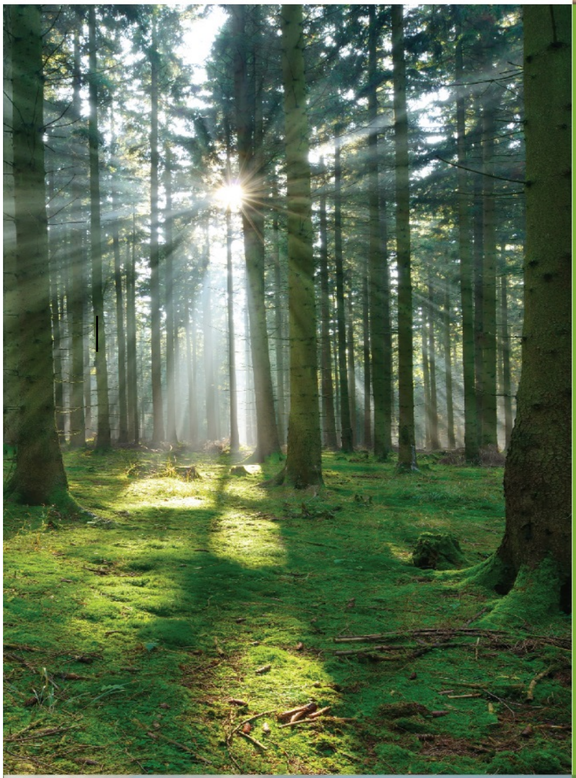
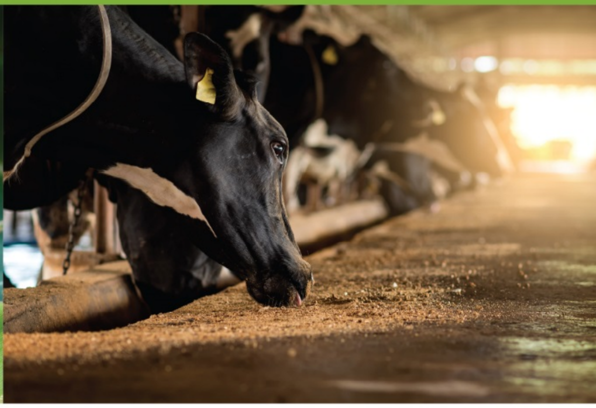


A Life-Cycle Analysis of the Greenhouse Gas Emissions from Corn-Based Ethanol



September 5, 2018

A Life-Cycle Analysis of the Greenhouse Gas Emissions from Corn-Based Ethanol

September 5, 2018

Prepared for

U.S. Department of Agriculture
Office of Energy and Environmental Policy
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A Life-Cycle Analysis of the Greenhouse Gas Emissions from Corn-Based Ethanol

ICF prepared this final project report under USDA Contract No. AG-3142-D-17-0161 in support of the project: Technical Support Communicating Results of “Retrospective and Current Examination of the Lifecycle GHG Emissions of Corn-Based Ethanol” Report.

This final project report is presented in the form in which ICF provided it to USDA. Any views presented are those of the authors and are not necessarily the views of or endorsed by USDA.

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Persons with Disabilities

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Conversion Factors

1 kilogram (kg)	1000 grams (g)
1 kilogram (kg)	2.20462 pounds (lbs)
1000 kilograms (kg)	1 metric ton (MT)
1 metric ton (MT)	1.10231 short tons (ton)
1,000,000 metric tons (MT)	1 million metric ton (MMT)
1 metric gigaton (GT)	1,000 million metric tons (MMT)
1 hectare (ha)	2.47105 acres (ac)
1 megajoule (MJ)	947.817 British thermal units (Btu)
1,000,000 British thermal units (Btu)	1 million metric British thermal units (MMBtu)
1 gallon of ethanol	76,330.0 British thermal units (Btu) of energy[a]

[a] Based on the lower heating value (LHV) of ethanol.

Introduction

Between 2004 and 2014, U.S. ethanol production, virtually all from corn starch, increased from 3.4 to 14.3 billion gallons per year. This increase in production was largely the result of two pieces of legislation that mandated the nation's supply of transportation fuel contain specified quantities of renewable fuels (i.e., biofuels). Specifically, the Energy Policy Act of 2005 established the Renewable Fuel Standard (RFS), which included a schedule of required biofuel use that started at 4 billion gallons in 2006 and rose to 7.5 billion gallons by 2012. Two years later, the Energy Independence and Security Act of 2007 replaced the RFS with the Revised Renewable Fuel Standard (RFS2). The RFS2 included a new schedule of required biofuel use that began at 9 billion gallons in 2008 and ramped up to 36 billion gallons in 2022 (including corn ethanol, biomass based diesel, cellulosic biofuels and other renewable advanced biofuels). Corn ethanol's mandate started at 9 billion gallons in 2008, gradually increased to 15 billion gallons in 2015, and is held constant at that level through 2022.

A key objective of the RFS2 is to reduce greenhouse gas (GHG) emissions associated with transportation fuels. Except for ethanol from grandfathered refineries, a biofuel must have a life-cycle GHG profile at least 20 percent lower than the fossil fuel it replaces to qualify as a renewable fuel. Biofuels with a 50 percent or higher reduction qualify as "advanced biofuels." Over time, advanced biofuels receive an increasing share of the annual renewable fuel mandate.

Quantifying the GHG profile of corn ethanol has been contentious since Searchinger et al. (2008) and Fargione et al. (2008) concluded that the emissions associated with its production and combustion exceeded the emissions associated with production and combustion of an energy equivalent quantity of gasoline. These authors argued that using billions of bushels of U.S. corn to produce ethanol reduces supplies of, and increases prices for, corn and other commodities in domestic and world food and feed markets. Farmers in the United States and elsewhere respond by bringing new land into production. These land-use changes (LUC) are related to ethanol production because the new land is used to grow more corn and to replace some of the decreased production of other commodities that occur when U.S. farmers allocate more existing cropland to corn. Bringing new land into commodity production typically results in CO_2 emissions and these emissions can be large if the former land use was native grassland, wetland, or forest. Searchinger et al. (2008) and Fargione

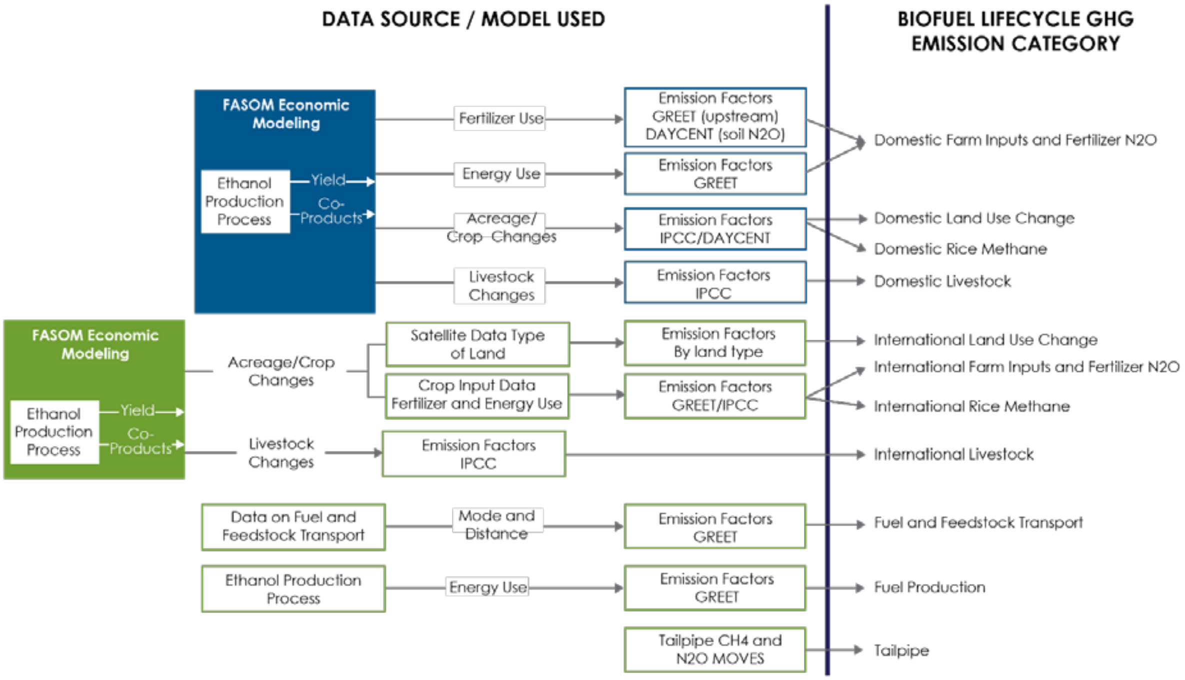
et al. (2008) argued that counting emissions related to LUC, particularly international LUC (iLUC), results in corn ethanol having a higher GHG profile than gasoline.

The RFS2 directed the U.S. Environmental Protection Agency (EPA) to do a full GHG life-cycle analysis (LCA) for corn ethanol and to include both direct and significant indirect sources of emissions. EPA designated iLUC, international livestock, international rice methane, and international farm inputs as significant indirect sources. The LCA was released in the 2010 Regulatory Impact Analysis (RIA) of the RFS2 (EPA, 2010a). The EPA RIA developed projections through 2022 of the GHG emissions associated with 11 specific emission categories that, conceptually, capture the full range of direct and indirect GHG emissions associated with corn-ethanol production and combustion (i.e., from corn field to tailpipe). These emission categories include:

1. Domestic farm inputs and fertilizer N_2O
2. Domestic land-use change
3. Domestic rice methane
4. Domestic livestock
5. International land-use change
6. International farm inputs and fertilizer N_2O
7. International rice methane
8. International livestock
9. Fuel and feedstock transport
10. Fuel production
11. Tailpipe

Figure 1-1 presents these emission categories and the data sources and models that EPA used to estimate their GHG emissions.

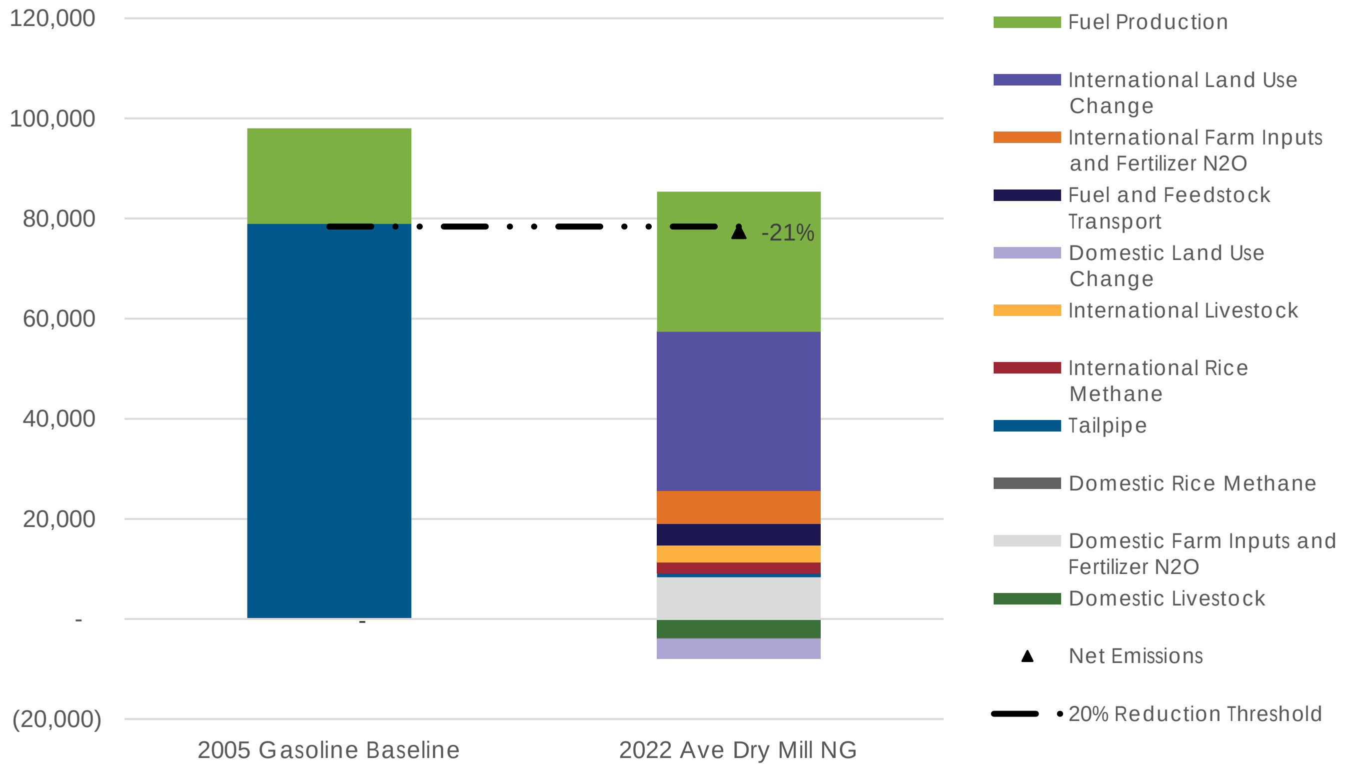
Figure 1-1: Summary of Data Sources and Models Used in the Development of the Eleven Emission Sources



Source: EPA, 2010a (see Figure 2.2-1).

EPA evaluated the emissions and energy use associated with each emission category and the upstream components. EPA concluded that in 2022, the GHG emissions associated with production of a unit of corn-based ethanol from a new natural gas powered refinery would be about 21 percent lower than the emissions from an energy equivalent quantity of an "average" gasoline in 2005.[1] Figure 1-2 shows the EPA RIA emissions profiles for corn ethanol and the average gallon of gasoline.

Figure 1-2: Summary of LCA emission Factors Showing the Relative Contributions Across the 11 Emission Categories



Source: EPA, 2010a (See Figure 2.6-2 entitled Results for a New Natural Gas Fired Corn Ethanol Plant by Lifestyle Stage (Average 2022 plant: natural gas, 63% dry, 37% wet DGS (with fractionation)).

Figure 1-2 shows that for corn ethanol—refined in a dry mill plant using natural gas as its process fuel —the largest sources of emissions are international land-use change, fuel production, and domestic farm inputs and fertilizer N_2O. Within the iLUC category, the largest source of emissions is projected land-use change in Brazil, particularly in Brazil's Amazon region (EPA, 2010a). Assessing the actual

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[1] The "average" gasoline was constructed as a weighted blend of different gasolines that were consumed in the United States in 2005.

contribution of iLUC to the GHG emissions profile of corn ethanol is an important focus of our analysis.

In 2010, the EPA RIA was the most comprehensive modeling framework yet developed for projecting how the GHG profile of corn-based ethanol might change in response to anticipated changes in market conditions and/or renewable energy policies. Much of the EPA RIA analysis still reflects our best understanding of the relationships between some emission categories, the key emissions drivers within them, and corn ethanol's GHG profile. At the same time, a large body of new information has become available since 2010—including new data, scientific studies, industry trends, technical reports, and updated emissions coefficients. Collectively, the new information indicates that for many of the emission categories in the EPA RIA, the actual emissions pathways that have developed since 2010 differ, sometimes significantly, from those projected in the RIA. The primary purpose of this report is to consider the complete set of information now available related to the life-cycle emissions for corn-based ethanol and based on this information, assess its current GHG emissions profile.

This report also develops two projected emission profiles for corn ethanol in 2022 (the last year of the RFS2). Starting with our current emission profile, the first projection, labeled the business-as-usual (BAU) scenario, assumes that recent trends observed in corn inputs, per-acre corn yields, refinery technologies, vehicle fleets, and other factors continue through 2022. The continuation of these trends has implications for the path that GHG emissions attributable to corn ethanol production will follow over the next few years even if refineries take no actions to actively reduce emissions. The second projection, labeled the High Efficiency-High Conservation (HEHC) scenario, adds to the BAU scenario the assumption that refineries adopt a set of currently available technologies and practices that are known to reduce emissions in corn production, ethanol refining, transportation, and co-product management. The HEHC scenario can be viewed as a case where refineries take a more aggressive approach to reducing emissions.

General Approach

Since 2010, EPA's estimated GHG mitigation value for corn ethanol (i.e., 21 percent lower emissions than an energy equivalent quantity of gasoline) has dominated academic, industry, and policy discussions of GHG issues related to renewable transportation fuels, as well as the design of federal renewable fuels policy (specifically, the RFS2). For these reasons, the structure for the LCA developed for this report is designed so that comparisons of its results with those in the RIA are relatively straightforward. For example, to match boundary conditions and emissions coverage, this study employs the same 11 emission categories that make up the EPA RIA. Due to the RIA's comprehensive coverage of GHG emissions, both in aggregate and within each category, it is generally straightforward to assess where new information indicates that current emissions

differ from the paths projected in 2010, as well as what the magnitudes and directions of the differences are.

