allow for the treatment of CDO including displacement with soybean oil, and diesel, or energy allocation with ethanol and DGS. Each allocation method results in a different effect on the CI of corn ethanol shown in Table 4.2 as the estimated reduction in ethanol CI due to CDO production. Although the RIA accounted for CDO using the FASOM model, which focuses on the displacement of agricultural products, the energy allocation method is a better choice since corn oil us for biodiesel production has expanded in recent years. The effect of the different allocation approaches is shown in Table 4.2, energy allocation method results in more reduction in CI of corn ethanol than displacing with soybean oil. While displacing CDO with diesel is an extreme case, biodiesel from corn oil is an alternative for diesel fuel, so displacing with diesel is an option.  EPA should factor into its analysis the fuel value of CDO. Energy inputs and emissions for ethanol plants as well as ILUC associated with corn usage should be assigned to both ethanol and CDO.

**Table 4.2.** The Effect of Displacement Method of CDO on CI of Corn Ethanol.

| Modeling Approach | CI (g $CO_2e$/MJ Ethanol) |
|---|---|
| EPA RIA | ~-1.14 |
| CDO displacing with soybean oil[a] | -1.20 |
| CDO displacing with diesel | - 4.94 |
| Energy Allocation | -2.12 |

[a] Based on 166 g/bu of nitrogen fertilizer.

## 4.3 Replacement Feed

Corn stover (cobs and residue) is an important part of the life cycle of corn, either as fuel or as animal feed, but most LCA models treat them separately from starch ethanol (Welshans, 2014; Mueller, 2015). Corn stover is used as a cellulosic feedstock for ethanol production. Corn stover can also be used as a replacement for corn and hay or corn silage in animal feed. Mueller et al. (2015) conducted a study to investigate the effect of corn stover removal on overall emissions of ethanol. The analysis included a displacement credit for the 30% corn stover used as corn replacement feed (CRF) as well as the DGS produced from the grain corn. The displacement credit for CRF is based on a substitution ratio of 0.5 kg corn and 0.5 kg hay being equivalent to 1.0 kg of CRF on a dry matter basis. Although CRF is a suitable substitute for feed ingredients such as corn and hay, it requires pretreatment which involves consumption of chemicals such as calcium hydroxide. On the other hand, CRF has a feed and LUC credit. The results showed that using corn stover as animal feed has a co-product credit of -6.6 g $CO_2e$/MJ which potentially reduced the corn ethanol CI. The extent of CRF was not explicitly modeled by EPA in the 2010 RIA, but should be considered by EPA in reassessing the CI of corn ethanol.

# 5. BIOREFINERY TECHNOLOGIES

The performance of biorefineries affects life cycle GHG emissions due to the use of feedstock and fuel resources as well as chemical inputs. The key factors affecting GHG emissions for dry mill ethanol plants are shown in Table 5.1. The future energy inputs and yield for ethanol plants were examined in the 2010 RIA. Many of the technologies that affect dry mill ethanol plants were identified. The factors that affect energy inputs and yields, as well as the differences between the performance projected in the RIA and actual performance are examined here.

**Table 5.1.** Ethanol Plant Performance Parameters.

| Performance Trend | Key Drivers | Effect on LCA |
|---|---|---|
| Increased Yield | Starch hydrolysis and fermentation efficiency<br>Cellulosic conversion | Higher yield reduces corn upstream emissions and ILUC as well as DGS mass and co-product credit. |
| Reduced Natural Gas Consumption | Reduced drying energy, plant heat integration, corn oil extraction, advanced separation processes | Natural gas combustion and upstream emissions are proportional to use rate. |
| Reduced Electric Power Consumption | Ongoing improvements in efficiency and yield and cogeneration reduce power requirement. Corn oil separation requires additional electrical power. | Power generation and upstream emissions are proportional to use rate. |
| Increased Corn Oil Production | Corn oil in DGS is extracted by centrifuge or with solvents. | Several approaches. Substitution for agricultural products or allocation. |
| Reduced DGS Mass | Increased ethanol and corn oil yield reduce starch and oil component of DGS without changing protein output. | Affects co-product credit. Protein content is not affected. Only carbohydrate and fat fractions are affected by yield improvements. |
| Reduced Chemical Consumption | Increased yield and improved monitoring. | Reduced upstream life cycle for chemical production. |
| $CO_2$ Capture | Growth in $CO_2$ capture from ethanol plants which have a pure $CO_2$ stream. Avoids $CO_2$ production from other sources. | Several possible approaches, none used in RIA. Credit or allocation for $CO_2$ storage/ productive use. |

The efficiency of corn ethanol biorefineries has improved (see following sections) in the past decade resulting in the use of less corn per gallon of ethanol and lower energy inputs. Corn ethanol plants also produce about 5% of their energy output as corn oil.[7] The primary factors affecting ethanol plant performance are discussed below.

[7] 0.25 lb/gal ethanol × 15,993 Btu/lb (GREET soy and canola LHV) /77,000 Btu/gal denatured ethanol = 5.2%.

## 5.1 Corn Ethanol Yield

Several technologies have contributed to improvements in the ethanol yield per bushel of corn. Increased ethanol yield results in less corn used per gallon of ethanol which results in lower farming emissions, lower land use, and LUC per gallon of ethanol. Figure 5.1 shows trends in historical yield data as well as projections. Data from the GREET model that was available at the time of the 2010 RIA (Version 1.8c) is compared with industry data. These values are consistent with EPA's projections in the RIA with the trend line from the industry data slightly under the 2022 RIA projection. However, the input to the FASOM and FAPRI modeling system is 5% lower than the yield projected by EPA[8] for dry mill ethanol plants.

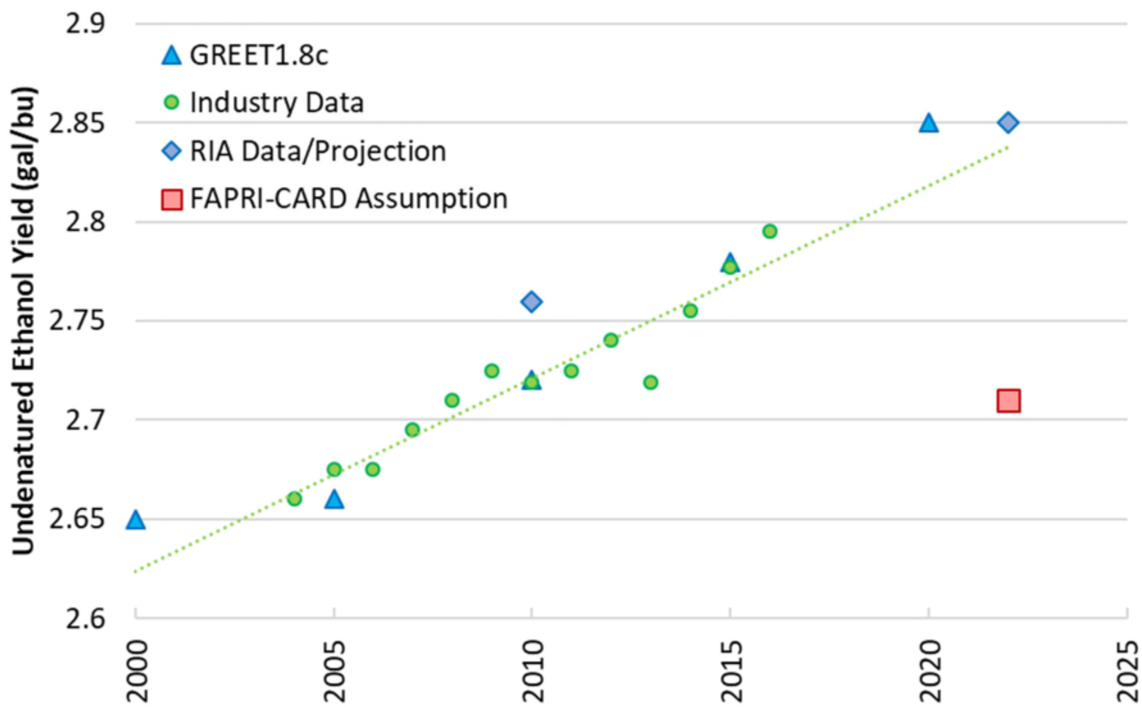


**Figure 5.1.** Dry Mill Corn Ethanol Yield Data and Projections.

### 5.1.1 Ethanol Yield in EPA 2010 RIA

EPA assumed ethanol yields of 2.71 gallons per bushel for dry mill plants and 2.5 gallons per bushel for wet mill plants and FASOM and FAPRI-CARD models used these yield assumptions. With the growth of dry mill plants, the aggregate yield should be higher than the values in the 2010 RIA. A higher yield would result in lower fertilizer use and ILUC. A first-order approximation is that corn farming and LUC related emissions should be 10% lower than those predicted by EPA due to actual yield improvements.

[8] 2010 RIA Section 2.4.7.1 EPA states the FASOM assumption

EPA identified yield projections that are consistent with industry data.[9] The discrepancy may be due to the use of the modeling systems for other programs or challenges associated with changing a modeling assumption. In any event, the lower corn ethanol yield overestimates the corn feedstock requirement for ethanol production. An offsetting factor would be that the model predicted higher production of DGS and greater co-product displacement but the net effect would still be an overestimate of corn farming emission and land use effects.

### 5.1.2 Plant Debottlenecking

The debottlenecking process helps to increase the yield and reduce energy consumption in corn ethanol plants. New technologies and reviews of material and steam flows optimize the utilization of critical processes to boost overall throughput, increase yield from base throughput, or both. Membrane dehydration technology is one such technology which helps in energy reduction, purity flexibility, and debottlenecking distillation capacity and dehydration. These improvements have contributed to the overall improvement in U.S. ethanol plants.

### 5.1.3 Enzymes and Chemicals

Enzymes are among energy-intensive inputs for corn ethanol production. Companies like Syngenta and DuPont are providing enzymes that are more efficient in terms of increasing the ethanol yield and simultaneously reducing the enzyme consumption. In a new study by Kumar and Singh (2016) that investigates using amylase corn and superior yeast in corn ethanol production, the authors concluded that use of amylase corn and superior yeast in the dry-grind processing industry can reduce the total external enzyme usage by more than 80%. Combining their use with in situ removal of ethanol during fermentation allows efficient high-solid fermentation. Also, their study showed that the ethanol yield in their process is 4.1% higher than the conventional process of corn ethanol production.

## 5.2 Energy Consumption

Ethanol plants have reduced natural gas and power consumption through numerous factors such as heat integration, combined heat and power technologies, variable frequency drives, advanced grinding technologies, various combinations of front and back end oil separation, and innovative ethanol and dried distillers' grains (DDG) recovery (Mueller, 2016). These technologies directly affect the CI of corn ethanol. These energy-saving technologies were identified in the 2010 RIA and EPA modeled the natural gas and electric power consumption for corn ethanol plants that EPA projected would be built with wet and dry DGS (Figure 5.4).

[9] RIA Section 1.1.1.1

Plant configurations modeled by EPA.

- Baseline plant
- Combined heat and power (CHP)
- CHP with corn oil fractionation
- CHP with corn oil fractionation and membrane separation
- CHP with corn oil fractionation, membrane separation, and raw starch hydrolysis

EPA placed considerable emphasis on modeling CHP. This technology has proven borderline economical with the lower costs of natural gas as well as lower costs of electric power. EPA projected that 70% of dry mill plants would adopt corn oil fractionation and this adoption rate has been exceeded.

Ten years of experience has provided insight on the actual energy use for dry mill ethanol plants. Data from ethanol plant operation has become available from industry surveys as well as pathway registrations under the California LCFS (Cooper, 2008; ACE, 2018; CARB, 2018 list of plants).

The GHG intensity of dry mill ethanol plants that were registered under the LCFS in 2016 is shown in Figure 5.2. These data are based on the CA-GREET2 model and the current CI values for these facilities with the CA-GREET3 model would be lower. However, the broader data set was available for more facilities in 2016. These ethanol plants that register under the LCFS tend to be closer to California and the lower CI ethanol plants are also represented here. The lower CI of advanced corn ethanol is attributed to the use of biomass or biogas from anaerobic digester as sources of energy. The CI values combined with LCFS applications allows for an estimation of the distribution of natural gas usage among these facilities. The range of natural gas usage was distributed equally among six bins and the range of each bin is shown in Figure 5.3. The average natural gas usage is 20,706 Btu/gal, LHV. These energy use rates and trend in reduced energy consumption over time are consistent with a survey of dry mill ethanol plants shown in Figure 5.4. These data are consistent with an industry average natural gas use rate of 22,500 Btu/gal by 2022, which is used in the assessment of GHG emissions in Section 8.

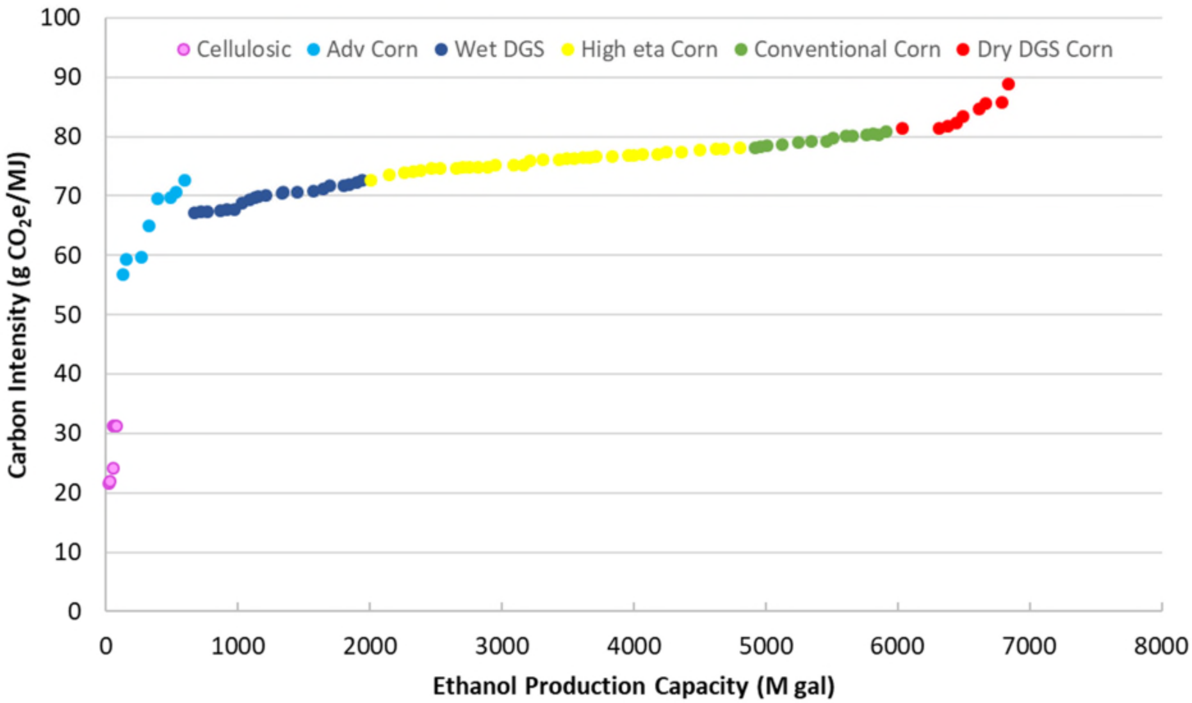


**Figure 5.2.** CI of Corn Ethanol with Various Technologies Registered under CARB (CA-GREET2 model) (CARB LCFS Pathway List)