Another structural similarity that facilitates comparisons between the LCA developed here and that in the RIA is a focus on the increase in corn ethanol production attributable to the RFS2 in assessing corn ethanol's GHG profile. This focus results in an emphasis on the relationships that currently exist between the 11 emission categories, the key GHG drivers within them, and ethanol's GHG profile. The RIA modeled three difference cases s that were used to quantify the impacts from corn ethanol: reference case, control case, and corn ethanol only case. The reference case includes the "business as usual" volumes in 2022 without the RFS as predicted by the Energy Information Agency's Annual Energy Outlook (AEO) for 2007. The control case includes the 36 billion gallons of renewable fuels (including corn ethanol and advanced biofuels) mandated by the RFS for 2022. For the corn ethanol only case, corn ethanol is held at its Reference Case level and all other biofuels are set at their Control Case levels. Hence comparing the Control Case with the Corn Only Case isolates the impacts of the RFS2 corn ethanol mandate. EPA projected that the RFS2 would increase corn ethanol production by 2.6 billion gallons in 2022 over the baseline EIA projection (e.g., baseline of 12.3 billion gallons in 2022 plus 2.6 billion gallons from the RFS rounded to 15.0 billion gallons).[2] We use the 2.6 billion gallon increase in ethanol production to assess the contribution of most of the emission categories in the current GHG profile and the two projected scenarios for 2022 (i.e., the BAU and HEHC scenarios). Table 1-1 shows the biofuel volumes modeled in the Forestry and Agriculture Sector Optimization Model (FASOM) for the reference, control and corn ethanol only cases. The volumes shown account for approximately 80% of the 36 billion gallons of total biofuels required in the RFS2.

Table 1-1: 2022 Fuel Volumes Modeled in FASOM (Billions of Gallons)

Type of Biofuel	Reference Case – Low Volume	Control Case – High Volume	Corn Ethanol Only Case
Soybean Biodiesel	0.1	0.6	0.6
Corn Ethanol	12.3	15.0	12.3
Corn Stover Ethanol	0	4.9	4.9
Switchgrass Ethanol	0	7.9	7.9

Source: EPA, 2010a (See Tables 2.3-1 and 2.4-1).

While the analysis developed in this report draws extensively from the EPA RIA, it does not replicate the methodology developed by EPA for the RIA. The task before EPA in 2010 was to look ahead and project how various emission pathways associated with ethanol production would develop through 2022 under the RFS2. The task here is more straightforward. Namely, to consider the complete set of information currently available—including the RIA, and observed

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[2] In January of 2007, total ethanol production capacity in place and under construction was 11.6 billion gallons (RFA, 2007).

industry trends, new research, new data, and other information that has become available since 2010—and assess where and to what degree various RIA emission projections do not reflect what has actually occurred. For example, in the RIA, iLUC is the single largest source category, accounting for about 40 percent of all net emissions associated with corn ethanol. Since 2010, however, a large body of new research and new data have been developed that collectively indicate the projected RIA emissions for iLUC are much higher than what has occurred (see section entitled International Land-Use Change in Chapter 2).

Another type of new information accounted for in this assessment are new values that have been developed since 2010 for many of the GHG emission coefficients and conversion factors used in the RIA. These coefficients and factors are used to assign GHG emissions values to specific changes in economic activity, input use, land management practices, and output levels. In general, updated values for specific emissions coefficients and factors are discussed in the sections where they are applicable. One set of updated conversion factors, however, applies across emission categories and is discussed below.

Since 1990, researchers and policy analysts have generally converted emissions of all GHGs to equivalent units of carbon dioxide (CO_2) using the Global Warming Potentials (GWPs) endorsed at the time by the United Nations Framework Convention on Climate Change (UNFCCC). These GWPs are reported by the Intergovernmental Panel on Climate Change (IPCC) and are updated in each IPCC Assessment Report (AR). In 2010, the UNFCCC required Parties to use the GWPs from the IPCC's Second Assessment Report (SAR); today, the UNFCCC requires Parties to use the GWPs contained in the Fourth Assessment Report (AR4).[3] Both sets of GWPs are shown in Table 1-2. Simply due to the changes in the GWPs shown in Table 1-2, emissions of methane (CH_4) will receive more weight in this report than in the EPA RIA and emissions of N_2O will receive less.

Table 1-2: Global Warming Potentials

Greenhouse Gas	Second Assessment Report GWP	Fourth Assessment Report GWP
CO_2	1	1
CH_4	21	25
N_2O	310	298

Finally, throughout this report many metrics are used to quantify the emissions associated with different activity levels, production processes, use of inputs, and outputs levels. Within a given source category, the set of metric(s) presented generally reflect those commonly used in the related literature. For example, emissions related to the use of nitrogen and other chemicals in corn production are summarized in kilograms (kg) CO_2e/acre, kg CO_2e/bushel, and kg CO_2e per

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[3] The choice of GWPs is a methodological decision. For example, the IPCC currently mandates the use of AR4 GWPs for countries reporting their national GHG emissions to the United Nations Framework Convention on Climate Change (UNFCCC).

gallon of ethanol (see Domestic Farm Inputs and Fertilizer N_2O section). For purposes of adding emissions across source categories in this analysis, and for facilitating comparisons with various emissions levels reported in the RIA, emissions for all source categories are also presented in grams CO_2e/million Btu (g CO_2e/MMBtu).

Organization of the Report

In this report, Chapter 2 reviews the scientific papers, technical reports, data sets, and other information that have become available since 2010 that relate to current emission levels in each emission category. It also develops a current GHG emission value for of the 11 each emission categories based on the literature review. Each emission category is considered in a separate section of Chapter 2. Each section includes a summary of the methods, data sources, and emissions projection developed in the EPA RIA, describes the methods ICF used to quantify the contribution to corn ethanol’s current GHG profile attributable to that category, and quantifies that contribution.

Based on the current GHG emissions profile of corn ethanol developed in Chapter 2, Chapter 3 develops two projected profiles for corn ethanol in 2022. The first projection considers a continuation through 2022 of observable trends in corn yields (per acre), process fuel switching toward natural gas, and fuel efficiency in trucking. The second projection adds a number of changes refineries could make in their value chain to further reduce the GHG intensity of corn ethanol. These changes include contracting with farmers to reduce tillage and manage nitrogen applications, switching to biomass as a process fuel, and locating confined livestock operations in close proximity to refineries.

Assessing Current Lifecycle GHG Emissions for Corn Ethanol

This chapter develops a current GHG lifecycle analysis (LCA) for U.S. corn ethanol. In developing this emissions profile, we draw on scientific papers, technical reports, data sets, and other information in the peer-reviewed and credible non-peer-reviewed literature that have become available since 2010 and relate to assessing current emissions levels for each of the 11 source categories included in the 2010 Regulatory Impact Analysis (RIA). The chapter is organized by emission category. In each section, also we review the methodology and emissions value developed by EPA in the RIA. Where applicable, information, data, and emission factors from the more recent literature is compared to corresponding information and data used in the RIA.[4]

The remainder of this chapter is organized as follows:

1. Domestic farm inputs and fertilizer N_2O
2. Domestic land-use change
3. Domestic rice methane
4. Domestic livestock
5. International livestock
6. International land-use change
7. International farm inputs and fertilizer N_2O
8. International rice methane
9. Fuel and feedstock transport
10. Fuel production
11. Tailpipe

Domestic Farm Inputs and Fertilizer N_2O

The domestic farm inputs evaluated in the RIA include fertilizers, herbicides, pesticides, and on-site fuel use. The fertilizers evaluated included nitrogen, phosphorous, potash, and lime. Representative herbicides and pesticides were also included. On-site fuels included diesel, gasoline, natural gas, and electricity. N_2O emissions due to application of synthetic fertilizers were also quantified.

The RIA estimates domestic agricultural use of fertilizer, pesticides, and energy by comparing simulation results of the Forestry and Agriculture Sector Optimization Model (FASOM) for the Control and Corn Only cases. Since 2010 additional data

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[4] Many of the data inputs and emissions factors used in 2010 RIA come from established data sources. We reviewed updated output datasets and emission factors from more recent versions of these models. In these cases, it is straight forward to compare the impacts associated with the updated inputs and emission factors with those in the RIA. . For example, the RIA obtained many of its emissions coefficients from Argonne National Laboratory's 2009 GREET model. Our study obtains many of the same coefficients from the 2015 GREET model.

and other information have become available that allow us to assess the current contribution of this source category to corn ethanol's LCA emissions. For example, the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS) reports much of these data under the Agricultural Chemical Use Program.

Literature Review Findings

Domestic Farm Chemical Use

The NASS Agricultural Chemical Use Program is USDA's official source of statistics about on-farm chemical use and pest management practices.[5] Since 1990, NASS has surveyed U.S. farmers to collect information on the chemical fertilizers and pesticides they apply to agricultural commodities. On a rotating basis, the program currently includes fruits; vegetables; major field crops such as cotton, corn, potatoes, soybeans, and wheat; and nursery and floriculture crops.

Each survey focuses on the top-producing states that together account for the majority of U.S. acres or production of the surveyed commodity. Data are available at the state level for all surveyed states, as well as at a multi-state level including all surveyed states. Data items published include, but are not limited to:

- For fertilizers: percent of acres treated, number of applications, rates of application, and total amounts applied of the primary macronutrients nitrogen (N), phosphate (P_2O_5), and potash (K_2O) as well as (since 2005) the secondary macronutrient sulfur (S). These data are available annually for field crops.
- For pesticides: percent of acres or production treated, number of applications, rates of application, and total amounts applied of the individual active ingredients composing all registered pesticides used. Active ingredients are classified as herbicides, fungicides, insecticides, or other (regulators, desiccants, etc.), according to the pesticide product classification. Rates and amounts applied are published in the acid or metallic equivalent, as applicable. Some items are not available for all commodities.

Domestic Farm Energy Use

Periodically, USDA produces an updated inventory of GHG emissions and carbon sequestration for the agriculture and forestry sectors. These reports are prepared with contributions from the USDA Agricultural Research Service, USDA Forest Service, USDA Natural Resources Conservation Service, USDA Office of Energy Policy and New Uses, USDA Climate Change Program Office, U.S. Environmental Protection Agency (EPA), and researchers at Colorado State University. The estimates in the USDA GHG Inventory are consistent with those published by the EPA in the official *Inventory of U.S. Greenhouse Gas Emissions and Sinks,* but provide an enhanced view of emissions by regional, commodity,

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[5] More information on the program, and access to the Chemical Use data is available online at: http://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Chemical_Use/

and by land use. The last USDA GHG inventory was published in September 2016. Chapter 5 of the *USDA Agriculture and Forestry Greenhouse Gas Inventory: 1990–2013* provides information on energy use in agriculture (USDA, 2016a).

The methodology for developing empirical data on farm use of energy inputs and the associated GHG emissions is described in USDA (2011).

> *Estimates of CO_2 from agricultural operations are based on energy expense data from the Agricultural Resource Management Survey (ARMS) conducted by the National Agricultural Statistics Service (NASS) of the USDA. The ARMS collects information on farm production expenditures, including expenditures on diesel fuel, gasoline, LP gas, natural gas, and electricity... NASS also collects data on price per gallon paid by farmers for gasoline, diesel, and LP gas... Energy expenditures are divided by fuel prices to approximate gallons of fuel consumed by farmers. Gallons of gasoline, diesel, and LP gas are then converted to Btu based on the heating value of each of the fuels. The individual farm data are aggregated by state, and the state data are divided into 10 production regions, allowing fuel consumption to be estimated at the national and regional levels. Farm consumption estimates for electricity and natural gas are also approximated by dividing prices into expenditures. Since electricity and natural gas prices are not collected by NASS, we use data from the Energy Information Administration (EIA) that reports average prices by state… NASS regional prices were derived by aggregating the EIA state data into NASS production regions (USDA, 2011).*

Domestic Farm Nitrogen (N) Application

As indicated by recent USDA data (see Table 2-1), N applied to corn in the United States increased from 137 to 143 pounds per acre from 2005 to 2010. However, yield per acre also increased during the same period, thereby resulting in a net decrease in N application per unit of crop yield. According to The Fertilizer Institute:

> *Between 1980 and 2014, U.S. farmers more than doubled corn production using only slightly more fertilizer nutrients than were used in 1980. This analysis is based on fertilizer application rate and corn production and acreage data reported by the U.S. Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS). Specifically, in 1980, farmers grew 6.64 billion bushels of corn using 3.2 pounds of nutrients (nitrogen, phosphorus and potassium) for each bushel and in 2014 they grew 14.22 billion bushels using less than 1.6 pounds of nutrients per bushel produced. In total, this represents an 114 percent increase in production using only 4.5 percent more nutrients during that same timeframe.*

Between 2010 and 2014 there was a 4.5 percent decrease in N applied per bushel of corn (i.e., from 1.63 to 1.56 pounds of N per bushel) (The Fertilizer

Institute, 2016). This decrease in fertilizer application, combined with the direct change in acres, could reduce the emissions impact of domestic applied N.

Table 2-1: N Application for Corn

		2010		2005	
All Farms: TOTAL	**Units**	**Estimate**	**RSE[a]**	**Estimate**	**RSE[a]**
Planted acres	1,000 acres	81,740.030	0.0	76,121.603	0.0
Manure applied	percent of planted acres	15.026	9.0	12.875	7.0
Ever treated with lime	percent of planted acres	53.777	2.8	55.972	2.0
Treated with chemical fertilizer and manure	percent of planted acres	12.189	10.1	10.81	7.7
Nitrogen inhibitor used	percent of planted acres	12.457	10.3	8.493	13.9
Soil tested for N, P_2O_5, K_2O	percent of planted acres	33.114	5.4	36.126	4.2
Soil tested for N	percent of planted acres	22.269	5.4	28.118	4.2
Plant tissue test used	percent of planted acres	4.495	19.5	4.157	22.3
Acres treated with N	percent of planted acres	96.394	1.0	96.588	0.9
Acres treated with P_2O_5	percent of planted acres	78.194	2.2	81.652	1.5
Acres treated with K_2O	percent of planted acres	61.187	2.8	65.388	2.2
N applied	pounds per treated acre	143.484	1.3	137.027	1.6
P_2O_5 applied	pounds per treated acre	60.959	2.5	57.627	2.7
K_2O applied	pounds per treated acre	79.135	3.5	82.626	2.8
Compost applied	percent of planted acres	0.332	31.4	NA	NA

[a] The Relative Standard Error (RSE) is the standard error of the estimate expressed as a percent of the estimate.
NA—estimate does not comply with NASS disclosure practices, is not available, or is not applicable
Source: USDA ERS, 2013a.

Domestic Farm Inputs and Fertilizer N_2O Emission Factors

For the RIA, EPA used Argonne National Laboratory's (ANL) 2009 GREET model to create emission factors for herbicides, pesticides, and nitrogen, phosphate, potash, and lime fertilizers. The GREET emission factors include emissions associated with the production of these chemical and their transport to the farm. GREET does include emissions that occur with, and after, application to the field but both EPA and ICF chose to use more detailed emission factors and sources to quantify those emissions. The GREET emission factors were documented in two locations within the docket. Based on the file, "Renewable Fuel Lifecycle Greenhouse Gas Calculations (2).xls" (Docket ID: EPA-HQ-OAR-2005-0161-0950) (EPA, 2009a).[6]

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[6] Based on the docket file, "GREET_Model_Spreadsheets_Used_in_the_Lifecycle_Analysis_(3).xls" (Docket ID: EPA-HQ-OAR-2005-0161-3176) (EPA, 2009a), the values taken from GREET were

Since 2010, GREET has been updated nine times. Common updates include the addition of new pathways, updated natural gas and oil data, and updated electricity generation mix. During the GREET 2014 update, ethanol production from corn, soy, and cellulose were updated and expanded. For our analysis, we obtain energy related inputs and emissions factors from the 2015 GREET model. Between 2009 and 2015, Argonne adjusted energy use for nitrogen fertilizer manufacturing by increasing natural gas use across all nitrogen fertilizer types.

Domestic Farm Input and Fertilizer N_2O Management Practices

While the EPA RIA includes comprehensive information on emission factors, it does not account for more recent literature discussing an increase in crop and nutrient management strategies. These strategies have the potential to reduce the emissions from agriculture production, particularly N_2O emissions from corn grown for ethanol. Two of the most common of these strategies are use of nitrification inhibitors and precision agriculture. USDA statistics already reflect the effects of precision agriculture through the reduced fertilizer use per bushel of corn harvest, however use of nitrification inhibitors is not reflected in estimation of N_2O emissions.

Nitrification inhibitors work by slowing the nitrification process when nitrogen-based fertilizer is applied to crops, which allows for an increase in nitrogen use efficiency. Inhibitors can be mixed into fertilizers or applied separately. They give crops access to a larger percentage of applied fertilizer. As Trenkel (2010) explains in his comprehensive paper on enhancing nutrient use efficiency in agriculture through slow- and controlled-release and stabilized fertilizers, the Association of American Plant Food Control Officials (AAPFCO) defines a nitrification inhibitor as "a substance that inhibits the biological oxidation of ammoniacal-N to nitrate-N". Maintaining the nitrogen in its ammonium form longer gives crops a more prolonged chance for nitrogen-uptake, thereby using applied nitrogen more efficiently and reducing emissions through nitrogen loss.

Precision agriculture refers to crop production technologies and practices that use "information gathered during field operations, from planting to harvest, to calibrate the application of inputs and economize on fuel use" Schimmelpfennig and Ebel (2011). These practices include Global Positioning System (GPS) - and sensor-based mapping systems that regulate the application rate of inputs such as fertilizers and eliminate the potential for overlapping application on corners and irregular fields. Systems that regulate and optimize the application rate are typically called variable rate technology (VRT) or variable rate application (VRA), while systems that reduce or eliminate overlap in application are typically called swath control.

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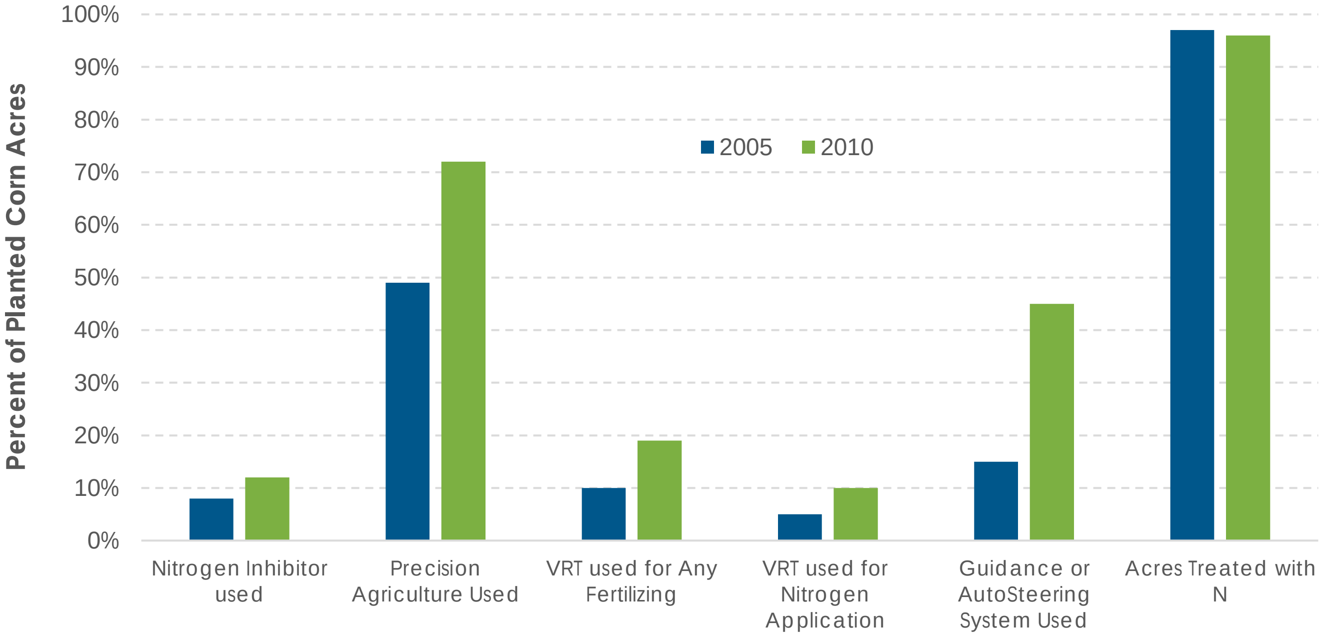
multiplied by 1.1. The RIA does not include any explanation for the multiplication. One possible reasoning is that the 1.1 multiplicative is to adjust the GREET lower heating value (LHV) to align with EIA's higher heating value (HHV).

Studies released since 2010 show that use of inhibitors on crops can reduce emissions around 20 to 60 percent, depending on factors such as timing of application and soil moisture (Halvorson, 2014; Thapa et al., 2015). In a slightly more modest range, recent literature indicates that variable rate technology can decrease emissions in the range of 19 to 35 percent (Vazquez-Amabile et al., 2013). Although there is no individual agreed-upon emissions reductions rate across the literature, there is a consensus in the literature that these practices can reduce overall emissions in tangible ways, such as by improving the efficiency of nitrogen use, reducing the use of inputs such as nitrogen-based fertilizer, and decreasing on-farm fuel use.

Using USDA ARMS data, Schimmelpfennig and Ebel (2011) describe an upward trend in use of precision agriculture (USDA ERS, 2013b). According to the USDA ARMS data, use of many nitrogen management strategies did increase from 2005 to 2010. As the RIA does not reflect data from 2010, it would not have included changes in emissions data caused by these increasingly common practices. Figure 2-1 shows the changing prevalence of corn acres treated with nitrogen (N) and the use of: (1) nitrogen inhibitors, (2) precision agriculture, (3) VRT for any fertilizer application, (4) VRT for nitrogen application specifically, and (5) guidance or AutoSteering systems (e.g., swath control). All of the nutrient management practices increased in use between 2005 and 2010 (when the N application rate increased from 137 to 143 pounds per treated acre and the total number of corn acres treated with nitrogen declined slightly).

Figure 2-1: Changes in Corn Production Practices from 2005 to 2010



Sources: Scimmelpfennig and Ebel (2011) and USDA ERS (2013)

Practices such as use of nitrification inhibitors and precision agriculture decrease both upstream and downstream emissions from agriculture and will likely play an important mitigation role in the sector.

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology and Data Sources

In the RIA, EPA projected domestic agricultural use of fertilizer, pesticides, and energy by comparing simulation results from the Forestry and Agriculture Sector Optimization Mode (FASOM) for the Control and Corn Only cases.[7] The amount of each input was determined based on the inputs required for the specified crops and the changes in demand for those crops based on increased biofuel production. FASOM constructed crop budgets for 11 market regions, which varied by crop, management practice, and region. Within these crop budgets, data on crop yield, fertilizer, pesticides, and fuels used were included. These budgets did not reflect input or yield changes that may result in altered crop rotation patterns or the use of marginal land. Energy use in FASOM represented the fuels used to dry grain. It was based on the assumptions that 17.5 gallons of propane and 9 kWh of electricity were required to remove 10 percentage points of moisture from 100 bushels of grain. Total energy use per acre was determined by multiplying the energy use per percentage point per yield unit for each crop that is dried (i.e., bushel of grain) by the total number of percentage points to be removed and the yield per acre.

The emission factors used for the fertilizers and pesticides were from GREET. The electricity emission factors represent average U.S. grid electricity production and were also based on GREET (EPA, 2009c).

The N_2O emissions were based on different N-input sources including fertilizer application, nitrogen-fixing crops such as soybeans, and crop residues. The N_2O emissions from manure management systems (and manure application) are addressed in the Domestic Livestock section. To model the domestic impacts of N_2O emissions from fertilizer application, Colorado State University's CENTURY and DAYCENT models were used.[8] CENTURY and DAYCENT simulate plant-soil systems and simulates plant production, soil carbon dynamics, soil nutrient dynamics and soil water and temperature. These simulations account for all nitrogen inputs into the soil and provide regression equations with the coefficients accounting for N_2O estimates by region, crop type, irrigation status, and crop residue treatment. The regression equations were then used to calculate the N_2O emission per acre. FASOM was used to evaluate the N_2O emissions from crop residues and residue

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[7] FASOM is a dynamic, partial equilibrium, sectoral model used to simulate potential future impacts of polices on land use, GHG fluxes, and commodity markets within the agricultural and forestry sectors (Adam et al., 2005). It has collaborators at Oregon State, Research Triangle Institute, Electric Power Research Institute, EPA, USDA, and USDA-Forest Service.

[8] Colorado State's CENTURY and DAYCENT models are related models focused on nutrient cycling. The CENTURY model is a general model of plant-soil nutrient cycling which is being used to simulate carbon and nutrient dynamics for different types of ecosystems including grasslands, agricultural lands, forests, and savannas. The DAYCENT model simulates carbon and nitrogen fluxes through the ecosystem at daily time-step intervals.

burning using IPCC guidelines and assumed that 1 percent of nitrogen (N) residing in crop residues that remain on the field is emitted as N_2O emissions, following IPCC guidelines. The crop residue emissions estimates consider:

- N content by crop based on yield,
- Residue-to-crop ratio,
- Percent dry matter,
- Percentage of rice area burned in each state,
- Burn and combustion efficiency, and
- Percent of residue burned by crop.

Field burning of crop residues is not considered a net source of CO_2, because the carbon released to the atmosphere as CO_2 during burning is assumed to be reabsorbed during the next growing season. Field burning of crop residues, however, does emit N_2O and CH_4. These are considered a net source of GHG emissions.

EPA RIA Results

National-level input data for domestic farm inputs based on the FASOM output are shown in Table 2-2. The RIA provides the domestic inputs in units per MMBtu as they are attributed to the corn ethanol production.

Table 2-2: Summary of Domestic Agricultural Inputs for Corn Ethanol, 2022

Input	Units per MMBtu	Corn –Only Case	Control Case	Difference	Percent Change
Total N	Pounds	136.6	138.8	2.1	1.5%
Total P_2O_5	Pounds	31.2	31.7	0.5	1.5%
Total K_2O	Pounds	38.8	39.5	0.7	1.9%
Total Lime	Pounds	104.2	104.7	0.5	0.5%
Herbicide	Pounds	1.9	2.0	0.0	2.2%
Pesticide	Pounds	0.4	0.4	0.0	2.8%
Total Diesel Fuel	Gallon	14.3	14.2	−0.1	−0.5%
Total Gasoline Fuel	Gallon	1.7	1.7	0.0	−0.9%
Total Electricity	kWh	1.0	1.0	0.0	0.3%
Total Natural Gas	Btu	248,002	234,746	−13,257	−5.6%

Source: EPA, 2010a (See Table 2.4-5) and FASOM output; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Inputs_Ag” tab.

These values were combined with the upstream emission factors from GREET to calculate the GHG emissions from the production of fertilizer, herbicides, pesticides, and fuels. Upstream emissions for diesel, gasoline, electricity, and natural gas are discussed in the Fuel Production section.

The FASOM output for the N_2O emissions is shown in Table 2-3. In the calculation spreadsheets, the analysis in some cases was only performed for the volume difference between the Corn Only case and the Control case to determine the impact from the RFS2 driven increases in U.S. corn production. Negative values in Table 2-3 represent a decrease in emissions.

Table 2-3: Relative Change in N_2O Emissions (DAYCENT/CENTURY)

		2012			2017	2022
Emission Category	**Units**	**Corn Only Case**	**Control Case**	**Difference**	**Difference**	**Difference**
N Fertilizer Application Practices under Managed Soil	000 Metric Tons CO_2e	N/P	N/P	363.5	574.8	442
Emissions from N Fixing Crops	000 Metric Tons CO_2e	N/P	N/P	−823.5	−1,330	−1,157
Emissions from Crop Residue Retention	000 Metric Tons CO_2e	N/P	N/P	−152.8	−180.1	−218
Domestic Fertilizer Use	000 Metric Tons CO_2e	73,282	73,565	−612.7	−935.1	−933

Source: FASOM output; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Inputs_Ag” tab.
N/P = Not Provided.

The activity data from Table 2-2 was multiplied by the emission factors shown in Table 2-4 to calculate total emissions by domestic farm-chemical inputs. The energy use values reflect emissions related solely to the production and transportation to the farm of the associated chemical.

Table 2-4: Emission Factors and Energy Use for Domestic Farm Inputs and Fertilizer N_2O

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
Emissions (grams per metric ton of nutrient)						
CO	2,726	1,091	214.8	244.2	6,582	10,091
NO_x	2,274	6,206	1,103.4	781.632	23,188	29,312
PM10	436.1	1,468	137.6	544.366	11,269	12,874
PM2.5	230.1	901.2	57.1	181.8	5,145	6,113
SO_x	1,007	54,455	423.17	904.6	21,979	17,007
CH_4	2,632	1,610.3	888.8	830.9	27,147	32,196
N_2O	1,481	16.68	9.116	7.762	216.3	281.7
CO_2	2,211,527	894,413	602,485	949,543	18,767,361	21,967,813
CO_2e	2,726,048	933,401	623,976	969,398	19,404,522	22,731,268
Energy Use (MMBtu per metric ton of nutrient)						
Coal Energy	2.56	2.52	2.73	2.72	50.66	62.68
Natural Gas Energy	36.92	5.54	2.14	2.11	63.76	76.01
Petroleum Energy	1.67	3.49	2.23	1.63	114.89	134.39

Source: GREET output; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Emission Factors” tab.

In the RIA, emissions for the domestic agricultural inputs source category were projected to be 10,313 g CO_2e/MMBtu in 2022.

ICF Methodology and Data Sources

ICF analyzed the GHG emissions associated with the increased use of nitrogen (N) fertilizer, phosphorus (P) fertilizer, potassium (K) fertilizer, herbicides, insecticides, fungicides, and diesel fuel consumption needed to meet the RFS2 corn ethanol mandate. Upstream emission factors are included for all applied chemicals and the direct and indirect N_2O emissions from nitrogen fertilizer applications are evaluated. The upstream and on-site diesel fuel impacts are also included in the analysis.

For chemical application rates (calculated based on the percent of acres applying a particular chemical and pounds applied per acre), ICF utilized the most recent ARMS data for corn, which is for 2010 and is provided separately for the ten USDA Farm Production Regions (USDA ERS 2016). ICF utilized the national average fungicide application rate for all regions except for the Corn Belt region, due to the lack of data for these regions. We assume that the diesel fuel use is 7.74 gallons per corn-acre under conventional tillage, based on 2015 University of Tennessee (UT) farm budget worksheets (UT 2015).

To calculate the effective chemical application rates, ICF multiplied the application rates in each region (pounds per acre) by the percent of acres in each region that apply each fertilizer or pesticide (USDA ERS 2016).[9] Table 2-5 presents the results of this analysis. ARMS data did not report corn acres in the Delta and Pacific regions, hence these regions are excluded from Table 2-5 (USDA ERS 2016).

Table 2-5: Effective Chemical Application Rates (Pounds per Acre)

Chemical	Appalachia	Corn Belt	Lake States	Mountain	Northeast	Northern Plains	Southeast	Southern Plains	Weighted Average for United States
Nitrogen	146.7	152.6	109.7	127.7	75.1	138.6	160.6	130.3	138.3
Phosphorus	66.0	61.6	35.8	15.4	23.4	34.7	50.9	26.8	47.7
Potassium	81.2	72.8	47.9	0.0	23.4	9.8	77.0	5.3	48.4
Herbicide	2.94	2.13	1.63	2.37	2.92	2.22	2.14	1.63	2.10
Insecticide	0.016	0.015	0.012	0.058	0.022	0.018	0.018	0.056	0.017
Fungicide	0.009	0.014	0.009	0.009	0.009	0.009	0.009	0.009	0.011

Source: 2010 USDA ARMS Data.

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[9] For example, 95.2 percent of acres in Appalachia apply nitrogen and, in that region, the average application rate is 154.1 lbs N/acre. By multiplying the adoption rate by the application rate, ICF calculated the effective nitrogen application rate across the region (146.7 lbs N/acre).

ICF used the RIA's projected number of additional bushels of corn in the Control case compared to the Corn Only (773,956,000 bushels in 2017) to determine the additional number of corn acres that can be attributed to the RFS2. This projected change in bushels was divided by the most recent USDA corn yield data (168.4 bushels per acre in 2015) (USDA NASS, 2016). The resultant additional acres of corn are presented in Table 2-6. These acres are allocated by region based on regional corn acreage data in ARMS (USDA ERS, 2016). The purpose of generating emission factors by region and estimated acres per region is to calculate the emissions per average, or "representative," acre and apply corn and ethanol yield factors to determine emissions per gallon for that acre.