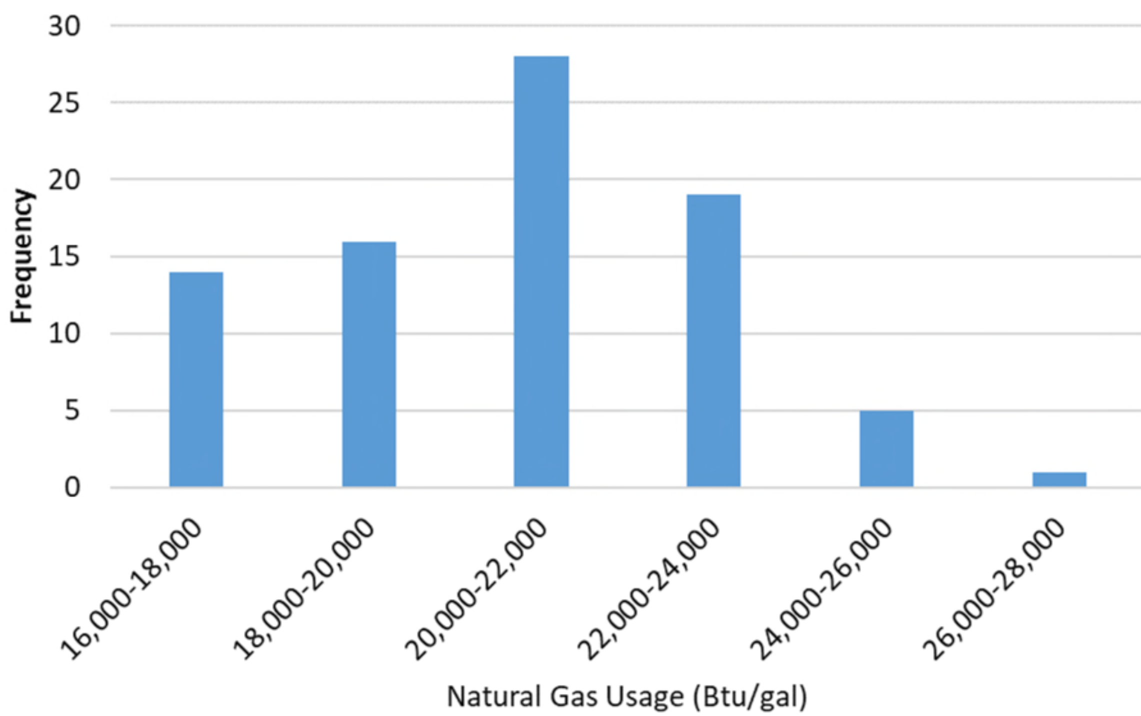


**Figure 5.3.** Distribution of Natural Gas Usage Among Ethanol Production Facilities.

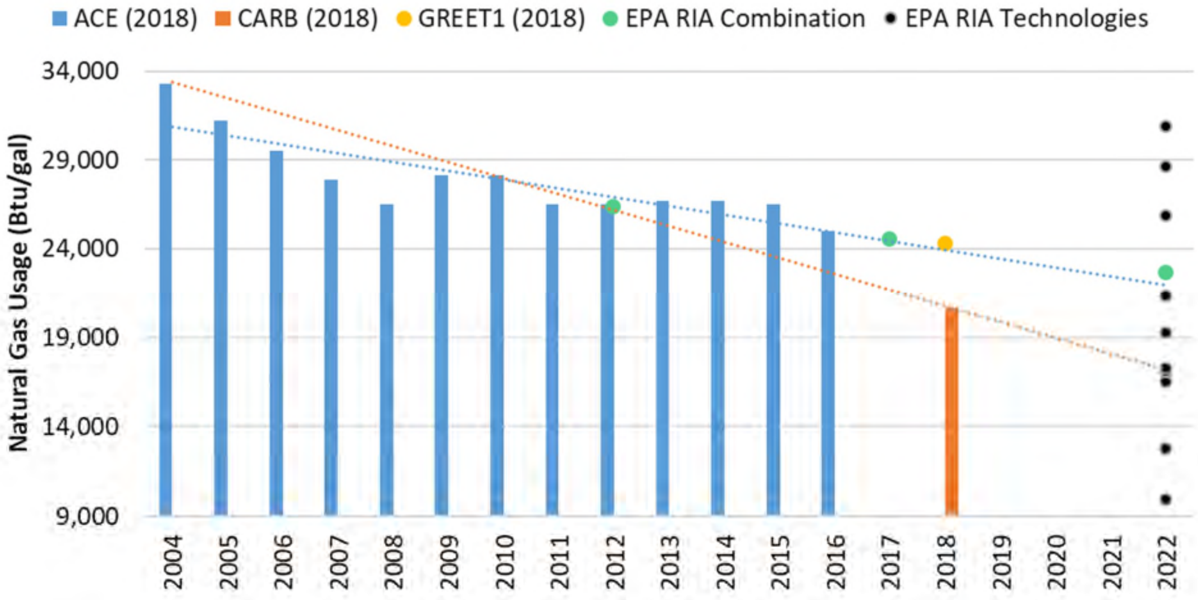


**Figure 5.4.** Decrease in Natural Gas Usage Since 2004 (EPA RIA combination denotes dry mill plant with only natural gas which produces 63% dry DGD and 37% wet DGS).

While the electricity consumption has not decreased significantly since 2010 (Figure 5.5), it has a decreasing trendline which implies lower electricity is being consumed by ethanol plant due to employing newer technologies. The overall impact of electric power should be examined as described in Section 6.6.

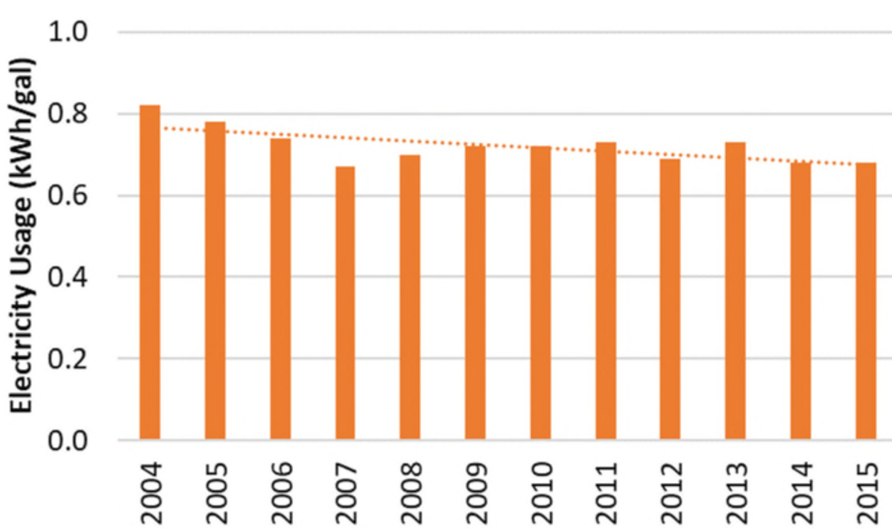


**Figure 5.5.** Electricity Conusmption in Corn Ethanol. (ACE, 2018)

## 5.3 $CO_2$ from Corn Ethanol

Many corn ethanol plants provide $CO_2$ for beverage and industrial purposes. The $CO_2$ generated in the fermentation process of corn-ethanol plants has a high market share such that it is the largest single-sector $CO_2$ source for the U.S. merchant gas markets. As a valuable product for the food industry, not only is the $CO_2$ not a waste product, but it also generates GHG savings credit which lowers the final CI of corn ethanol (Mueller, 2017). Absent ethanol plants, other sources of $CO_2$ would need to be utilized for refrigeration, beverages, and other applications (Mueller, 2019). Carbon in the fermentation $CO_2$ corresponds to half of the carbon in ethanol or about 37,000 g $CO_2$/MMBtu. After electric power for capture and liquefaction the GHG savings are over 30,000 g $CO_2$/MMBtu for ethanol plants that capture $CO_2$. In addition, at least 4 different ethanol plants are deploying carbon capture and EPA did not take into account the benefits of $CO_2$ capture or utilization in the 2010 RIA. The effect of these technologies is not included in the analysis in Section 8.

# 6. PROCESS FUELS

## 6.1 EPA RIA Fuel Production

In 2010, EPA considered several process fuels and different ethanol production practices (dry mill and wet mill) and came up with a combination of use rates for process fuels. EPA used the ASPEN models developed by the USDA to estimate the energy use at dry mill plants. The use rates are for a new dry mill corn ethanol refinery in 2022 that uses natural gas as its process fuel. The plant has a fractionation technology to extract corn oil and will produce a composite DGS coproduct that is 63% dry and 37% wet. Fuel Production emissions for this refinery were estimated as ~28,000 g $CO_2e$/MMBtu in 2022. The 2010 RIA used the GREET model to estimate the GHG CI of natural gas and electricity. These data have evolved and more recent estimates are included in the analysis in Section 8.

## 6.2 Phase Out of Coal

The use of coal as a fuel for ethanol plants has declined since 2010. The majority of ethanol plants are using natural gas as process fuel and only a small portion of the energy used in ethanol plants is coming from coal. According to corn ethanol pathways in the 2015 GREET model, on average, only 8 percent of the energy for steam production at U.S. ethanol plants comes from coal (ANL, 2018). EPA's projection of reduction in coal use were consistent with actual experience.

## 6.3 Natural Gas Production and Methane Emissions

Further refinements of the LCA of natural gas have led to many publications addressing the issue of energy inputs and methane emissions from natural gas production and distribution. GHG emissions associated with natural gas extraction have resulted in an increase in the GHG intensity of natural gas process fuel, which is taken into account in this study. As can be seen from Figure 6.1, the CI used for natural gas in this study was slightly higher than the CI used in the 2010 RIA.

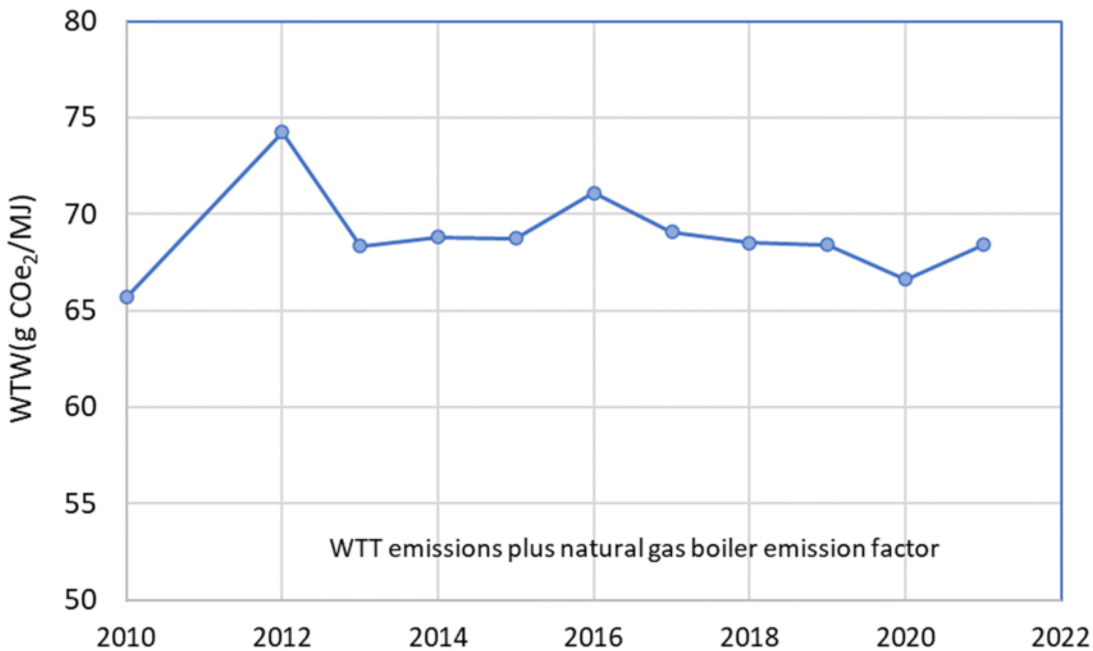


**Figure 6.1.** Well to Wheel (WTW) Carbon Intensity of Natural Gas plus Boiler Emission Factor in GREET. (ANL, 2018, GREET versions from 1.8b to 2021)

## 6.4 Biogas and Biomass Process Fuel

Landfill gas and biogas are potential process fuels for biorefineries which help to reduce the CI of biofuel (Table 6.1). The introduction of low GHG process fuel at biorefineries has been motivated by the RFS2 as well as the California LCFS. Below are several strategies employed by biorefineries to reduce the CI. All of these technology improvements lead to low CI ethanol that could be analyzed by EPA in the current rulemaking.