Table 2-6: Calculated Changes in Corn Production in the Current Conditions Control Scenario (Acres)

Year	Appalachia	Corn Belt	Lake States	Mountain	Northeast	Northern Plains	Southeast	Southern Plains	Total Acres
2014	127,070	2,170,333	787,171	74,777	134,942	1,155,449	16,871	129,326	4,595,938
2017	125,009	2,135,131	774,400	73,564	132,753	1,136,703	16,597	127,228	4,521,374
2022	86,533	1,477,955	536,048	50,922	91,893	786,839	11,489	88,068	3,129,747

ICF multiplied the acreages in Table 2-6 by the individual fertilizer and fuel emission factors. Life-cycle emission factors for diesel fuel (on-site and upstream), fertilizers (N, P, and K) and insecticide were based on ANL's 2015 GREET model (Argonne National Laboratory, 2015). Emission factors for herbicides and fungicides are from ecoinvent v2 found in SimaPro. These emission factors are cradle to gate and include the emissions from the upstream production of agricultural chemicals (Weidema et al. 2013), but do not include emissions from, or after, application.

The direct and indirect N_2O emissions from N-fertilizer applications (on-site and downstream) are based on IPCC guidance for rates for each kilogram of N fertilizer applied (IPCC, 2006). IPCC provides N mineralized from mineral soil as a result of loss of soil carbon, as well as volatilization and leaching (as N_2O-N). The factors of 168.4 bushels of corn per acre (USDA NASS, 2016) and 2.8 gallons of ethanol per bushel of corn from (GREET, 2015) were used to convert emissions per acre to emissions per MMBtu of ethanol. It is important to note that the total emissions calculated from the emission factors in Table 2-4 and regional acres in Table 2-6 were divided by the total acres to give emission results for an average incremental acre. Therefore, the emissions calculated and shown in Table 2-7 deviate from the methodology in the RIA and do not take into account acreage reductions from the use of distiller grains and solubles as an animal feed. An ethanol co-product is calculated separately in the next section.

Table 2-7: N_2O from Fertilizer, Fertilizer and Pesticides, and Fuel Use Emissions Impacts

	Emissions Impacts (kg CO_2e/Acre)	Emissions Impacts (kg CO_2e/Bushel)	Emissions Impacts (kg CO_2e/Gallon Ethanol)	Emissions Impacts (g CO_2e/MMBtu)
N_2O from Fertilizer Application	389.26	2.31	0.83	10,815
Production of Fertilizer and Pesticides	301.67	1.79	0.64	8,382
On Farm Fuel Use	94.19	0.56	0.20	2,617
Total	**785.12**	**4.66**	**1.67**	**21,814**

Note: 1 metric ton = 1,000 kg = 1,000,000 g

Ethanol Co-Product Credit

Co-products of the ethanol production processes include distillers grains and solubles (DGS, from dry mill ethanol processing), and corn gluten meal and corn gluten feed (CGM and CGF, from wet milling ethanol process). These products are sold into the animal feed market. The standard LCA approach for handling these animal feed co-products (see ANL's GREET model (GREET, 2015), the California Air Resources Board (CARB, 2009), and EPA (EPA, 2010a)) is the displacement method. With the displacement method, all of the energy and emissions for farming, fertilizer production, and feedstock transport are allocated to the primary product from ethanol production (i.e., the ethanol); the ethanol pathway is then given an emissions credit reflecting the emissions that would have occurred if the feed crops the co-product displaced had in fact been produced.

ICF utilized the 2015 GREET model assumptions for the breakdown of the animal feed components, including corn, soybean meal, urea, and soybean oil, that are being displaced. Table 2-8 indicates that feed displacement values vary by ethanol refining process and displaced animal feed.

Table 2-8: Ethanol Production Market Breakdown and Animal Feed Displacement by Ethanol Plant Type

		Total Displaced Animal Feed (Pounds per Gallon of Ethanol)			
Ethanol Plant Type	**Ethanol Market Share**	**Corn**	**Soybean Meal**	**Urea**	**Soy Oil**
Dry Mill w/o Corn Oil Extraction	17.7%	4.402	1.731	0.128	-
Dry Mill w/ Corn Oil Extraction	70.9%	4.210	1.656	0.122	-
Wet Mill	11.4%	7.149	-	0.109	0.980

Source: GREET, 2015.

ICF modified the GREET default values for corn farming inputs and fertilizer N_2O to incorporate the values presented earlier in this section and quantify the displaced emissions from the use of DGS as animal feed. Utilizing the AR4 GWP

for CH_4 and N_2O, Table 2-9 shows the resulting DGS credit per gallon of ethanol and per MMBtu.

Table 2-9: Ethanol Co-Product Credit by Ethanol Plant Type

Ethanol Plant Type	Ethanol Market Share	Co-Product Credit (g CO_2e/Gallon Ethanol)	Co-Product Credit (g CO_2e/MMBtu)
Dry Mill w/o Corn Oil Extraction	17.7%	-991	-12,981
Dry Mill w/ Corn Oil Extraction	70.9%	-948	-12,417
Wet Mill	11.4%	-1,103	-14,449
Weighted Average	**100%**	**-973**	**-12,749**

ICF Results

The ICF emissions value for the domestic agricultural inputs source category is 9,065 g CO_2e/MMBtu. This value is the sum of the ethanol co-product credit in Table 2-9 (−12,749 g CO_2e/MMBtu) and the domestic inputs emissions in Table 2-7 (+21,814 g CO_2e/MMBtu). The difference in emissions from the EPA RIA is relatively small and primarily reflects the lower GWP value for N_2O in AR4 and the slightly higher chemical application rates used in our analysis.

Limitations, Uncertainty, and Knowledge Gaps

ICF allocated the change in acres by region based on the ARMS corn acreage data by region (USDA ERS 2016) in order to apply region-specific fertilizer and insecticide application rates. This methodology assumes that the increased demand for corn ethanol affects all regions proportionally.

To model the energy associated with tillage and chemical application, ICF used a dataset that is specific to Tennessee, however recognizes that other datasets, such as the ARMS data, could be used. The University of Tennessee dataset provides the necessary granularity in energy used by activity. ICF recognizes that crop budgets are based on recommendations.

Finally, the current emission profile developed here did not include the impacts from the current use of nitrogen inhibitors and other advanced farming and agricultural practices. Potential emissions reductions from adoption of these practices are considered in the projection scenarios in Chapter 3.

Domestic Land-Use Change

The domestic LUC source category includes: 1) direct land-related emissions associated with U.S. farmers shifting cropland and land from other uses into corn production; and 2) indirect emissions related to U.S. farmers bringing new lands into production to replace some of the decreases in output of non-corn commodities that occur when more existing cropland is used to grow corn.

Literature Review Findings

Since 2010, a number of studies, data sets, and other information have become available to indicate the relationship between U.S. corn ethanol production and domestic LUC emissions may differ significantly from the way it was modeled in the RIA. In this review, we consider evidence related to three factors that suggest the current GHG intensity of this source are lower than the level projected in the RIA and one factor that suggests it may be higher. The three factors supporting a lower GHG intensity are recent trends in corn yields per acre, recent trends in ethanol yields per bushel of corn, and evidence that the domestic LUCs that have occurred to produce the additional corn needed for the increases in ethanol production since 2004 have been less in magnitude and different with respect to the types of land shifted into crop production than was modeled for the RIA.

Table 2-10 presents USDA NASS corn data for total production, acres harvested and planted, and corn used for ethanol production for the period 2007 – 2015. While there are fluctuations in yields per acre, there is a clear upward trend (increasing from about 150 bushels per acre at the start of the period to about 170 bushels per acre at the end). USDA has formally recognized this productivity gain by incorporating a yield increase of 2 bushels per acre per year into its annual 10-year Baseline projections for U.S. agriculture (USDA, 2016). The LUC implication of this trend is that it takes less cropland to produce a given quantity of corn ethanol today than it did in 2010; if the trend continues, we can expect it will take less cropland to produce that same quantity of ethanol in 2022 than it does today.

Table 2-10: U.S. Corn Crop Actual Performance

	USDA National Agricultural Statistics Service Data				ICF Analysis		
	Corn Use in Fuel Ethanol	U.S. Corn Production	Corn Planted Acreage	Corn Harvested Acreage	Corn Allocation to Ethanol	Average Crop Yield	Harvested/ Planted Acreage
Year	Million bushels	Million bushels	Million acres	Million acres	%	bushels/ acre	%
2007	3,049.21	13,037.88	93.53	86.52	23%	150.7	93%
2008	3,708.89	12,043.20	85.98	78.57	31%	153.3	91%
2009	4,591.16	13,067.16	86.38	79.49	35%	164.4	92%
2010	5,018.74	12,425.33	88.19	81.45	40%	152.6	92%
2011	5,000.03	12,313.96	91.94	83.88	41%	146.8	91%
2012	4,641.13	10,755.11	97.29	87.37	43%	123.1	90%
2013	5,123.69	13,828.96	95.37	87.45	37%	158.1	92%
2014	5,200.09	14,215.53	90.60	83.14	37%	171.0	92%
2015	5,219.40	13,601.96	88.02	80.75	38%	168.4	91%

Source: USDA, 2016.

Table 2-11 presents EIA data on U.S. ethanol production over the period 2007 – 2014. As with per acre corn yields, there are fluctuations in ethanol yields per

bushel of corn but over the period yields have marginally increased. For the FASOM simulations developed for the RIA, it was assumed that ethanol yields were, respectively 2.71 gallons/bushel and 2.50 gallons/bushel (Beach and McCarl, 2010) for dry-mill and wet-mill refineries. Using these yields, a weighted average ethanol conversion factor of 2.69 gallons/bushel was calculated (EPA, 2010d). To the extent that ethanol yields per bushel of corn have increased relative to the value used in the RIA, less cropland will be required to produce a given quantity of corn ethanol.

Table 2-11: U.S. Ethanol Production and Ethanol Conversion 2007 to 2014

	National Agricultural Statistics Service and U.S. Energy Information Administration Data			
	Ethanol Production Calendar Year	Corn Use in Fuel Ethanol Market Year	Ethanol Production Market Year	Ethanol Conversion for Market Year
Year	Millions of Gallons	Million bushels	Millions of Gallons	(gallons/bushel)
2007	6,521	3,049.21	8,367	2.74
2008	9,309	3,708.89	10,305	2.78
2009	10,938	4,591.16	12,670	2.76
2010	13,298	5,018.74	13,811	2.75
2011	13,929	5,000.03	13,765	2.75
2012	13,218	4,641.13	12,822	2.76
2013	13,293	5,123.69	14,103	2.75
2014	14,313	5,208.50	14,660	2.81

Source: EIA, 2015.

With respect to the magnitude and make-up of RFS2 driven changes in domestic land use, a variety of new LUC studies and other information strongly support the conclusion that the actual emissions paths of the LUC source categories (both domestic and international LUC) differ from those projected in the RIA. For our analysis, we estimate domestic LUC emissions using results of a 2013 simulation of the Global Trade Analysis Project-Biofuels (GTAP-Bio) model and Century/COLE land use change emissions coefficients available in ANL's Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) tool (Dunn et al., 2014). The 2013 GTAP-Bio results developed in Taheripour and Tyner (2013) include domestic and international land-use changes related to U.S. corn ethanol production increasing from its 2004 level (GTAP-Bio's base period) to the RFS2 cap of 15 billion gallons per year. Globally, the GTAP-Bio estimates regional acreage changes for 18 Agro-ecological Zones (AEZs), and within each AEZ, for changes in four land types (forests, grassland, cropland-pasture, and young forest shrub). Only AEZs 7–16 apply to U.S. agriculture. For the United States, summing acreage changes across AEZs shows increasing U.S. ethanol production resulted in conversions to cropland of 13,999 hectares of young forest shrub, 64,773 hectares of forest, 92,617 hectares, of grassland, and 1,788,462 hectares of cropland pasture; conversions by AEZ and land type are shown in Table 2-12.

The CCLUB tool also includes LUC results for a similar analysis by Taheripour, Tyner, and Wang (2011) using a 2011 GTAP model. These LUC changes are also shown in

Table 2-12. Comparing the 2011 and 2013 GTAP results highlights how much new information has improved our understanding of how increases in corn ethanol production affect changes in land use relative to our understanding in 2010. GTAP-Bio expands the set of land transformation elasticities from a single value to a set of region-specific values. GTAP-Bio also incorporates an improved cost structure that reflects the higher cost of converting forest to cropland vs. converting pasture to cropland. Comparing the LUC results, shows conversions of young forest shrub, forest, and grasslands in the 2013 GTAP-Bio simulation are, respectively 79 percent, 80 percent, and 86% percent less than in the 2011 simulation. There is also a 53 percent increase in conversions of cropland pasture to cropland. Overall, the GTAP-Bio analysis shows the large increase in U.S. corn ethanol production since 2004 resulted in a large increase in land in corn production, a relatively small increase in aggregate agricultural land, and increases in cropland coming predominantly (over 90 percent) from cropland pasture.

Table 2-12: Comparing U.S. Cropland Changes in Taheripour et al. (2011) and Taheripour and Tyner (2013) by AEZ and Land Type

AEZ Number	Forest to Cropland (ha)		Grassland to Cropland (ha)		Cropland-Pasture to Cropland (ha)		Young Forest Shrub to Cropland (ha)	
	2013	2011	2013	2011	2013	2011	2013	2011
AEZ 7	-2,322	-3,479	-53,856	-340,320	-456,667	-224,128	639	957
AEZ 8	-4,619	-16,931	-19,576	-133,912	-163,222	-102,281	-2,636	-9,662
AEZ 9	-860	-2,022	-1,166	-10,238	-84,275	-64,792	19	44
AEZ 10	-26,768	-179,636	-12,259	-82,626	-539,324	-403,376	-7,037	-47,224
AEZ 11	-16,888	-93,360	-5,579	-42,881	-413,120	-298,278	-79	-436
AEZ 12	-8,384	-30,064	-587	-14,111	-118,649	-74,470	-1,822	-6,532
AEZ 13	-2,654	-736	-132	-11,662	-9,406	-1,340	-1,668	-463
AEZ 14	-2,148	-5,032	503	-3,518	-3,799	-278	-1,332	-3,120
AEZ 15	-128	-200	34	-214	0	0	-81	-127
AEZ 16	-2	-5	1	-3	0	0	-2	-4
TOTAL	**-64,773**	**-331,465**	**-92,617**	**-639,484**	**-1,788,462**	**-1,168,943**	**-13,999**	**-66,568**

The last factor to consider here is evidence suggesting that domestic LUC emissions associated with U.S. corn ethanol production may not have been fully accounted for to date. This evidence is developed in a set of recent studies that utilize USDA's Cropland Data Layer (CDL) series to examine changes in U.S. agricultural land use that accompanied the increase in U.S. corn ethanol production between 2004 and 2012. Examples include Wright and Wimberley (2013), Lark et al. (2015), Motamed et al. (2016), Morefield et al. (2016), and Wright et al. (2017).

While differing in objectives, geographic focus, and years analyzed, the results all support the conclusion that for the Corn Belt and Great Plains, increases in U.S. corn ethanol production between 2006 and 2012 helped drive: 1) a shift of

millions of acres from grassland uses, and to a much smaller extent forest and wetland uses, to cropland: and 2) a large increase in the number of cropland acres planted to corn and corn/soybean systems. Wright and Wimberly (2013), Lark et al. (2015), and Wright et al. (2017) extend their analyses to explicitly link grassland conversions to: 1) significant losses of native prairie and other long-term grassland uses; and 2) not previously accounted for GHG emissions that should be reflected in corn ethanol's GHG profile. Wright et al. (2013) and Wright et al. (2017) make these links qualitatively. Lark et al. (2015) present estimates of acreage and emissions impacts but these are only indicative of the link they argue exists between decreases in native prairie and increases in corn ethanol production. For the period 2008 – 2012, they estimate that nationally: 1) 1.6 million acres of long-term (20 + years) unimproved grasslands were converted to cropland; 2) 1.04 million acres of land not cultivated for at least 40 years were converted to cropland; and a range for GHG emissions of 94 to 186 $MMTCO_2e$ for recently converted lands used to grown corn or soybeans. For the reasons discussed below, the CDL based approach cannot yet accurately identify ethanol driven conversions of native grasslands to cropland or confidently estimate the associated GHG emissions. For the reasons developed below. We do not incorporate the results of these analyses into our analysis.