- Landfills collocated with ethanol plants;
- On-site anaerobic digestions of manure with avoided methane emissions;
- Anaerobic digestion of stillage;
- Electricity cogeneration;
- Solid fuel biomass combustion.

**Table 6.1.** Effect of Biogas on Carbon Intensity of Corn Ethanol.

| Process Fuel | Biogas Fraction | CI (g $CO_2$/MJ), LHV | |
|---|---|---|---|
| | | NG/Biogas | Ethanol |
| Natural Gas | 100% | 69 | 50 |
| On-site Landfill | 50% | 1 | 40 |
| Dairy Anaerobic Digester | 15 to 25% | -250 | 0 |

## 6.5 Electric Power

Corn ethanol plants use electric pumps, hammer mills, and other electrical equipment. The electrical load has steadily declined over time from over 1 kWh per gallon of ethanol to an average of 0.65 kWh per gallon (ACE, 2018) over a 10-year period. Over the same time period, the GHG intensity of the U.S. grid has declined from 750 to 505 g $CO_2e$/kWh on a life cycle basis. On the other hand, the 2010 RIA projected power use of 1.09 kWh/gal with projects of reduced power consumption. Actual power use had dropped to about 30% less than the projected value.

### 6.5.1 Grid Carbon Intensity

The carbon intensity of electric power has declined with the expansion of natural gas production and the declining price of natural gas (Figure 6.2). Carbon intensity of electric power based on GREET has declined by 34% from 2010 to 2021 due to reduction in coal use and growth in renewable power generation. The decrease in grid electricity CI directionally reduces the corn ethanol CI since electricity is used in different stages of corn ethanol production, which was not anticipated in the 2010 RIA with an overstatement of about 1000 g $CO_2e$/MJ ethanol.

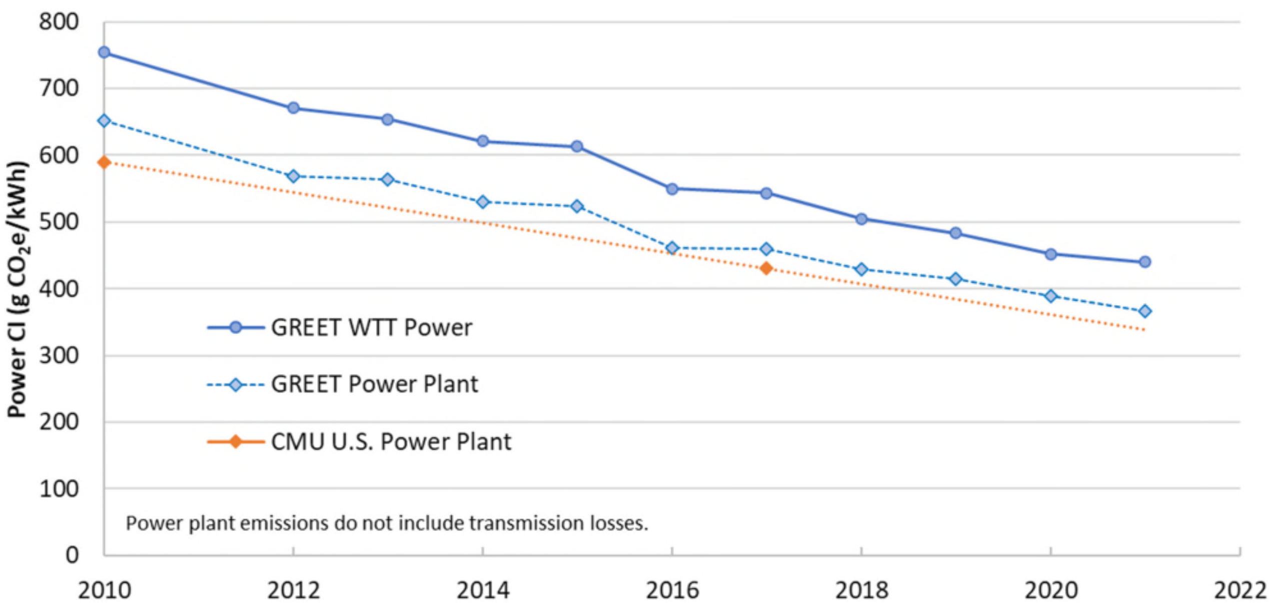


**Figure 6.2.** Carbon Intensity of Electric Power (U.S. Average).
(Power plant emissions do not include transmission losses, Source GREET)

A study at Carnegie Mellon University (CMU) examined the direct GHG emissions from the power sector in the U.S. and found that between 2001 and 2017 the average annual carbon intensity of electricity production in the U.S. decreased by 30%, from 630 g $CO_2e$/kWh to 439 $gCO_2e$/kWh (Schivley et al., 2018; EIA 2021). A similar proportional reduction in emissions occurred for power plants in the corn belt states where most ethanol plants are located (Figure 6.3). Schivley et al. (2018) used the U.S. Energy Information Administration (EIA) database to calculate aggregate GHG emissions and reports only power plant emissions[10]. The power plant emissions are consistent with the power plant component GREET. Based on both EIA and GREET, the CI of electricity is dropping. Note that the more recent EIA data shows a continuous downtrend in the GHG intensity of U.S. electric power.

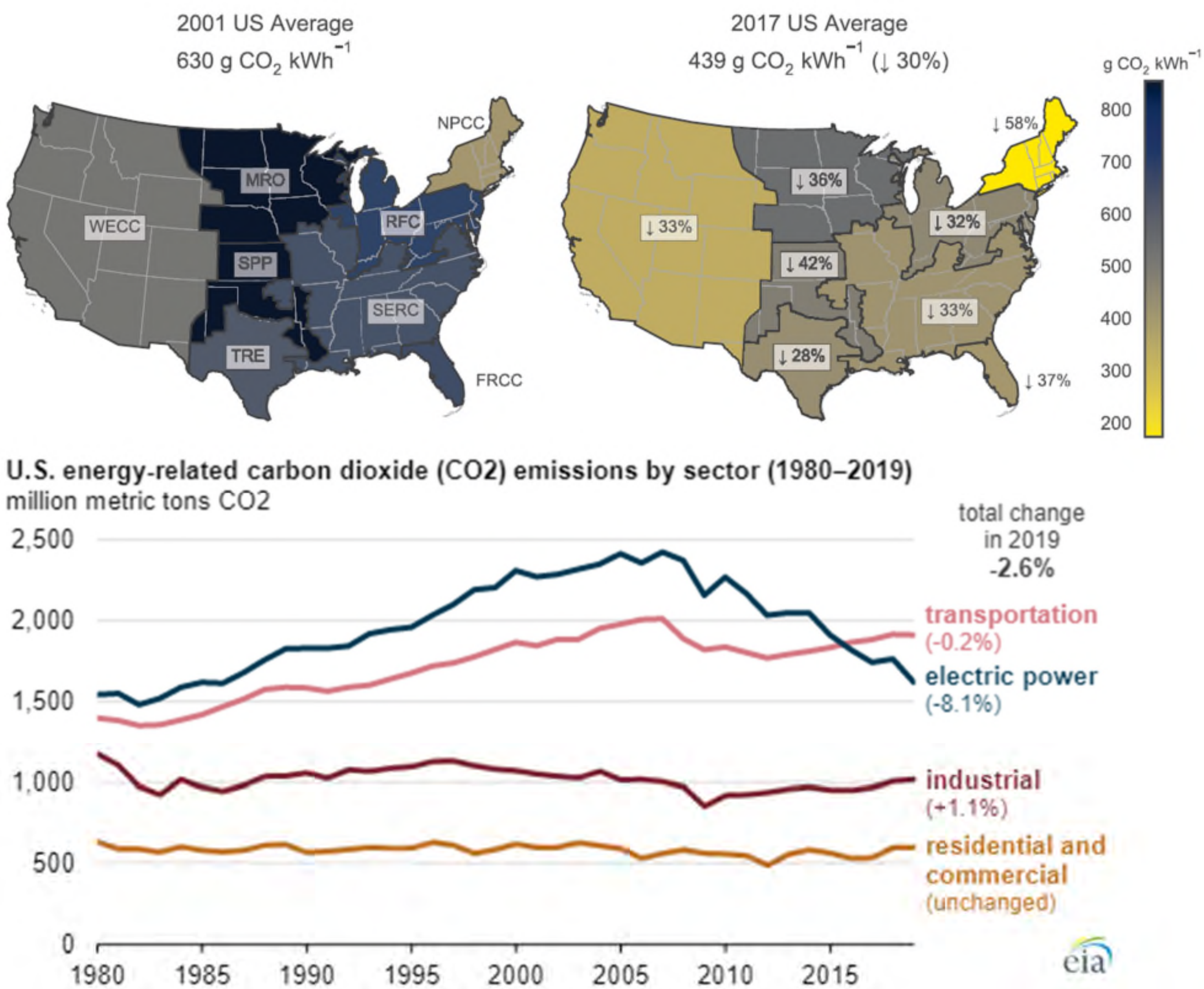


**Figure 6.3.** Change in Carbon Intensity of Electricity. (Schivley et al., 2018; EIA, 2021)

### 6.5.2 Renewable Power

Ethanol plants also have the opportunity to obtain lower GHG sources of electric power. Under current fuel policies, such as California's Low Carbon Fuel Standard, ethanol plants must use renewable power that is directly connected to the generation source. However, renewable power had contributed to the overall reduction in GHG emissions from the grid in the U.S.

[10] Power plant emissions at the plant from GREET correspond to the "fuel" phase × (1 – loss factor)

## 6.6 Summary of Ethanol GHG Analysis Issues

Many factors affect the CI of corn ethanol. A summary of the issues and recommended analysis method is shown in Table 6.2.

**Table 6.2.** Evaluation Issues related to GHG Analysis.

| LCA parameter | Analysis Issue | Recommendation |
|---|---|---|
| Ethanol refinery energy efficiency has increased. | The energy efficiency has increased in a few refineries and it does not reflect the average. | Based on our analysis, the current energy usage at the fuel production stage is close to EPA RIA's estimate, however, both electricity and natural gas consumption have a declining trend which should be considered. |
| Electric power GHG intensity. | The GHG intensity of electric power has dropped faster than projected in the 2010 RIA. | Update electricity mix for electric power generation. |
| Emissions associated with gasoline is under estimated. | EISA requires that the EPA compare biofuel emissions to a 2005 petroleum baseline. | The 2005 petroleum bassline analysis excluded methane leakage and the thermal cracking of petroleum which has lead to underestimation of emissions associated with gasoline. |
| Co-product allocation method | EPA RIA used the replacement method which results in lower co-product credit. | Since corn oil is used as biodiesel feedstock (energy source) energy allocation is a better option which results in more reduction in corn ethanol CI. |
| Fertilizer use rate for soybean | EPA RIA used lower fertilizer use rate for soybean. | According to recent USDA statistics, the N fertilizer use rate in soybean is almost three times more than what EPA used. Higher fertilizer rate for soybean results in more co-product credit for DGS which replaces the soybean meal. |

# 7. PETROLEUM BASELINE EMISSIONS FOR 2005 ARE LARGER THAN PROJECTED.

## 7.1 EPA 2010 RIA Approach in Estimation of Petroleum Baseline

EPA estimated the lifecycle GHG emissions associated with baseline gasoline transportation fuel using the 2009 analysis performed by the National Energy Technology Laboratory (NETL). The NETL analysis considers the GHG emissions associated with crude oil extraction both in the U.S. refineries and refineries in other countries from which the U.S. imported oil. The emissions from the 2010 RIA for 2005 gasoline fuel are shown in Table 7.1.

**Table 7.1.** Carbon Intensity of 2005 Gasoline from Well to Wheel (WTW).

| | GHG Emissions (g /MMBtu) | | | |
|---|---|---|---|---|
| **Life Cycle Step** | $CO_2$ | $CH_4$ | $N_2O$ | $CO_2e$ |
| Fuel production | 16,816 | 2,282 | 103 | 19,200 |
| Tailpipe | 77,278 | 3 | 5 | 78,891 |

EPA established the baseline RBOB (Reformulated gasoline Blendstock for Oxygen Blending) CI for gasoline at 93.08 g $CO_2$ e/MJ in the year 2005.[11] EPA has not re-examined the CI of petroleum since the 2010 RIA; however recent studies have shown that EPA underestimated the emissions associated with 2005 gasoline. The key factors analyzed by these studies include:

- Fugitive methane;
- Flaring of associated gas;
- Enhanced production methods including water flooding and thermal oil recovery;
- Mix of oil sands;
- Refinery complexity.

The key findings of recent studies which have more accurate data are discussed below.

## 7.2 New Findings on Petroleum Baseline

Researchers have studied the life cycle GHG emissions of petroleum fuels for several decades. Many of these studies follow the process for LCA defined by International standards (ISO 14040, 2006). Initial studies examined the national inventory of GHG emissions from crude oil production and refining with calculations of crude oil and fuel transport (Wang, 1999). Even though GHG emissions from oil refineries are reported as part of most national GHG reporting systems, the distribution of emissions among refined products has remained a challenge since multiple refinery units produce a range of products.

[11] California, in 2006, established a baseline CARBOB (California Reformulated gasoline Blendstock for Oxygen Blending) CI of 95.86 g $CO_2$ e/MJ. However, this value was updated to the 2012 value of 99.18 g $CO_2$ e/MJ to reflect the steady shift to higher intensity crude oils fed into U.S. refineries.

Aspects of crude oil production including flaring, indirect effects of road building, thermal enhanced oil recovery, and crude production methods were identified as key aspects of the life cycle of petroleum fuels (Unnasch et al., 2009; Keesom et al., 2009). Subsequent studies expanded the modeling methods and detail for crude oil production in regions such as the EU (Keesom et al., 2012; ICCT, 2014; COWI, 2015). More detailed models of crude oil production have also been developed by Jacobs Consultancy (Keesom et al., 2012) and Stanford University (El-Houjeiri et al., 2014). The California Air Resources Board (ARB) also publishes annual estimates of the CI of crude oil (CARB, 2019b). Regional studies of crude oil for the U.S., China, and globally are also part of the scientific literature (Cooney et al., 2016; Masnadi et al., 2018a; Masnadi et al., 2018b; Gordon et al., 2015).

The GHG LCA emissions associated with gasoline have been examined in numerous studies conducted by Jacobs Consultancy, Argonne National Laboratory, MathPro, and the University of Calgary (Keesom et al., 2012; Elgowainy et al., 2014; Kwasniewski et al., 2016; Rosenfeld et al., 2009, Abella and Bergerson, 2012). These studies show that a CI of 97 g/MJ would be more accurate than the 93 g/MJ for the 2005 baseline value estimated in the EPA 2010 RIA due to emissions associated with a range of crude oil production practices including oil sands upgrading, venting and flaring or produced gas, and enhanced oil recovery technologies.

The quality and consistency of the raw crude fed into refineries determines the complexity of processing required such that lower quality crude oil is more difficult to refine into transportation fuels, thus resulting in higher CI. The total energy expended to recover crude oil and the resulting GHG emissions vary depending upon the crude characteristics and the recovery methods used. The carbon intensities per production method were analyzed in a study that examined the CI of fuels under the RFS2 (Boland & Unnasch, 2014). The results for different petroleum fuels are shown in Table 7.2.

**Table 7.2.** Petroleum Gasoline Carbon Intensity.

| Petroleum Source | Gasoline Carbon Intensity (g $CO_2$ e/MJ) | | |
|---|---|---|---|
| | **Low** | **High** | **Average** |
| Primary | 84.50 | 94.6 | 89.55 |
| Secondary | 93.58 | 98.18 | 95.88 |
| TEOR | 100.58 | 120.00 | 110.29 |
| Stripper Wells | 101.95 | 116.44 | 109.20 |
| Mining Upgrader | 100.42 | 104.91 | 102.67 |
| SAGD, Dilbit | 105.00 | 115.36 | 110.18 |
| Fracking | 97.48 | 111.54 | 104.51 |
| Oil Shale | 113.00 | 159.00 | 136.00 |

Conventional oil includes primary and secondary sources of oil and these are the most well defined and accessible sources of crude and hence the most drawn upon, the carbon intensity for gasoline from these crude oils ranges from approximately 84 to 98 g $CO_2$ e/MJ. TEOR (Thermally Enhanced Oil Recovery) methods are generally implemented where the crude characteristics (viscosity, API gravity) dictate and also to extend the life of a production well. Heating water to produce the steam or other *in-situ* TEOR techniques require additional energy inputs and can increase emissions by an additional 8 to 9% over conventional production. Compared to conventional oil deposits, oil sands require production techniques that are associated with greater environmental impacts. Shallow deposits are typically accessed using strip-mining techniques, while deeper deposits are generally accessed using in situ techniques whereby steam is injected into the reservoir to heat the bitumen until its viscosity decreases sufficiently to allow it to flow out of the reservoir. On a WTW basis, the GHG emissions from oil sands are generally between 5 to 15% higher than from most conventional oils. Heating water to produce the steam used for in situ techniques and bitumen-sand separation uses large amounts of energy, typically natural gas, and produces correspondingly large amounts of emissions. In addition, bitumen produced from tar sands must go through more extensive refining than conventional oil, producing additional emissions. Upgraded mining techniques have led to advances in emissions reductions by approximately 2% over other oil sands ranges. The emission ranges shown in Figure 7.1 show a range of crude oil types that were in production in 2005 and are higher than the baseline in the 2010 RIA.