The CDL is a land cover data product developed annually by USDA's National Agricultural Statistics Service (NASS) to provide detailed maps – from the sub-county to national levels - of commodity production (over 100 crops are identifiable) and to track crop progress through the growing season. To develop a CDL, NASS starts with a series of satellite images that cover the contiguous 48 States. Each image consists of pixels with a resolution of 30 square meters (56 square meters before 2010) and each pixel is photographed multiple times between April and October. This provides a dynamic visualization of the pixel over the growing season. A relatively small set of cropland pixels, about one million per State on average, are selected for a resource-intensive ground truthing process. The process uses site specific information available in the NASS June Ag Survey, and the Farm Service Agency's (FSA) Common Land Unit and 578 databases to exactly match sampled cropland pixels (called "training sites") to specific crops. The training sites are then used to develop spectral signatures by crop type, which are used with a software package to associate all non-sampled cropland pixels with specific crop types.

Based on comparisons of two or more CDLs, however, the extensions of grassland conversions to cropland to decreases in native grassland (and other long-term grasslands) is not straight forward. The CDL does not distinguish native grasslands from managed grasslands. In CDL-based studies to date, the "grasslands" category includes native grasslands, pasture, cropland pasture, grass-hay, land enrolled USDA's Conservation Reserve Program, and in some cases idled cropland. While Lark et al. (2015) incorporated additional land use data and other information to increase the probability of isolating conversions of native grasslands within the CDLs, their results are, at best, a first approximation of how much native grassland may have been converted to cropland over the period 2008 to 2012.

Extending CDL-based estimates of grassland conversions to cropland to related GHG emissions adds another layer of complexity. The emissions associated with the conversion of a given pixel of grassland will depend on what type of grassland use it was in. Native prairie, for example, will be likely be at or near its long-run soil carbon equilibrium level and so conversion to cropland will generally emit relatively high levels of CO_2. Cropland pasture on the other hand, is periodically put into crop production and so its soil carbon level at conversion, and the related CO_2 emitted will generally be relatively low. Additionally, emissions will depend on how the land in the pixel had been managed in the years prior to conversion. Satellite images do not show how a pixel of land has been used or managed previously.

Even assuming conversions of native grasslands (and other ecosystems) to cropland can be accurately identified, and the related emissions quantified, there remains the issue of determining what portion of the emissions to assign to the increase in corn ethanol production. Farm-level land-use and crop production decisions are based on farmers' expectations of future domestic and international commodity prices, which in turn, are largely based on past commodity prices. Since 2006, domestic and world corn and soybeans, have generally been well above the levels of the preceding 15 years (i.e., 1990 – 2005). But in addition to increased U.S. demand for corn to produce ethanol, the historically high corn and soybean prices have been driven by other factors as well. These include global population growth, a large increase in the global production and consumption of livestock products, and a series of major drought and other severe weather events that disrupted global and U.S. commodity markets. Analyzing the period of high U.S. corn prices between 2006 and 2009, Babcock and Fabiosa (2011) estimated that, relative to the average 2004 U.S. corn price, 32 percent of the average annual increase was related in some way to ethanol while 64 percent was related to other factors. This is consistent with a study by Condon et al. (2015) that estimates a 1 billion increase in the U.S. corn ethanol mandate (under the RFS2) would increase corn prices 3 to 4 percent.

Finally, two methodological issues are relevant to this discussion. First, the CDL is one of several satellite-based national scale land-cover data products developed by U.S. government agencies. Others include the Forest Service's Forest Inventory Assessment, the Natural Resources Conservation Service's Natural Resources Inventory; the U.S. Geological Survey's National Land Cover Database, and FSA's National Agricultural Imagery Program. While these data products are developed to serve different objectives and face different resource constraints (e.g., frequency of resampling, IT related assets, and the ability to ground truth satellite images – say with site visits or landowner survey data) they should yield at least broadly consistent land use results. However, focusing on 20 counties in the Prairie Pothole Region between 2004 and 2014, Dunn et al. (2017) show that estimates of conversions of grassland, forest, and wetlands to cropland can vary significantly depending on the land cover data product(s) and analytic techniques used. The second issue to note is that NASS has recently released updated CDLs for 2008 and 2009. The updated CDLs employ the 30-meter pixel resolution adopted in

2010 and incorporate other improvements that have been made since 2010. It would be informative to see to what degree the revised CDLs affect the results of studies that used the original 2008 and 2009 CDLs.

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

To model land-use change within the United States, EPA used FASOM simulations under the Control and Corn Only Cases. FASOM includes the land-use categories cropland, cropland pasture, forestland, forest pasture, rangeland, developed land, and acres enrolled in the Conservation Reserve Program (CRP). Except for CRP acres, which are set exogenously, the model determines how much of each land-use category is actively used in production and how much is idle during a specific time period. Total cropland acres and total corn acres, by case and for the difference in cases, are shown in Table 2-13. Importantly, FASOM included DGS replacement rates for corn and soybean meal in animal feed. The replacement rates were obtained from Argonne National Laboratory (Arora et al., 2008). This means the land use changes obtained by comparing the FASOM simulations of the Control and Corn Only Cases, include reductions in corn acres attributable to the substitution of the additional DGS (i.e., obtained from refining the additional ethanol mandated by the RFS2) for corn in animal feed markets.

Since 2010, FASOM has been updated to allow for the simultaneous analysis of land use changes across the forest and agricultural sectors (as opposed to modeling each separately). This feature was not available for the RIA analysis. Also, for the RIA analysis, FASOM did not explicitly account for corn oil extracted from distillers grain. The model now has this pathway as part of the dry milling process. EPA did assume that by 2022, 70 percent of dry mill refineries will withdraw corn oil via extraction, 20 percent will withdraw corn oil via fractionation, and 10 percent will do neither (EPA, 2010a).

Table 2-13: RIA Projection of 2022 Total Cropland and Corn Acres by Case (millions of acres)

Cropland in 2022	Control Case	Corn Only	Net Change
Total Ag Crop Land Use (dry and irrigated)	314.4	313.0	1.43
Corn Acres	81.5	77.8	3.65

Source: EPA RIA FASOM output; EPA-HQ-OAR-2005-0161-3179.

FASOM modeled land-use change across three phenomena:

1. **Developed Land**: For the RIA, developed land is assumed to be of higher value than all other land categories. In the FASOM simulations, the amount of developed land increased at a constant and exogenously set rate that was based on projections of population and income growth.

2. **Carbon Sequestration**: FASOM accounted for carbon storage in trees, understory, and litter within both forests and plantations of woody biofuel feedstocks but excluded carbon stored in annually cultivated crops. Changes in sequestration for land moved from the forestry and agricultural sectors into developed land was accounted for.
3. **Agricultural Land-Use Change GHG Emission Factors**: FASOM agricultural LUC emission factors were obtained from runs of a 2010 DAYCENT/CENTURY model (Beach, 2010).

EPA combined the FASOM LUC results with the appropriate DAYCENT/CENTURY emissions factors to obtain cumulative LUC emissions over the period 2000-2022 for both the Control and Corn Only scenarios. To these values were added cumulative land-related emissions that occur in the 30 years following 2022 (reflecting continuing emissions from agricultural soils, decaying biomass, and wood products). The difference in cumulative emissions between the two simulations was then annualized to get the RIA emissions value for the Domestic LUC source category. This value was -4,000 gCO2e/MMBtu (EPA, 2010a).

ICF Methodology, Data Sources, and Results

As noted above, we estimate domestic LUC emissions using results of a 2013 simulation of the Global Trade Analysis Project-Biofuels (GTAP-Bio) model available in ANL’s Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) tool (Dunn et al., 2014). The GTAP-Bio 2013 results include domestic and international land-use changes related to U.S. corn ethanol production increasing from its 2004 level of 3.41 billion gallons to the RFS2 cap of 15 billion gallons per year (recall GTAP-Bio’s base period is 2004). Also, as noted, GTAP-Bio estimates regional acreage changes by AEZ, and within each AEZ, by forests, grassland, cropland-pasture, and young forest shrub land types. GTAP-Bio 2013 land use change results for the United States, are shown in Table 2-12.

We pair the GTAP-Bio AEZ-land type acreage changes in Table 2-12 with LUC emissions coefficients from the Century/Cole model; these coefficients are also available in the CCLUB tool. Relative to the RIA, the Century coefficients used in our analysis have been updated and better reflect irrigation effects and N_2O emissions from cropland and pasture. The Century/Cole emission factors by AEZ and land type, for conventional and reduced tillage systems and soil depths of 30 cm and 100 cm, are shown in Table 2-14 and Table 2-15.[10]

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[10] We use the reduced tillage coefficients in the next chapter for developing the High Efficiency High Conservation projection for 2022.

Table 2-14: Soil Carbon Emission Factors for Conventional Till in Century/COLE

	Forest Carbon Emission Factor (Mg C/ha-yr)		Grassland Carbon Emission Factor (Mg C/ha-yr)		Cropland-Pasture Emission Factor Carbon (Mg C/ha-yr)		Young Forest-Shrub Carbon Emission Factor (Mg C/ha-yr)	
AEZ Number	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**
AEZ 7	-0.10	0.04	-0.44	-0.48	-0.54	-0.65	-0.06	0.03
AEZ 8	0.28	0.56	-0.26	-0.25	-0.40	-0.48	0.15	0.30
AEZ 9	0.49	0.90	-0.20	-0.15	-0.34	-0.41	0.28	0.50
AEZ 10	0.55	0.97	0.02	0.17	-0.27	-0.31	0.29	0.52
AEZ 11	0.24	0.51	0.20	0.42	-0.21	-0.22	0.11	0.23
AEZ 12	0.51	0.99	0.30	0.59	-0.17	-0.17	0.22	0.42
AEZ 13	-0.45	-0.45	-0.63	-0.71	-0.74	-0.88	-0.18	-0.19
AEZ 14	-0.42	-0.42	-0.57	-0.65	-0.61	-0.73	-0.11	-0.11
AEZ 15	0.14	0.39	-0.20	-0.13	-0.41	-0.48	0.03	0.08
AEZ 16	0.14	0.39	-0.20	-0.13	-0.41	-0.48	0.03	0.08

Source: Dunn et al., 2014a.

Table 2-15: Soil Carbon Emission Factors for Reduced Till in Century/COLE

	Forest Carbon Emission Factor (Mg C/ha-yr)		Grassland Carbon Emission Factor (Mg C/ha-yr)		Cropland-Pasture Emission Factor Carbon (Mg C/ha-yr)		Young Forest-Shrub Carbon Emission Factor (Mg C/ha-yr)	
AEZ Number	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**	**30 cm depth**	**100 cm depth**
AEZ 7	-0.14	-0.02	-0.48	-0.53	-0.57	-0.69	-0.08	-0.01
AEZ 8	0.23	0.49	-0.30	-0.30	-0.43	-0.52	0.13	0.27
AEZ 9	0.45	0.82	-0.24	-0.20	-0.38	-0.46	0.25	0.46
AEZ 10	0.50	0.90	-0.01	0.12	-0.30	-0.35	0.27	0.48
AEZ 11	0.21	0.47	0.17	0.38	-0.23	-0.26	0.09	0.21
AEZ 12	0.50	0.95	0.29	0.55	-0.19	-0.20	0.21	0.41
AEZ 13	-0.50	-0.51	-0.67	-0.76	-0.78	-0.93	-0.20	-0.21
AEZ 14	-0.47	-0.48	-0.61	-0.70	-0.65	-0.78	-0.12	-0.13
AEZ 15	0.10	0.33	-0.23	-0.18	-0.44	-0.52	0.02	0.07
AEZ 16	0.10	0.33	-0.23	-0.18	-0.44	-0.52	0.02	0.07

Source: Dunn et al., 2014a.

The CCLUB tool also includes LUC emissions coefficients from Woods Hole (WH), and Winrock International (WI). We chose the Century/COLE coefficients because they align with the GTAP-Bio's AEZ-land-use type structure. The WH and WI coefficients apply to regions and have fewer land types. The WH coefficient set includes forest and grasslands; the WI set includes forest, grassland, and cropland-pasture. Hence using the WH or WI coefficients with the AEZ-land type

requires some aggregation across AEZs and land types. Additionally, distinct Century/COLE emission factors are available for conventional and reduced tillage systems and soil depths of 30 and 100 centimeters (cm). We assume the 100 cm soil-depth coefficients present a more complete picture of soil carbon changes than the 30 cm coefficients. Based on these considerations, we use Century/Cole 100 cm conventional tillage coefficients to estimate ethanol driven changes in domestic LUC emissions.

For completeness, Table 2-16 shows the domestic LUC emissions results for various soil depth, tillage, and emission factor scenarios run using the CCLUB methodology. Using the Century/COLE 100 cm conventional till scenario, ICF assessed emissions for the domestic LUC source category at −2,038 g CO_2e/MMBtu.

Table 2-16: Final Scenario Results for 2013 GTAP Acreage Change Data

Scenario	Total Direct Emissions (Mg CO_2e)	Annualized Emissions (Mg CO_2e/year)	Direct Emissions (g CO_2e/gal)	Direct Emissions (g CO_2e/MMBtu)
Century/COLE—30cm—Reduced Till	−52,191,279	−1,739,709	−150	−1,965
Century/COLE—100cm—Reduced Till	−62,656,429	−2,088,548	−180	−2,359
Century/COLE—30cm—Conventional Till	−45,625,214	−1,520,841	−131	−1,718
Century/COLE—100cm—Conventional Till	−54,120,694	−1,804,023	−156	**−2,038**
Woods Hole	48,163,909	1,605,464	139	1,814
Winrock	280,879,558	9,362,652	808	10,577

Limitations, Uncertainty, and Knowledge Gaps

Since 2010, major advances have been made in ability of economic models to assess land use changes driven by increases in the production of biofuels as well as the associated GHG emissions. There are, however, still many factors that have not been incorporated into these models (e.g., previous land uses and management practices). Additionally, most of the land transformation and transformation cost parameters are still much too aggregate to fully capture the effects of region- or country- level diversity in land-types that might undergo conversions to other uses and the agricultural production systems that may get expanded or contracted. Hence, future improvements in our understanding of, and our capacity to model, the economic drivers of LUC will, in all likelihood, affect future estimates assessment of LUC emissions related to changes in biofuel product. Perhaps the largest source of uncertainty is the possibility that domestic LUC emissions have been biased downward due to not accurately accounting for emissions related to the conversion of native grasslands (and other native ecosystems) to agricultural production. The CDL based studies have raised this possibility even though their results are not yet convincing.

Domestic Rice Methane

Literature Review Findings

In recent years, U.S. rice production area has fluctuated between 2.4 and 3.9 million acres annually (see Table 2-17). Methane is the primary greenhouse gas related to rice production (Gathorne-Hardy, 2013). All rice is the United States is grown under continuously flooded, shallow water conditions (EPA, 2015a). Under flooded conditions, soils become anaerobic (lacking oxygen) resulting in the production of methane (CH_4) when soil organic matter is decomposed by anaerobic methanogenic bacteria. A percentage of the methane produced (10–40 percent) is released from the soil to the atmosphere either by diffusive transport through the rice plants, soil diffusion or bubbling through floodwaters (EPA, 2015a).

The amount of methane produced by rice cultivation is influenced by multiple factors (EPA, 2015a; Garthorne-Hardy, 2013; Hussain et al., 2014), including:

- Water management practices (e.g., deepwater (greater than one meter) production, dryland production, mid-season drainage, intermittent drainage)
- Fertilizer practices (e.g., use of urea, ammonium nitrate, ammonium sulfate, organic fertilizers)
- Residue management (e.g., straw removal, straw burning)
- Soil temperature and soil type
- Rice cultivar
- Cultivation practices (e.g., tillage, seeding, and weeding practices)
- Number of crops per season (e.g., primary and ratoon crop)

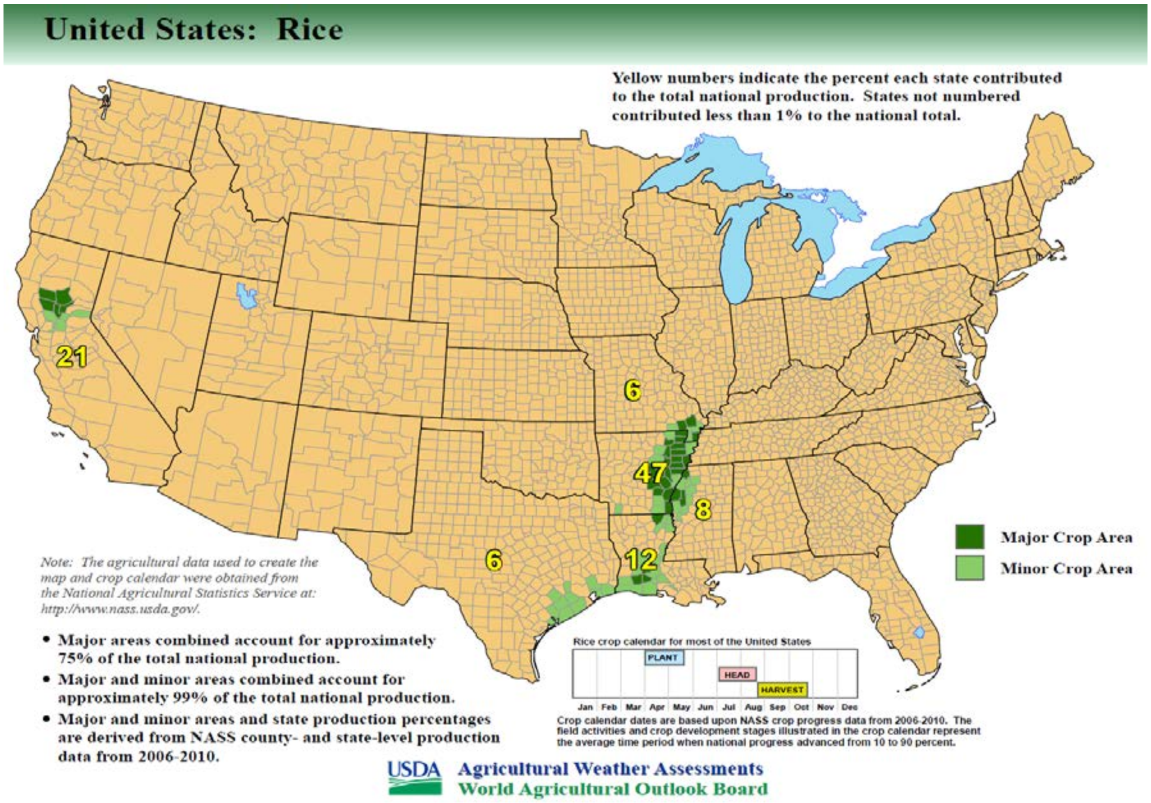
U.S. Rice Production Area

Rice is currently produced in Arkansas, California, Louisiana, Mississippi, Missouri, and Texas (EPA, 2015a; USDA ERS, 2015c). Figure 2-2 shows major (75 percent of total national production) and minor (99 percent of total national production) rice production areas based on USDA National Agricultural Statistics Service (NASS) county- and state-level production data from 2006–2010 (USDA OCE, 2013a).

Figure 2-3 shows major (75 percent of total national production) and minor (99 percent of total national production) corn production areas in the United States based on USDA NASS county and state-level production data from 2006–2010. (USDA OCE, 2013b) The yellow numbers in the figure represents the percent each state contributed to the total national production.

Comparing the two maps indicates that there is no overlap between major corn and rice crop areas, with the exception of one county in northern Louisiana and one county in southern Missouri. There is some overlap between a major crop area of one crop and a minor crop area of the other crop (i.e., a major crop area for corn and a minor crop area for rice or vice versa) and some overlap of

Figure 2-2: U.S. Map of Average 2006–2010 Major and Minor Rice Crop Areas



United States: Rice

Yellow numbers indicate the percent each state contributed to the total national production. States not numbered contributed less than 1% to the national total.

Note: The agricultural data used to create the map and crop calendar were obtained from the National Agricultural Statistics Service at: http://www.nass.usda.gov/.

- Major areas combined account for approximately 75% of the total national production.
- Major and minor areas combined account for approximately 99% of the total national production.
- Major and minor areas and state production percentages are derived from NASS county- and state-level production data from 2006-2010.

Rice crop calendar for most of the United States

Crop calendar dates are based upon NASS crop progress data from 2006-2010. The field activities and crop development stages illustrated in the crop calendar represent the average time period when national progress advanced from 10 to 90 percent.

USDA Agricultural Weather Assessments
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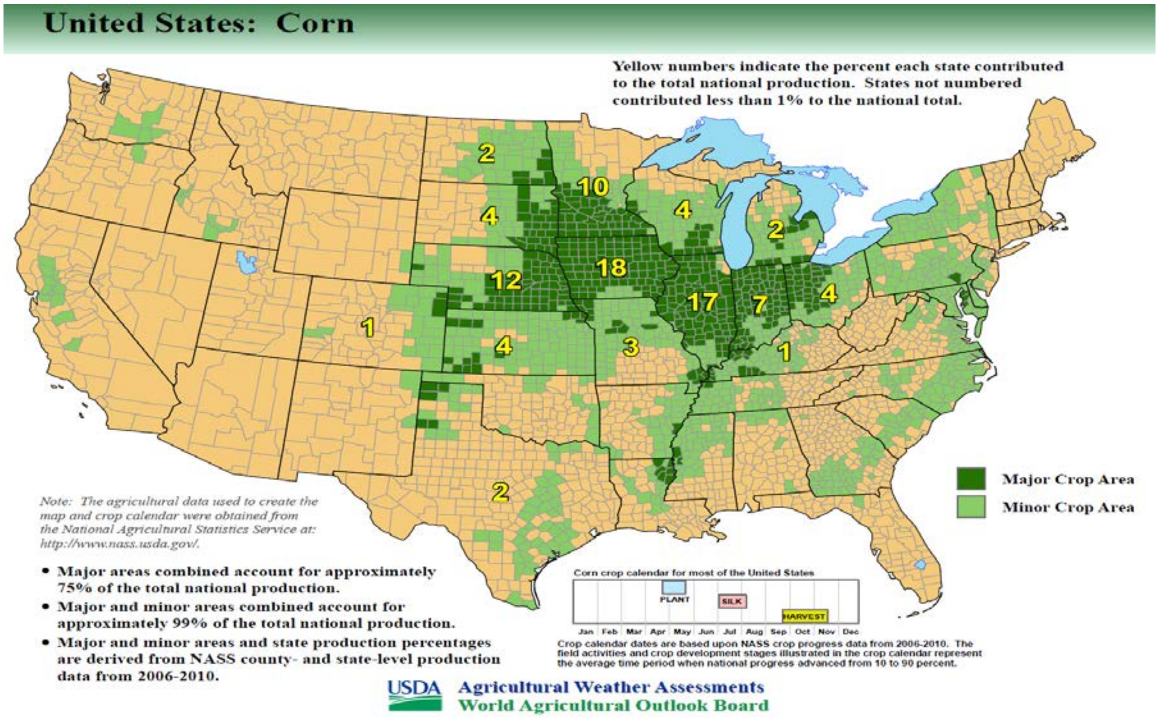
Figure 2-3: U.S. Map of Average 2006–2010 Major and Minor Corn Crop Areas



United States: Corn

Yellow numbers indicate the percent each state contributed to the total national production. States not numbered contributed less than 1% to the national total.

Note: The agricultural data used to create the map and crop calendar were obtained from the National Agricultural Statistics Service at: http://www.nass.usda.gov/.

- Major areas combined account for approximately 75% of the total national production.
- Major and minor areas combined account for approximately 99% of the total national production.
- Major and minor areas and state production percentages are derived from NASS county- and state-level production data from 2006-2010.

Corn crop calendar for most of the United States

Crop calendar dates are based upon NASS crop progress data from 2006-2010. The field activities and crop development stages illustrated in the crop calendar represent the average time period when national progress advanced from 10 to 90 percent.

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World Agricultural Outlook Board

minor areas of both crops. Overall the data indicate that expansion of corn would likely not result in displacement of rice given that the majority of corn is grown in different states (i.e., Iowa, Illinois, Nebraska, Minnesota, Indiana) than where the majority of rice is grown (i.e., Arkansas, California, Louisiana, Mississippi). In addition, the two states that have counties with overlapping major production areas (Louisiana and Missouri) are both minor corn producing states (Missouri contributes 3 percent of national corn production and Louisiana contributes less than 1 percent).

Table 2-17 presents acres of planted and harvested rice from 2005 –2014 and projections of harvested rice for 2014–2023 from multiple sources, including the RIA (see table for more details on data sources). Harvested acres in the U.S. GHG inventory are consistently higher than harvested acres in the USDA Rice Yearbook. This is likely due to the inclusion of both the primary and the ratoon crop harvested acres in the U.S. inventory.

Table 2-17: U.S. Planted and Harvested Rice (millions of acres)

Year	Area Planted (2015 Rice Yearbook)[a]	Area Harvested (2015 Rice Yearbook)[a]	Area Harvested (EPA 2015 Inventory)[b]	Area Harvested RFS2 RIA FASOM Control Case[c]	Area Harvested RFS2 RIA FASOM Corn Only Case[c]	Area Harvested USDA Projections[d]
2005	3.384	3.364	3.488	-	-	-
2006	2.838	2.821	2.949	-	-	-
2007	2.761	2.748	2.933	-	-	-
2008	2.995	2.976	3.253	-	-	-
2009	3.135	3.103	3.364	-	-	-
2010	3.636	3.615	3.931	-	-	-
2011	2.689	2.617	2.902	-	-	-
2012	2.700	2.679	3.048	3.358	3.500	-
2013	2.490	2.469	2.776	-	-	-
2014	2.939	2.919	-	-	-	2.919
2015	-	-	-	-	-	2.570
2016	-	-	-	-	-	2.771
2017	-	-	-	3.722	3.836	2.796
2018	-	-	-	-	-	2.824
2019	-	-	-	-	-	2.824
2020	-	-	-	-	-	2.849
2021	-	-	-	-	-	2.858
2022	-	-	-	3.871	4.042	2.883

[a] USDA ERS ,2015b; [b] EPA, 2015a. (Includes both primary and ratoon acres.); [c] EPA, 2010a.; [d] USDA OCE, 2016.

U.S. Methane Emission Factors for Rice Production

For the RIA, EPA used regional changes in rice acres obtained from simulations of the FASOM model and regional emission factors by acre based on 2001 data in the EPA's *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2003* (EPA, 2005). The model then calculated regional methane emissions from rice (EPA, 2010b). For the RIA, EPA did not differentiate between primary and ratoon rice crops (the second rice crop grown in a season) and assumed that changes in rice acreage was the only method to change emissions related to rice cultivation (so reductions in primary crops could not be offset by increases in ratoon crops).

In contrast, for inventories up to and including the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2011* (EPA, 2013), estimates for methane emissions from rice were based on the revised 1996 IPCC Guidelines[11] using separate national emission factors for primary and ratoon rice crops. After the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2012* (EPA, 2014a), subsequent inventories (EPA, 2015a, EPA, 2016) updated the rice emission factors for specific regions. Table 2-18 presents the two sets of emission factors using the same regional break down as the RIA used.

Table 2-18: Rice Methane Emission Factors from the Inventory of U.S. Greenhouse Gas Emissions and Sinks

	EPA Emission Factors (1994–2013)		EPA Emission Factors (2014)	
	(kg CO_2e/acre/season or year)			
Region	**Primary**	**Ratoon**	**Primary**	**Ratoon**
Corn Belt	2124.50	7891.22	2397.72	7891.22
South Central				
Southeast				
Southwest				
			Winter Flooded	Non-Winter Flooded
Pacific Southwest	2124.50	7891.22	2691.11	1345.55

As described above, the inventory and the RIA emission factors are not directly comparable as they use different formulas to determine rice emissions. However, it is possible to derive and compare the effective emission factors from the two studies. To derive the effective emission factors from the Inventory data we:

1. Put each rice producing state into the corresponding RIA region category
2. Added up total emissions in that RIA region annually from 1990–2013

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[11] The IPCC 1996 guidelines (IPCC, 1996) for estimating rice methane emissions were updated in the IPCC 2006 guidelines (IPCC, 2006). However, the EPA does not use the IPCC 2006 guidelines for estimating rice methane emissions as the 2006 guidelines recommend using a daily emission factor multiplied by the rice cultivation period, the data for which are not available for U.S. rice production. Using the IPCC 1996 guidelines to estimate rice methane emissions is consistent with the Good Practice Guidance and Uncertainty Management in National Greenhouse Gas Inventories (IPCC 2001).

3. Added up total area harvested in each region (including both primary and ratoon acres)
4. Divided each regional emission by the regional harvested area
5. Converted the effective emission factor to the same units as those used in the RIA (i.e., kg CO_2e/acre)

Additionally, we derived a national effective emission factor for the entire United States. A comparison of the effective inventory emission factors from 2005–2013 and RIA emission factors is shown in Table 2-19. The RIA values are not annual values and, hence, are provided in the last row of the table.

Table 2-19: Comparison of Inventory (2005–2013) and RFS2 RIA Effective Emission factors (kg CO_2e/acre)

	EPA Inventory Emission Factors by Region					
Year	South Central	Pacific Southwest	Southeast	Corn Belt	Southwest	United States
2005	2,553	2,149	2,399	2,399	3,563	2,556
2006	2,588	2,149	3,610	2,399	3,940	2,597
2007	2,758	2,149	3,666	2,399	3,853	2,706
2008	2,847	2,149	3,666	2,399	4,300	2,831
2009	2,780	2,149	3,968	2,399	4,415	2,791
2010	2,813	2,149	4,042	2,399	4,325	2,810
2011	2,827	2,149	3,605	2,399	4,788	2,895
2012	3,151	2,149	4,077	2,399	4,480	3,026
2013	3,035	2,149	3,732	2,399	4,622	2,964
RFS2 RIA	2,249	1,783	N/A	1,826	4,375	N/A

Comparing emission factors in Table 2-19 shows that in general, the RIA emission factors are lower than the effective emission factors for the inventory. Specifically, the RIA emission factors for the South Central, Pacific Southwest, and Corn Belt regions are lower than the effective inventory emission factors from 2005–2013. In contrast, the RIA Southwest emission factor is higher than that of the inventory effective emission factor except for in 2009 and 2011–2013, where it is lower. Interestingly, the RIA does not include emission factors for the Southeast region despite the fact that rice is grown there (albeit at very low levels). The majority of U.S. rice is grown in the South Central (an average of about 67 percent between 2006 – 2010) and the Pacific Southwest regions (an average of about 21 percent between 2006 – 2010). A smaller amount is grown in the Southwest region (an average of 6 percent between 2006 –2010). This suggests that the RIA most likely underestimated RFS2 driven change in U.S. rice methane emissions due to its use of underestimated emission factors in the major rice regions.

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

In the RIA, EPA estimated the impacts of the RFS2 corn ethanol mandate on rice acres and emissions by modeling the change in rice acreage with and without the RFS2 (i.e., by comparing simulations of the Control Case and the Corn Only Case). These acres are shown in Table 2-20. Regional acreage changes were combined with regional per acre emission factors based on the EPA's U.S. GHG inventory for 1990–2003 (EPA, 2005). The FASOM simulations projected the RFS2 corn ethanol mandate would decrease both domestic rice acres and rice methane emissions. The RIA used a composite emission factor for primary and ratoon acres rather than separate emission factors (as was done the 2010 EPA *Inventory of U.S. Greenhouse Gas Emissions and Sinks*). These are shown in Table 2-21.

Table 2-20: EPA RIA Domestic Rice Acreage for Corn Only Case and Control Case

	Thousands of Acres		
Year	**Corn Only Case**	**Control Case**	**Acreage Change Allocated to Ethanol**
2022	3,089.854	3,031.092	-58.762

Table 2-21: Methane Emission Factors from Irrigated Rice Cultivation by Region (kg CO_2e/acre)

Crop	Corn Belt	Great Plains	Lake States	North-east	Pacific Northwest-East side	Pacific South-west	Rocky Mountains	South Central	South-east	South-west
Rice	1,826.1	N/A	N/A	N/A	N/A	1,783.4	N/A	2,249.2	N/A	4,375.0

Source: EPA, 2010a (See Table 2.4-9).
N/A = Not Applicable.

EPA's analysis resulted in a reduction of 42,000 tons CO_2e (see Table 2.4-10 from EPA RIA). This converted to an emissions value of -209 g CO_2e /MMBtu (see: EPA, 2010a; Table 2.4-13).

ICF Methodology, Data Sources, and Results

Domestic rice is a small emissions category in corn ethanol's total GHG profile and little new information has emerged since 2010 indicating U.S. rice acres have responded to the RFS2 along a significantly different path than that projected in the RIA. Hence, ICF utilized the RIA change in total domestic rice acres (i.e., -58,762 acres) but allocated those acres across states based on their current geographic distribution (see Table 2-22). As discussed above, regional rice emission factors have been updated in recent EPA reports. Our assessment

uses these emission factors (EPA, 2016) to calculate for methane emissions in both Corn Only and Control cases. Table 2-21 shows these regional emission factors (which also reflect the new IPCC AR4 GWP for methane). Table 2-22 shows the ICF regional values for rice acres and emissions.