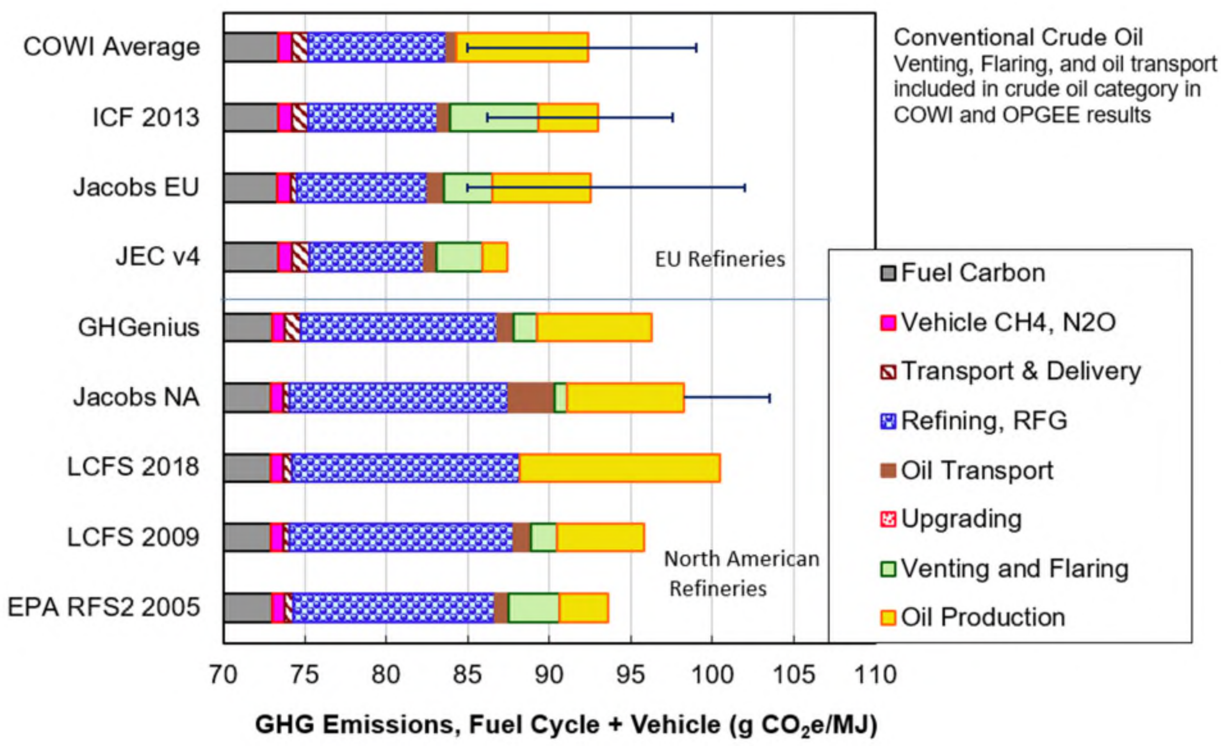


**Figure 7.1.** CI of Gasoline Estimated by Several Studies. (Unnasch et al., 2018)[12]

[12] The Jacobs EU, JCE v4, GHGenuis, Jacobs NA, LCFS 2018, LCFS 2009, and EPA RFS2 2005 were presented in Keesom et al. (2012), Edwards et al. (2012), S&T (2013), Keesom et al (2012), CARB (2018), CARB (2009), and EPA (2010), respectively.

# 8. Estimated GHG Emissions from Corn Ethanol

This study evaluated EPA's 2010 LCA of corn ethanol and specifically focused on the emission categories with the highest impacts. Since 2010 when the RIA was conducted, more data have become available, LUC models have been revised several times and more realistic assumptions have been made. Ten years of research provides a better understanding of the impact of biofuel expansion on LUC both in the U.S. and across the globe. Also, the energy consumption in the fuel production stage has been improved continuously since 2010 which should be accounted for in EPA's GHG LCA. Another important factor are the co-product credits where the role of corn oil as biodiesel and the substitute value of soybean meal displacement was not fully reflected in the 2010 RIA. The main factors analyzed in this study are discussed below.

1. International LUC has the highest share from total emissions of corn ethanol in the RIA. Recent studies have estimated much lower values for international LUC compared to EPA RIA. In this study, uses the GREET (2021)/CCLUB, to calculate both domestic and international LUC. GREET uses the GTAP model which has undergone several rounds of revision since 2010 and GTAP's estimate of international LUC due to corn ethanol production is almost five times lower than what EPA RIA estimated. GTAP includes refinements in pasture utilization and projections of yield improvement reflected by elasticities (Taheripour, 2017).
2. Corn ethanol yield affects both domestic and international LUC. EPA projected a yield of 2.71 gal/bu, however, recent data shows that the ethanol yield in dry mill process is 2.88 gal/bu and continues to improve (GREET, 2021).
3. Energy consumption in the fuel production stage has improved due to the application of new technologies. EPA projected the natural gas consumption as the main source of energy for dry mill process with corn oil fractionation as 25,854 Btu/gal. Data from LCFS applications show a trend below 20,000 Btu/gal by 2022. Also, the CI of electricity used as a source of energy in biorefining has a declining trend due to the consumption of cleaner fuels in the production stage.
4. DGS, a byproduct of corn ethanol, is a partial substitute for soybean meal. Nitrogen fertilizer use in soybean farming has increased recently and reached 166 g/bu (USDA NASS, 2018). The RIA assumed a nitrogen fertilizer use rate for soybean of approximately 64 g/bu. Higher nitrogen fertilizer use rates increases the GHG intensity of soybean meal which results in a higher credit for the DGS co-product.
5. Corn oil is a co-product of corn ethanol that has achieved a high adoption rate. The 2010 RIA used the displacement method; however, the evolving use of corn oil is biomass-based diesel production (2021 Draft RIA, Figure 5.2.3-1). Therefore, energy allocation is an appropriate option since the growing use of corn oil is as an energy product. The net effect is a lower CI when both ethanol and biodiesel are treated as energy products.

This study uses the GREET (2021) model to calculate the CI of corn ethanol configured with current ethanol plant and crop data. Since GREET lacks some consequential aspects of corn ethanol LCA such as international rice methane emission and international livestock emissions, the analysis in the ICF study (Rosenfeld et al., 2018) provides the basis for these parameters in order to be consistent with the emissions categories in the 2010 RIA. The allocation treatment of corn oil biodiesel is factored into the analysis also as shown in  Table 8.1.

The estimated GHG emissions represent a hybrid between the GREET and consequential LCA approach in the 2010 RIA.  The allocation effect of corn oil as a biodiesel feedstock is taken into account with emissions allocated between ethanol and corn oil-based diesel.  Note that the substitute value of corn oil is a small fraction of the DGS co-product and an acre of land that produces corn for ethanol makes as much animal feed as an acre of soy beans.

**Table 8.1.** CI of Corn Ethanol for Dry Mill, Natural Gas Operation with Corn Oil Extraction.

| Emission Category | 2005 Gasoline Revised | 2005 Gasoline RIA | GREET 1999 | EPA 2010 RIA | GREET 2021 | This Study[a] | ICF |
|---|---|---|---|---|---|---|---|
| Domestic Livestock | | | | -3,746 | **-2,202** | -2,463 | **-2,340** |
| Domestic Farm Inputs and Fertilizer $N_2O$ | | | 16,000 | 8,281 | **11,548** | 9,065 | **11,023** |
| International Farm Inputs and Fertilizer $N_2O$ | | | | 6,601 | **-987** | **-1,013** | -1,013 |
| Domestic Rice Methane | | | | -209 | 578 | 578 | 578 |
| Tailpipe | 79,004 | 79,004 | 880 | 880 | **2,420** | **2,483** | **2,359** |
| International Rice Methane | | | | 2,089 | **3,795** | **3,894** | **3,700** |
| International Livestock | | | | 3,458 | **-2,255** | -2,038 | **-2,199** |
| Domestic Land Use Change | | | | -4,033 | **1,374** | 3,432 | **1,374** |
| Fuel and feedstock transport | | | 5,000 | 4,265 | **2,160** | **2,217** | **2,217** |
| International Land Use Change | | | 30,000 | 31,797 | **6,139** | 9,082 | **5,986** |
| Fuel Production | 21,100 | 19,200 | 48,000 | 27,851 | 29,527 | 34,518 | 28,792 |
| **Net Emissions** | **100,104** | **98,204** | **99,880** | **77,233** | **47,468** | **52,096** | **59,755** |

[a] 95.2% allocation factor (fraction of ethanol output/ ethanol plus corn oil) applied to either **GREET** or **ICF** results as indicated in bold.