Table 2-22: Regional Acreage and GHG Emissions for Domestic Rice Methane

	Harvested Acreage (million acres)			GHG Emissions (MMT CO_2e)	
Region	**2014 Actual Acres**	**Control Case**	**Corn Only Case**	**Corn Only Case**	**Control Case**
Arkansas	1.98	1.53	1.50	5.69	5.59
California	0.68	0.52	0.51	1.12	1.10
Florida	0	0	0	0	0
Illinois	0	0	0	0	0
Louisiana	0.78	0.60	0.59	2.24	2.20
Minnesota	0.002	0.002	0.002	0.005	0.004
Mississippi	0.13	0.10	0.10	0.38	0.37
Missouri	0.26	0.20	0.20	0.61	0.60
Texas	0.18	0.14	0.13	0.63	0.62
Total	**4.00**	**3.09**	**3.03**	**10.68**	**10.48**

ICF calculated the difference in total GHG emissions (all regions) between the Control Case and the Corn Only Case to quantify the incremental GHG emissions of the RFS2 corn ethanol mandate. These emissions were then divided by the mandate's incremental corn ethanol production (2.6 billion gallons in 2022) to get an emissions value per gallon of ethanol. Applying a heating value for ethanol of 76,330 Btu/gallon, our final emissions value for Domestic Rice Methane is -1,013 g CO_2e/MMBtu.

Limitations, Uncertainties, and Knowledge Gaps

ICF's domestic rice methane assessment relies on the relationships (i.e., scenario acre ratios) derived from the FASOM model RIA projections for rice acreage in the Control and Corn Only cases (see Table 2-17). Future work could examine these relationships and acreage numbers more closely to better assess the difference, if any, between these two cases. While our assessment used updated emission factors, the lack of readily available data used for the RIA in the Corn Only and Control cases for acreage limit the evaluation of this assessment. Still, both our results and the RIA's show domestic rice methane to be a small portion of the overall corn ethanol life-cycle GHG emissions.

Domestic Livestock

Allocating billions of additional bushels of U.S. corn to ethanol production affects changes in livestock emissions through changes in feed prices, feed mixes, and animal populations. Corn is the most important feed input used in confined dairy,

beef, swine, and poultry operations. While increases in corn ethanol production have helped drive historically high corn and feed prices since 2005, feed price impacts have been moderated to a degree by increased production of feed co-products, mainly DGS. When substituted for corn in cattle feed, DGS (dried or wet) reduces CH_4 emissions from enteric fermentation (EPA, 2010a).

Literature Review Findings

Livestock Emission Sources

Although there are emissions associated with livestock production that are not directly emitted by animals or from their waste (e.g., emissions due to animal transportation and dairy/meat processing), this review focuses on the two sources of livestock emissions included in the RIA: enteric fermentation and manure management.

Enteric Fermentation

Enteric fermentation is a process through which microbes present in the digestive tract of livestock break down food, emitting CH_4 as a by-product. Ruminant animals, such as cattle, sheep, and goats, have multi-chambered digestive systems that produce more CH_4 than those of non-ruminant animals. Methane is also emitted by monogastric livestock (non-ruminant, e.g., swine), but at a magnitude much lower than for ruminant livestock.

Livestock methane emissions from enteric fermentation depend on a combination of factors including: animal type, the quantity and quality of diet, use of dietary additives, and activity performed (e.g., type of work, pregnancy, etc.) (ICF International, 2013; Eve et al., 2014). The literature indicates that enteric CH_4 emissions can be affected through the management of animal diets (i.e., feed intake and composition). For example, digestible energy (DE) in low-quality feed such as late-season forage is less than that in high-quality feed (e.g., mixed feed or spring forage). With lower quality food sources, cattle will need to eat more in order to get the same amount of energy, thus leading to greater emissions in most cases. Increasing the ratio of grains (and other concentrates) to forage increases dietary fat content and can decrease enteric CH_4 emissions from cattle (ICF International, 2013; Eve et al., 2014; Gerber et al., 2013). Diets high in DGS can also increase the fat content animal diets, and thus reduce enteric emissions from cattle (Lemenager et al., 2006; Latour and Schinckel, 2007). A number of dietary additives (e.g., ionophores, nitrates, and tannins) have been shown to reduce enteric CH_4 emissions in the short run but their long-term emissions impact is still unclear.

Dairy cows are fed high quality nutrition and they have a much higher typical animal masse (TAM) than beef cattle in the United States (EPA, 2015a). As a result, dairy cattle emit significantly more CH_4 through enteric fermentation than beef cattle on a per head basis.

Manure Management

Manure management is the collection, storage, transfer, and treatment of animal urine and feces (Eve et al., 2014). The decomposition of manure results in both direct and indirect N_2O emissions and, under anaerobic conditions, CH_4 emissions. Manure management systems include variations in solid storage, slurry systems, lagoons, and spreading. While the amount of CH_4 and N_2O generated from manure management practices depends on the animal type, diet, and activity, the primary determinant on any given livestock operation is the manure management system in place. The same quantity of manure can generate significantly different CH_4 and N_2O emissions under different management systems (ICF International, 2013; Eve et al., 2014; Gerber et al., 2013). Manure stored under anaerobic conditions produce a large portion of all manure-related CH_4 emissions. Hence, covering anaerobic lagoons or utilizing anaerobic digesters offer good opportunities to reduce these emissions (ICF International, 2013; Gerber et al., 2013).

Livestock Emissions

In 2014, enteric CH_4 emissions in the United States were 164.3 MMT CO_2e, (i.e., more than 65 percent of the emissions from animal production systems). More than 71 percent was from beef cattle and more than 96 percent was from beef and dairy cattle together (EPA, 2016). While dairy cattle have higher enteric CH_4 emissions on a per-head basis than beef cattle, there are many more beef cattle so overall, more enteric CH_4 is produced by beef cattle (ICF International, 2013).

Manure Management

In 2014, manure management practices in the United States resulted in GHG emissions of 78.7 MMT CO_2e. Emissions from cattle alone totaled 48.9 MMT CO_2e, 72 percent as CH_4 and 28 percent as N_2O. Beef cattle, dairy cattle, and swine collectively account for more than 93 percent of all emissions related to manure management. The remaining 7 percent is attributed to poultry, sheep, horse, and goat production (EPA, 2016).

Since 1990, domestic livestock GHG emissions have increased significantly overall. Enteric CH_4 emissions, however, have increased only slightly (less than 1 percent). Although cattle populations have decreased over this time, these emissions have increased due to an increase in emission per head. Manure management-related emissions of CH_4 and N_2O have increased more significantly (about 65 percent and 25 percent, respectively) due to the increased use of liquid manure management systems in large confined animal feeding operations or (CAFOs), which are more emission-intensive than dry storage systems (EPA, 2015a). While beef cattle emissions have increased on a per-head basis, emissions per pound of meat produced have decreased (ICF International, 2013). An increase in TAM of more than 10 percent has resulted in a 6 percent increase in enteric CH_4 (EPA, 2012).

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

For the RIA, EPA used simulations of the FASOM model under the Control and Corn Only Cases to assess changes in 2022 domestic livestock emissions related to the RFS2 corn ethanol mandate. The changes in dairy, beef, poultry, and swine populations are shown in Table 2-23.

Table 2-23: FASOM Changes in Domestic Livestock Herd in 2022

	Corn Ethanol	
Livestock Type	**Mm Head**	**% change**
Dairy	−0.02	−0.31%
Beef	0.09	0.14%
Poultry	−58.84	−0.79%
Swine	−0.22	−0.17%

Source: EPA, 2010a.

FASOM modeled enteric fermentation and manure management emissions on a per-head basis. Hence, changes in aggregate emissions are solely a function of changes in livestock populations. The per-head emission factors used in the RIA were obtained from the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2003* (EPA, 2005). These factors are shown in Table 2-24 and 25. Also shown in these tables are the livestock emission factors used by ICF (these factors are from the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2013* (EPA, 2015a)). Note that for dairy, EPA has increased all three per-head emission factors relative to what was used in the RIA. Per-head enteric CH_4 emissions for beef cattle have also been increased significantly. The higher emissions factors now in use reflect increases in TAM, changes in dietary factors, and changes in the sub-populations of cattle (i.e., bulls, heifers, calves) relative to 2010.

Table 2-24: Enteric CH_4 Annual Emission Factors

Livestock Type	RIA Emission Factor (kg CH_4/head)	2013 Emission Factor per EPA, 2015a (kg CH_4/head)
Dairy	121	144[a]
Beef	53	64[b]
Poultry	N/A	N/A
Swine[c]	1.5	1.5

[a] Includes only mature dairy cows; [b] Includes all but beef calves.
[c] Swine emissions are calculated using a Tier 1 emission factor.

Table 2-25: Domestic Manure Management Annual Emission Factors

Livestock Type	RIA CH_4 Emission Factor [a] (kg CH_4/head)	2013 CH_4 Emission Factor per EPA, 2015[b] (kg CH4/head)	RIA N_2O Emission Factor [a] (kg N_2O/head)	2013 N_2O Emission Factor per EPA, 2015[b] (kg N2O/head)
Dairy	38.6	68.8	0.68	1.03
Beef	1.71	1.6	0.23	0.34
Poultry	0.07	0.1	0.01	0.002
Swine	13.78	14.0	0.02	0.09

[a] EPA, 2010a; [b] EPA, 2015a.

Multiplying the changes in livestock populations by the appropriate enteric and manure management emission factors, EPA projected 2022 emissions for the Domestic Livestock source category at −3,746 g CO_2e/MMBtu. This value included a downward adjustment in CH_4 emissions (of, −3,381 g CO_2e /MMBtu ethanol) to reflect the substitution of the additional DGS in place of corn fed to cattle.

ICF Methodology, Data Sources, and Results

Since 2010, little new information has appeared to indicate the relationship between feed prices and domestic livestock populations in FASOM have changed significantly. Given this, the relatively small magnitude of the emissions category, and annual corn ethanol production in the RIA being 15 billion gallons from 2015 through 2022, we use the RIA’s 2022 projections for changes in current dairy cow (mature cows only), beef cattle, and swine populations in our analysis.

For poultry, we reduced the RIA population change by 75 percent, because the RIA appears to include changes in poultry slaughtered instead of the annual average poultry population. The time from hatch to slaughter for poultry species is generally 3 to 4 months. Hence, it takes 3 to 4 slaughtered birds to apply a per-head annual emissions factor. The change in livestock populations in our analysis are shown in Table 2-26.

Table 2-26: Differences in Livestock Populations

Livestock Type	Change in Population (Head)
Dairy (mature cows)	−20,000
Beef	+90,000
Poultry [a]	−12,564,607
Swine	−220,000

[a] Changes in poultry population have been adjusted to represent annual average population changes rather than changes in total head slaughtered.

We combined the changes in animal populations with annual emission factors obtained from the *Inventory of U.S. Greenhouse Gases Emissions and Sinks: 1990–2014* (EPA 2016). EPA has used these per head emission factors since the 2013

Inventory (EPA, 2013), which incorporate changes they have made in methodologies for computing emissions for different types of livestock and the AR4 GWPs for CH_4 and N_2O. Table 2-27 shows the RIA and ICF livestock emission factors per head in CO_2 equivalents.

Table 2-27: Livestock GHG Emissions Per Head (g CO_2e/head)

	Enteric Methane (g CO_2e/head)		Manure Management (g CO_2e/head)	
Livestock Type	**RIA (AR2)**	**ICF (AR4)**	**RIA (AR2)**	**ICF (AR4)**
Dairy	2,541	3,625	1,021	2,065
Beef	1,113	1,850	107	143
Poultry	N/A	N/A	4.57	3.21
Swine	31.5	37.5	296	378

As a result of the changes in livestock populations shown in Table 2-26 and the revised emission factors shown in Table 2-27, the associated changes in emissions related to enteric fermentation and manure management for 2022 are shown in Table 2-28.

Table 2-28: Livestock GHG Emissions

Livestock Type	Enteric Methane Emissions (g CO_2e/MMBtu)	Manure Management Emissions (g CO_2e/MMBtu)	Combined Emissions (g CO_2e/MMBtu)
Dairy	−351	−200	−551
Beef	+807	+62	869
Poultry	N/A	−195	−195
Swine	−40	−403	−443
Total	416	-736	**−320**

The substitution of DGS for corn in animal feed for beef cattle reduces the methane emissions from beef cattle. ICF utilized the 2015 GREET reduction factors of 0.084 kg CO_2e/dry lb. of dry DDGS and 0.059 kg CO_2e/dry lb. of WDGS for every dry pound of DGS consumed by beef cattle. Based on Renewable Fuels Association data,[12] 45 percent of DGS is consumed by beef cattle. ICF utilized the DGS production per gallon of ethanol by ethanol production type, which is consistent with the inputs in the fuel production section and market share by production type. Table 2-29 shows the factors and results for reduced emissions per gallon and per MMBtu.[13]

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[12] http://www.ethanolrfa.org/resources/industry/co-products/#1456865649440-ae77f947-734a

[13] Calculations take into account GREET defaults of 12% moisture content for DDGS and 65% moisture content for WDGS

Table 2-29: Reduced Methane Emissions from DGS as Animal Feed by Ethanol Plant Type

Ethanol Plant Type	Ethanol Market Share	DDGS Yield (lb/gallon)	WDGS Yield (lb/gallon)	Emissions Reduced (g CO_2e/gallon)	Emissions Reduced (g CO_2e/MMBtu)
Dry Mill w/o Corn Oil Extraction	17.7%	4.207	5.522	−191	−2,506
Dry Mill w/ Corn Oil Extraction	70.9%	4.024	5.282	−183	−2,397
Wet Mill	11.4%	-	-	-	-
Per Average Gallon	-	3.598	4.723	−163.56	**−2,143**

Combining the changes in emissions shown in Table 2-28 and Table 2-29 (i.e. (-320) + (-2,143)), our emissions value for the Domestic Livestock source category is −2,463 g CO_2e/MMBtu. The differences between the results of this analysis and the RIA's analysis are largely attributable to the revised assumptions used in the 2015 GREET model to calculate the reduced methane emissions from DGS fed to livestock.

Limitations, Uncertainty, and Knowledge Gaps

Because ICF did not have access to the RIA's original Control and Corn Only case data, there is uncertainty about the populations utilized to create the original changes in livestock. Additionally, it does not appear that the RIA accounted for increases in livestock production over time (e.g., changes in per animal milk and meat production) when accounting for the population changes in future years. Therefore, the population changes also do not consider any related production or emissions impacts. Finally, the change in poultry populations used in the RIA appears to represent the total number of animals alive during each year. ICF adjusted this number to represent a steady-state population to account for the lifetime of the animals. ICF's adjustment for the number of steady-state heads is more appropriate for the emission factors used from EPA (2016) which are on an emissions per head per year basis.

International Livestock Emissions

As in domestic feed markets, large increases in the U.S. ethanol industry's demand for corn have helped drive higher prices in international feed markets. This has affected changes in global livestock populations, which in turn, has affected changes in CH_4 emissions from enteric fermentation and CH_4 and N_2O emissions from manure management.

Literature Review Findings

The international livestock sector is characterized by a dichotomy between developing and developed countries. Much of the growth in total meat production between 1980 and 2002 was concentrated in countries with rapid

economic growth. In developed countries, production and consumption of livestock products are growing slowly or not at all. Livestock production in industrialized countries accounts for 53 percent of agricultural GDP (Thornton, 2010). Particularly of interest are the practices in South America. The continent's livestock industry (especially swine and cattle production) is concentrated in Brazil and is characterized by landless monogastric production systems (LLM) and Grassland-based livestock production systems (Roman et al., 2006).

Gerber et al. (2013) assess global GHG emissions from livestock production[14] at 3.4 metric gigaton CO_2e per year for the 2005 reference period. Cattle represent about 65 percent of sector emissions, with swine, poultry, buffalo and small ruminants each having emissions levels between 7 and 10 percent of sector emissions (Gerber et al., 2013). About 2.7 metric gigaton CO_2e of global livestock emissions are due to enteric fermentation (about 79 percent). Of the enteric CH_4 emissions, most is produced by cattle (77 percent), with buffalo producing 13 percent and the rest by small ruminants (such as sheep) (Gerber et al. 2013). In Brazil, a country that is a source of American animal product imports, cattle enteric fermentation accounts for 68 percent of all CH_4 emissions from agriculture (Barioni, n.d.). Globally, manure management practices account for about 0.7 metric gigaton of CO2 e (or about 21 percent of global agricultural emissions).