Natural gas consumption of 24,305 Btu/gal, LHV. International farming inputs are based on the ICF analysis even though the full burden of domestic corn farming is represented with the GREET inputs. Domestic and international rice methane and livestock emissions are based on the ICF values combined with the allocation factor. International and domestics land use change are based on the GREET result combined with the allocation factor. This study does not investigate categories including international farm inputs and fertilizer N2O, domestic and international rice methane emissions and international livestock emissions and relies on the ICF study estimates for these emission categories and are combined with the allocation factor for corn oil. Livestock emissions include two major factors, enteric fermentation, and manure management. It has been shown by several studies that replacing DGS with soybean meal reduces the enteric fermentation. The manure management emissions refer to emissions during collection, storage, transfer, and treatment of manure. While the replacement of DGS reduced the enteric fermentation in domestic livestock, it was not included in estimating the international livestock emissions in RIA analysis. Inclusion of reduction in enteric fermentation for international livestock would decrease the emissions associated with international livestock.

Figure 8.1 shows the estimated CI is 50,417 g $CO_2$e/MMBtu while 2010 RIA estimated the CI of corn ethanol as 77,233 g $CO_2$e/MMBtu. The GREET (2021) estimation of corn ethanol CI is the lowest since it does not account for international livestock and rice emissions. The emission estimates from the ICF analysis provide the basis for the analysis presented here. While in GREET (2021) a small percentage (~7%) of energy for fuel production is coming from burning coal, this analysis represents natural gas dry mill facilities, which are the new facilities incentivized by the RFS2 and does not attempt to examine the entire range of ethanol production technologies.

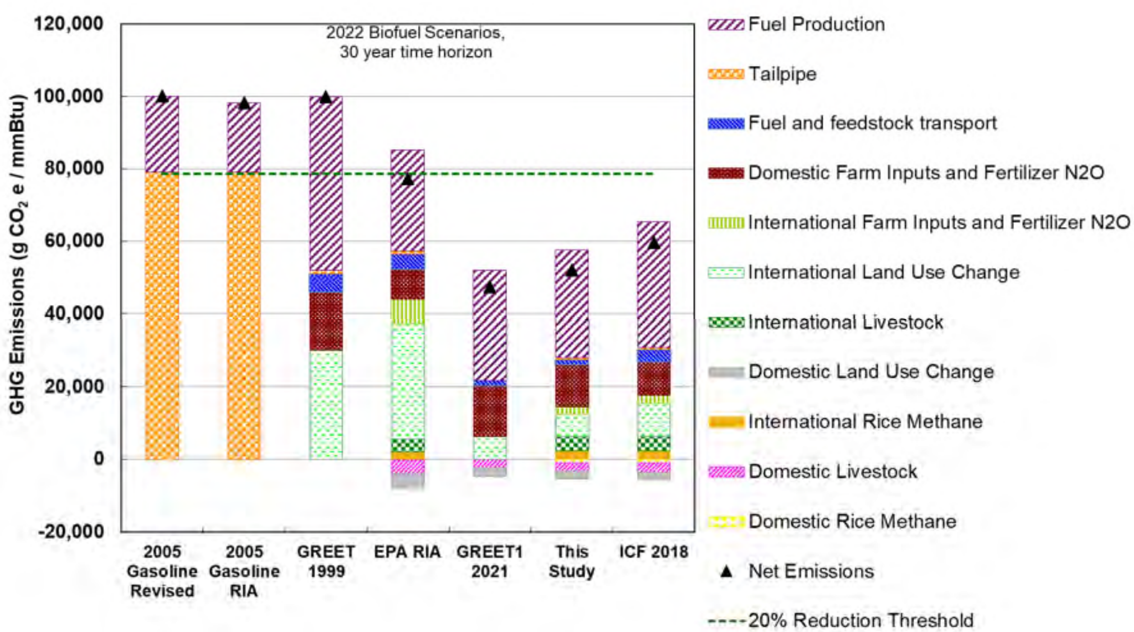


**Figure 8.1.** CI of Corn Ethanol for Dry Mill, Natural Gas Operation with Corn Oil Extraction.

Under the current situation and in the year 2022, Rosenfeld et al. (2018) calculated the CI of corn ethanol as 59,755 g $CO_2$e/MMBtu and 54,588 g $CO_2$e/MMBtu, respectively. Rosenfeld et al. (2018) also defined a scenario in which new technologies and better practices are employed to reduce the emissions in corn and fuel production. They concluded that by employing advanced technologies and introducing new co-products in the fuel production stage, and efficient management practices such as reduced tillage, nutrient management and cover crops in the farming stage the GHG emissions can be reduced to 27,852 g $CO_2$e/MMBtu. These estimates are consistent with ongoing trends in regenerative agriculture.

# 9. CONCLUSIONS

Life cycle GHG emission from the corn ethanol was analyzed over a range of production technologies and analysis methods. The data in this study show that life cycle GHG emissions for corn ethanol plants can range from 26 to 57 g $CO_2e$/MJ. Typical dry mill facilities have a CI in the 40 to 55 g $CO_2e$/MJ range. The CI for the 2005 petroleum baseline is also higher than originally projected; so, most of the ethanol plants in the U.S. produce fuel with a 45 to 55% reduction in GHG emissions. The key factors that result in GHG emissions that are lower than projected in the 2010 RIA include the following:

- Reduced energy consumption;
- Reduced GHG intensity for electric power;
- Shift from coal to natural gas fuel;
- Adoption of corn oil extraction with energy allocation;
- Reduced rates of deforestation;
- Improved rates of DGS use as animal feed;
- Displacement of ILUC and $N_2O$ emissions from soy beans;
    - Higher nitrogen application rates to soybeans than originally modelled;
- Use of corn replacement feed from crop residue;
- Introduction of lower CI process fuels for ethanol plants;
- Higher GHG emissions from 2005 petroleum baseline fuels.

EPA overestimated international land use conversion in the 2010 RIA and has not updated the analysis in the draft 2021 RIA. New ILUC studies that take into account pasture intensification show a lower level of international ILUC and are represented in the CCLUB model from Argonne National Laboratory (ANL). The CCLUB model incorporates the most recent modeling from Purdue University's GTAP program. EPA also analyzed negative direct and indirect land use conversion emissions in the 2010 RIA. These results are confirmed in the CCLUB model from ANL and are consistent with the basic factors affecting the growth of corn ethanol production. Total agricultural land has not increased significantly in the U.S.

In addition, much of the growth in corn ethanol has come from a reduction in soybean production. Corn farming increases soil carbon relative to soy farming with no till practices and due to the fact that corn builds up soil carbon from its root mass. Criticisms of the CCLUB model based on the choice of the CENTURY emission factors associated with crop activity are misplaced as the emission factors based on Winrock and Woods Hole are simple approximations that are unsubstantiated. The CENTURY approach is used in the development of the U.S. emission inventory and is also consistent with regenerative agriculture practices that generate voluntary carbon credits.

In addition, EPA did not sufficiently document advancements in corn ethanol technology. Numerous ethanol plants are starting to use biogas and biomass fuel as well as implementing carbon capture and sequestration.

Finally, EPA understated the 2005 petroleum baseline and has not acknowledged the revised estimates of emissions in the 2021 draft RIA for this rulemaking. The refining of heavy oil as well as flaring emissions from many international sources of crude oil, which occurred in 2005 contribute to higher GHG emissions associated with gasoline than those in the 2010 RIA.

# 10. Appendix A – Nitrogen Application Rates

Nitrogen application rates affect the GHG intensity of corn production. In addition, ethanol plant DGS provides a replacement for crops with nitrogen application rates that are higher than anticipated in the 2010 RIA.

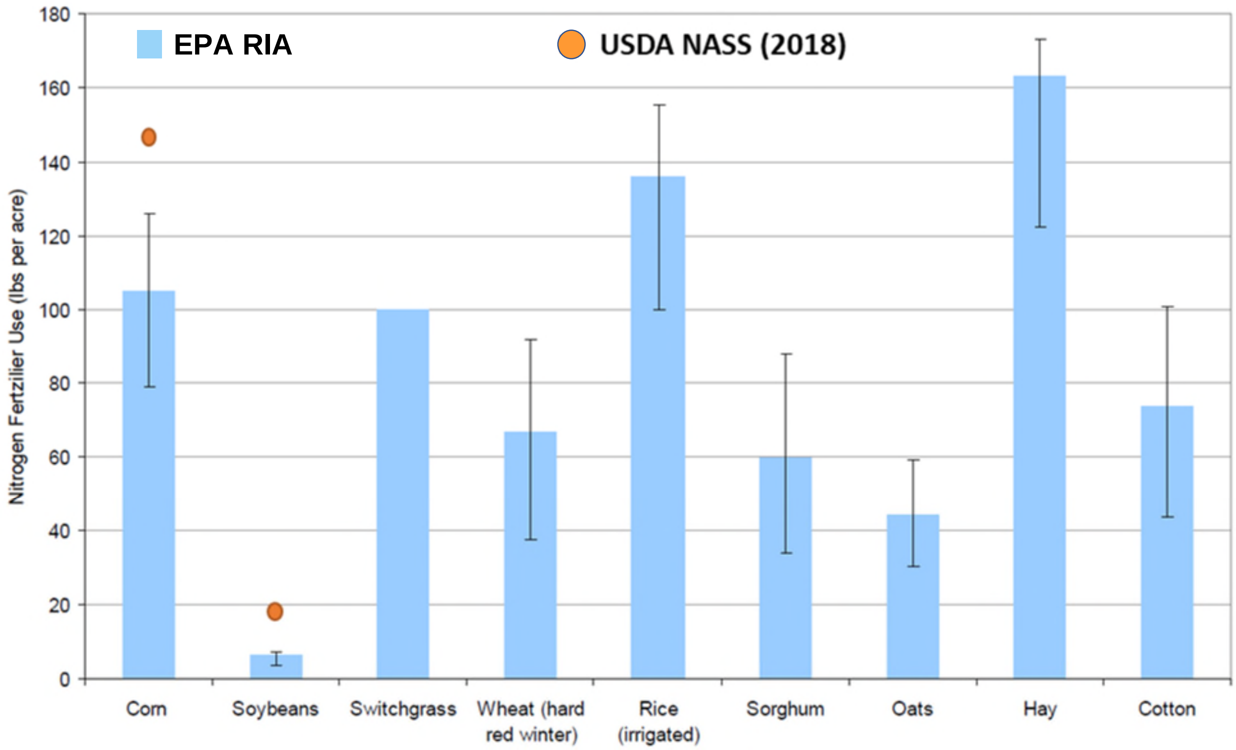


**Figure A.1.** FASOM Average Nitrogen Fertilizer Use by Crop. (EPA, 2010, not updated in EPA 2021)

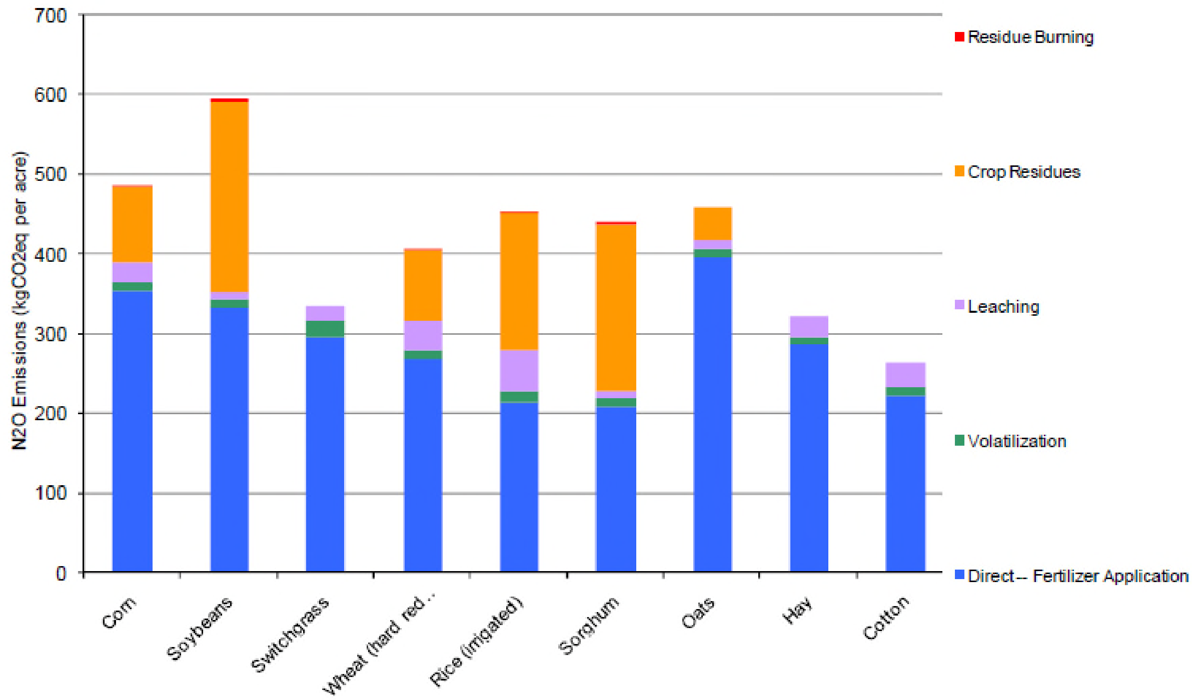


**Figure A.2.** $N_2O$ emissions per acre from crop production.

Correcting the actual N fertilizer use in soybean farming, i.e., 166 g/bu, results in about a 460 g $CO_2e$/MMBtu of ethanol reduction in carbon intensity (CI) of corn ethanol with the soybean meal substitution rates in the GREET model.[13]

In summary: EPA attributed a certain amount of N fertilizer to soy production. DGS displaces soybeans that would otherwise be used as animal feed. Soybeans are more energy intense to grow than considered in the 2010 RIA and this displacement credit should be taken into account. The displacement value of DGS may be understated in the 2010 RIA also.

The literature review presented below examines the discrepancy between USDA NASS database and GREET on nitrogen fertilizer use in soybean farming. Soybean, which is an annual legume, requires a high amount of nitrogen (~5 lb of N per each bushel). However, 50 to 60% of the required nitrogen is supplied through the N-fixation process, which is a result of a symbiotic relationship between the plant and soil bacteria (Nafziger, 2014). The nitrogen fixation process consumes about 10% of the soybean's energy in the form of sugars produced by photosynthesis. According to Nafziger (2014), "at high yield levels, the crop might not be able to produce enough sugars to go around, and that either yield will suffer, or N fixation will be reduced." One of the methods to overcome this issue is to add nitrogen fertilizer in the growing season of soybean. Several studies have investigated the impact of nitrogen fertilizer application rate on soybean yield (Mourtzinis et al., 2018; La Menza et al., 2017; Schmidt, 2016. Mourtzinis et al. (2018) conducted one of the most comprehensive studies on soybean yield

[13] (166 – 48) lb/bu ÷60 lb/bu. 0.307 lb SBM displaced per lb DDGS, 3.78 g $CO_2e$/g N fertilizer, 0.0153 g $N_2O$/g N.

response to N fertilizer in the U.S. which included 207 environments (experiment × year combinations) for a total of 5991 N-treated soybean yields. While this study reported that the soybean yield increased by an increase in N fertilizer application, in most individual environments, the effect of a greater N-rate on soybean yield was not significant.

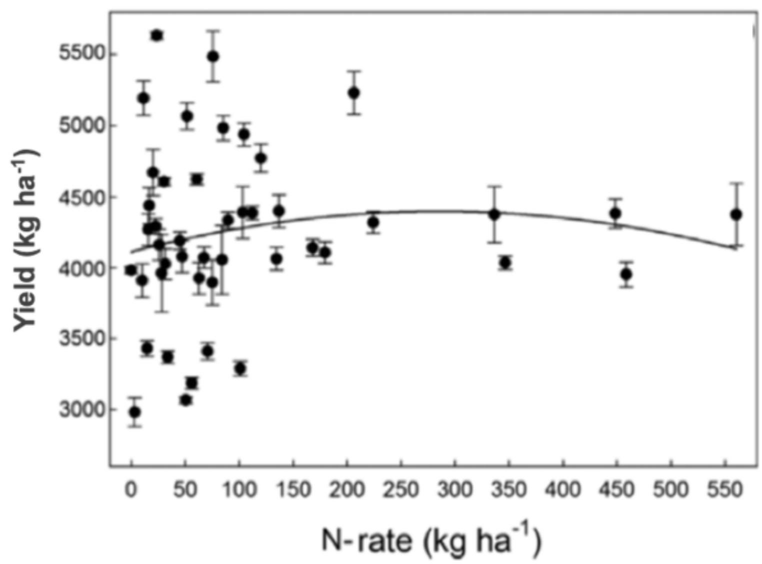


**Figure A.3.** Effect of Nitrogen Application Rate on Soybean Yield. (Mourtzinis et al., 2018)

While there was a large yield variability among environments within the same N rates, Mourtzinis et al. (2018) generated a second-degree N polynomial function that was significant ($p$ = 0.0297), and it estimated the nitrogen rate of 340 kg ha$^{-1}$ for maximization of soybean yield. This rate translates to 1.8 kg N per bushel of soybean (Figure A.**3**). Similarly, Nafziger (2014) studied the impact of nitrogen fertilizer on soybean yield over several years and concluded that soybean yields response to N fertilizer ranged widely among the trials.

In another study, La Menza et al. (2017) tested the hypothesis that indigenous nitrogen sources (N fixation and soil mineralization) are insufficient to meet crop N requirements for high yields. For this purpose, they developed a protocol to ensure an ample N supply during the entire crop season. They reported that soybean yield under ample N was 11% higher than the zero-N condition. Based on the literature review, we can conclude that adding N fertilizer to soybeans to achieve higher yields is gaining more attention, however, there is no clear trend between N application rate and soybean yields. There are several other factors which can affect the soybean yield such as planting date, N application timing, irrigation, etc. which need further studies.   The higher emissions associated with soybean meal have been included in the more recent versions of GREET.

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