Recent studies that have examined the impact of the biofuel sector on livestock production find strong evidence of the increasingly tight linkage between the energy and agricultural sectors as a result of the expanding biofuel sector. The biofuel sector expands with higher energy prices, raising prices of agricultural commodities through demand-side adjustments for primary feedstocks and supply-side adjustments for substitute crops and livestock (Hayes et al., 2009). Demand for distillers grains is growing in foreign markets. In 2013, total U.S. exports of distillers grains were 9.7 million metric tons, more than double the 4.5 million metric tons of total exports in 2008. China has played a key role in driving this growth, with total distillers grains exports to China rising from 1.4 million metric tons in 2011 to 4.5 million metric tons in 2013 (EIA, 2014). This trend has continued through 2015 with 12.7 million metric tons of total U.S. exports of distillers grains, of which 6.5 million metric tons went to China (USDA, 2016b).

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

For the RIA, EPA assessed changes in international livestock emissions associated with the RFS2 corn ethanol mandate using simulations from the Food and Agricultural Policy Research Institute (FAPRI) Center for Agricultural and Rural Development (CARD) model (FAPRI, 2004) under the Control and Corn Only Cases. The GHG impacts associated with changes in livestock populations were assessed across seven regions; specifically, Canada, Western Europe, Eastern

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[14] Although Gerber et al. (2013) assesses the livestock supply chain, in this context we incorporate only the direct emissions from livestock production (enteric fermentation and manure management).

Europe, Oceania, Latin America, Africa, the Middle East, and India. The livestock types evaluated were dairy and beef cattle, swine, sheep, and poultry. The FAPRI-CARD model determined the changes in livestock production and animal populations based on RFS2 driven changes to regional feed prices. Enteric fermentation emissions were determined based on the change in number of livestock by type, multiplied by the appropriate average per-animal emissions factor. Similarly, manure management emissions were determined by multiplying the regional default methane and nitrous oxide emission factors by the appropriate change in regional livestock populations (FAPRI, 2004). The emission factors for both the enteric fermentation and the manure management emissions are based on the default IPCC emission factors by regional practice (IPCC, 2006).

FAPRI-CARD projected changes for region livestock population in 2022 are shown in Table 2-30. The values shown are the difference (in thousand livestock head) between the Control and Corn Only Cases.

Table 2-30: 2022 International Livestock Changes Due to Corn Ethanol Production (thousands of head)

Region	Dairy	Cattle	Swine	Sheep	Poultry
Canada	-3.0	61.2	-307.8	0.0	700.7
Western Europe	-1.1	-28.7	-9.9	0.0	733.8
Eastern Europe	0.1	18.3	-51.6	0.0	3,528.7
Oceania	3.6	196.0	-4.3	35.4	1,342.1
Latin America	-105.0	-377.4	36.0	0.0	2,072.8
Asia	-46.6	964.3	-72.6	-702.2	1,477.3
Africa and Middle East	-214.8	-37.3	0.0	0.0	-312.1
India	-0.1	-31.2	0.0	0.0	26.2

Source: FAPRI output; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Input_Ag” tab.

The enteric CH_4 emission factors used in the RIA are provided in Table 2-31.

Table 2-31: Enteric CH_4 Emission Factors Used in the RFS2 RIA

Enteric Fermentation (kg CH_4/head/year)	Diary	Cattle	Swine	Sheep
North America	121	53	1.5	8
Western Europe	109	57	1.5	8
Eastern Europe	89	58	1.5	8
Oceania	81	60	1	5
Latin America	63	56	1	5
Asia	61	47	1	5
Africa and Middle East	40	31	1	5
Indian Subcontinent	51	27	1	5

Source: EPA, 2010a.

The RIA models CH_4 and N_2O emissions from manure management with default regional emission factors (IPCC, 2006). Therefore, similar to the method for calculating domestic livestock emissions, changes in emissions are based only on changes in projected livestock populations.

The CH_4 and N_2O emission factors used for international manure management practices in the RFS2 RIA are provided in Table 2-32 and Table 2-33.

Table 2-32: Manure Management CH_4 Emission Factors Used in the RFS2 RIA

Manure Management (kg CH_4/head/year)	Diary	Cattle	Swine	Sheep	Poultry
North America	78	2	23.5	0.28	0.02
Western Europe	51	15	15.5	0.28	0.02
Eastern Europe	27	13	6.5	0.28	0.02
Oceania	29	2	18	0.15	0.02
Latin America	1	1	1	0.15	0.02
Asia	18	1	4	0.15	0.02
Africa and Middle East	1.5	1	2	0.15	0.02
Indian Subcontinent	5	2	4	0.15	0.02

Source: EPA, 2010a

Table 2-33: Manure Management N_2O Emission Factors Used in the RFS2 RIA

	Diary	Cattle	Swine	Sheep	Poultry
Region	(kg N_2O /head/year)				
Canada	1.85	1.51	0.24	0.15	0.00
Western Europe	2.07	1.11	0.31	0.30	0.00
Eastern Europe	1.28	0.98	0.37	0.32	0.00
Oceania	2.37	2.05	0.42	0.23	0.00
Latin America	2.34	1.34	0.40	0.24	0.00
Asia	1.43	1.39	0.12	0.24	0.00
Africa and Middle East	2.04	1.44	0.47	0.24	0.00
Indian Subcontinent	1.15	0.34	0.10	0.24	0.00

Source: EPA, 2010a

The RIA projected emissions due to U.S. corn ethanol production from changes in international livestock production at 3,458 g CO_2e/MMBtu in 2022.

ICF Methodology, Data Sources, and Results

There are very limited data related to international livestock populations for determining the current population of livestock. ICF utilized the RIA's changes in regional livestock populations shown in Table 2-33 above.

For international livestock emission factors, ICF analyzed updated factors as available for enteric CH_4 and manure management CH_4 and N_2O. The only available updated factors for international livestock that matched the RIA regions were for Canadian cattle. While updated factors exist for a number of individual countries, these cannot be applied at the RIA region level. Hence, we were unable to update effective emission factors.

ICF assessed the current emissions value for the International Livestock source category at 3,894 g CO_2e/MMBtu. This is slightly higher than the RIA 2022 value and reflects the use of the AR4 CH_4 and N_2O GWPs and the updated emission factors for Canada.

International Land-Use Change

International LUC (iLUC) is the largest emissions source category in the RIA LCA. It encompasses indirect emissions associated with farmers outside the Unites States shifting new land into commodity production in response increases in global commodity prices driven by the RFS2 corn ethanol mandate. Since 2010, new studies, data sets, and other information have become available that, taken collectively, make a compelling case that RIA LCA significantly over estimated emissions for this source category.

Literature Review Findings

For the RIA, EPA compared simulation results from the FAPRI-CARD model under the Control and Corn Only Cases to assess global agriculture's response to the RFS2. FAPRI-CARD can assess changes in area and production across 20 crops and 54 regions in response to changes in international and domestic commodity prices. For 2022, FAPRI-CARD projected the RFS2 corn ethanol mandate would increase cropland outside the Unites States 789,000 hectares (1.872 million acres) and decrease pasture by 446,000 hectares (i.e., 1.070 million acres). FAPRI-CARD generated changes in cropland area by country/region and crop commodity are shown in Table 2-34 and Figure 2-4. Among regions, Brazil accounted for the largest share of new cropland (approximately 316,000 hectares).

Table 2-34: FAPRI-CARD Projected Changes in Harvested Hectares in 2022

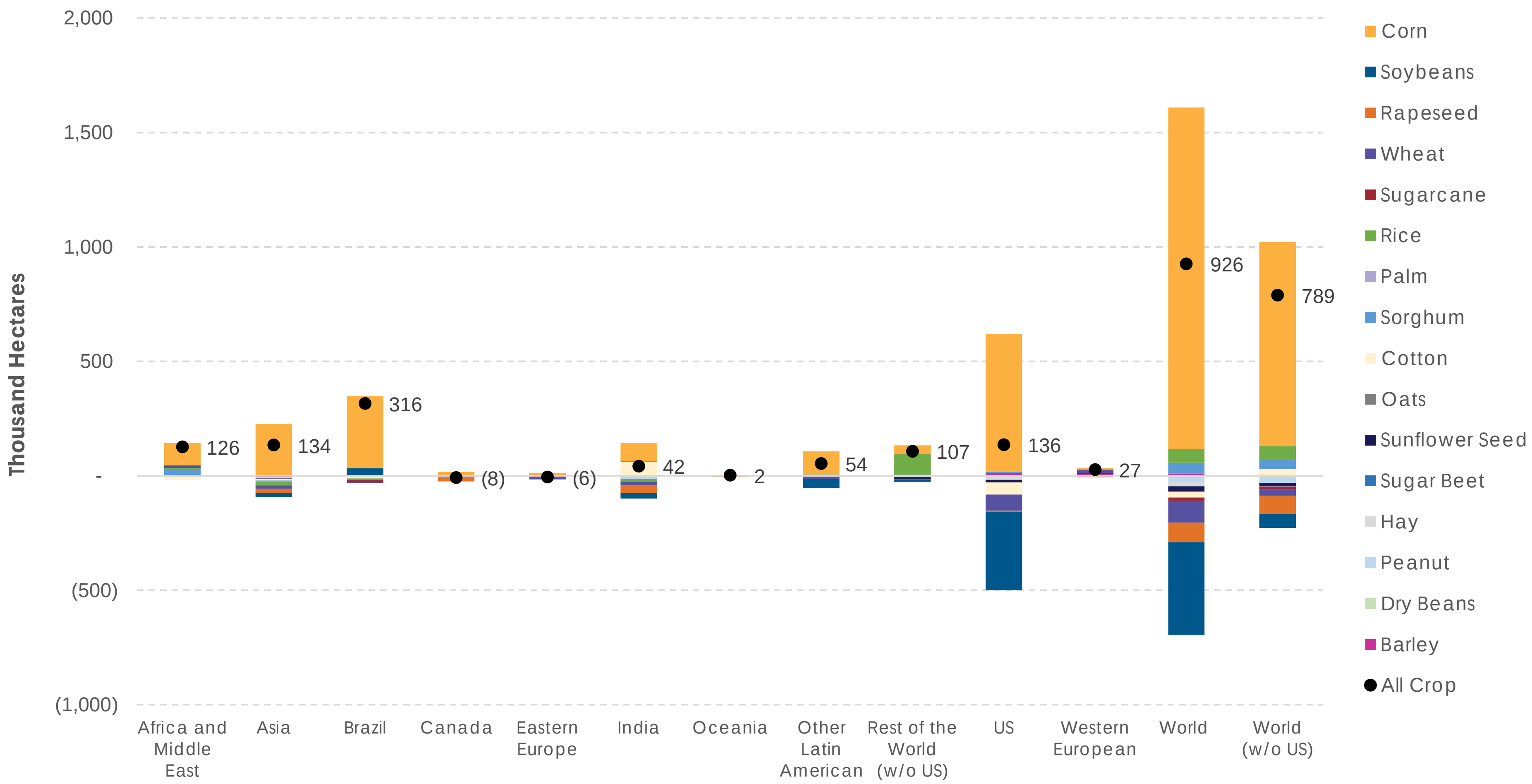
Country/Region	Change in Crop Harvested Area (Thousand Hectares)																				
	Barley	Barley, Winter	Corn	Corn Safrinha	Cotton	Dry Beans	Dry Beans 2	Oats	Palm	Peanut	Rapeseed	Rice	Sorghum	Soybeans	Sugar Beet	Sugarcane	Sunflower Seed	Wheat	Wheat, Winter	Hay	TOTAL Cropland Change
Algeria	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
Argentina	1	0	36	0	0	0	0	0	0	0	0	0	0	−36	0	0	−4	−9	0	0	**−13**
Australia	−2	0	0	0	0	0	0	0	0	0	−3	0	0	0	0	0	0	2	0	0	**−2**
Bangladesh	0	0	0	0	0	0	0	0	0	0	0	−17	0	0	0	0	0	0	0	0	**−17**
Brazil: Amazon Biome	0	0	13	1	0	0	0	0	0	0	0	1	0	21	0	1	0	0	0	0	**36**
Brazil: Central-West Cerrados	0	0	65	94	−9	0	0	0	0	0	0	−7	0	55	0	2	0	0	0	0	**105**
Brazil: Northeast Coast	0	0	21	0	0	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	**24**
Brazil: North-Northeast Cerrados	0	0	5	8	0	−1	0	0	0	0	0	0	0	29	0	0	0	0	0	0	**32**
Brazil: South	0	1	125	90	0	−4	2	0	0	0	0	−1	0	−55	0	−14	0	0	−2	0	**51**
Brazil: Southeast	0	0	87	12	0	−1	0	0	0	0	0	0	0	−18	0	−1	0	0	0	0	**67**
Canada	−1	0	16	0	0	0	0	0	0	0	−18	0	0	−1	0	0	0	−4	0	0	**−8**
China	0	0	149	0	−6	0	0	0	0	−6	−18	−78	0	−18	0	−1	−2	11	0	0	**30**
New Zealand	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Colombia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Cuba	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Egypt	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−3	0	0	**5**
EU	10	0	7	0	0	0	0	0	0	0	−7	0	0	0	0	0	2	15	0	0	**27**
Guatemala	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
India	0	0	78	0	60	0	0	0	0	−14	−32	−11	5	−24	0	−1	0	−17	0	0	**42**
Indonesia	0	0	29	0	0	0	0	0	−1	0	0	5	0	0	0	0	0	0	0	0	**32**
Iran	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	4	0	0	**5**

Country/Region	Change in Crop Harvested Area (Thousand Hectares)																				
	Barley	Barley, Winter	Corn	Corn Safrinha	Cotton	Dry Beans	Dry Beans 2	Oats	Palm	Peanut	Rapeseed	Rice	Sorghum	Soybeans	Sugar Beet	Sugarcane	Sunflower Seed	Wheat	Wheat, Winter	Hay	TOTAL Cropland Change
Iraq	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**1**
Ivory Coast	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	**2**
Japan	0	0	0	0	0	0	0	0	0	0	0	56	0	0	0	0	0	0	0	0	**56**
Malaysia	0	0	0	0	0	0	0	0	−2	0	0	0	0	0	0	0	0	0	0	0	**−2**
Mexico	1	0	39	0	0	0	0	0	0	0	0	0	3	0	0	0	0	−1	0	0	**43**
Morocco	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
Myanmar (Burma)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Nigeria	0	0	0	0	0	0	0	0	0	0	0	0	30	0	0	0	0	0	0	0	**31**
Africa, Other	−1	0	61	0	−4	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**57**
Asia, Other	−1	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−8	0	0	**−4**
CIS, Other	0	0	0	0	2	0	0	0	0	0	0	0	0	−1	0	0	−2	1	0	0	**−1**
Eastern Europe, Other	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−1	0	0	**2**
Latin America, Other	0	0	26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	**26**
Middle East, Other	−3	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**−1**
Pakistan	0	0	11	0	−1	0	0	0	0	0	0	3	−1	0	0	0	0	−17	0	0	**−4**
Paraguay	0	0	0	0	0	0	0	0	0	0	0	0	0	−4	0	0	0	0	0	0	**−4**
Peru	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Philippines	0	0	17	0	0	0	0	0	0	0	0	11	0	0	0	0	0	0	0	0	**29**
Rest of World	1	0	38	0	0	0	0	0	0	−6	−2	89	4	−10	0	1	−7	−1	0	0	**107**
Russia	−4	0	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
South Africa	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**29**
South Korea	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Taiwan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**

Country/Region	Change in Crop Harvested Area (Thousand Hectares)																				
	Barley	Barley, Winter	Corn	Corn Safrinha	Cotton	Dry Beans	Dry Beans 2	Oats	Palm	Peanut	Rapeseed	Rice	Sorghum	Soybeans	Sugar Beet	Sugarcane	Sunflower Seed	Wheat	Wheat, Winter	Hay	TOTAL Cropland Change
Thailand	0	0	5	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	**7**
Tunisia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	**3**
Turkey	0	0	0	0	−4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**−4**
Ukraine	−5	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	−8	0	0	**−7**
Uruguay	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	**1**
United States	12	0	601	0	−52	0	0	−3	0	−1	−5	0	7	−343	−1	0	−9	−70	0	−16	**136**
Uzbekistan	0	0	0	0	−1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**−1**
Venezuela	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Vietnam	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**6**
Western Africa	0	0	0	0	−7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	**−7**
WORLD TOTAL	**8**	**1**	**1,492**	**205**	**−23**	**−4**	**3**	**−3**	**−4**	**−28**	**−84**	**59**	**47**	**−404**	**−1**	**−13**	**−21**	**−94**	**−2**	**−16**	**926**
FOREIGN TOTAL	**−4**	**1**	**891**	**205**	**28**	**−4**	**3**	**0**	**−4**	**−27**	**−79**	**58**	**40**	**−60**	**0**	**−13**	**−12**	**−24**	**−2**	**0**	**789**

Source: EPA, 2010c.

Figure 2-4: Corn Only Scenario Compared to Control Scenario: Changes in Harvested Hectares by 2022

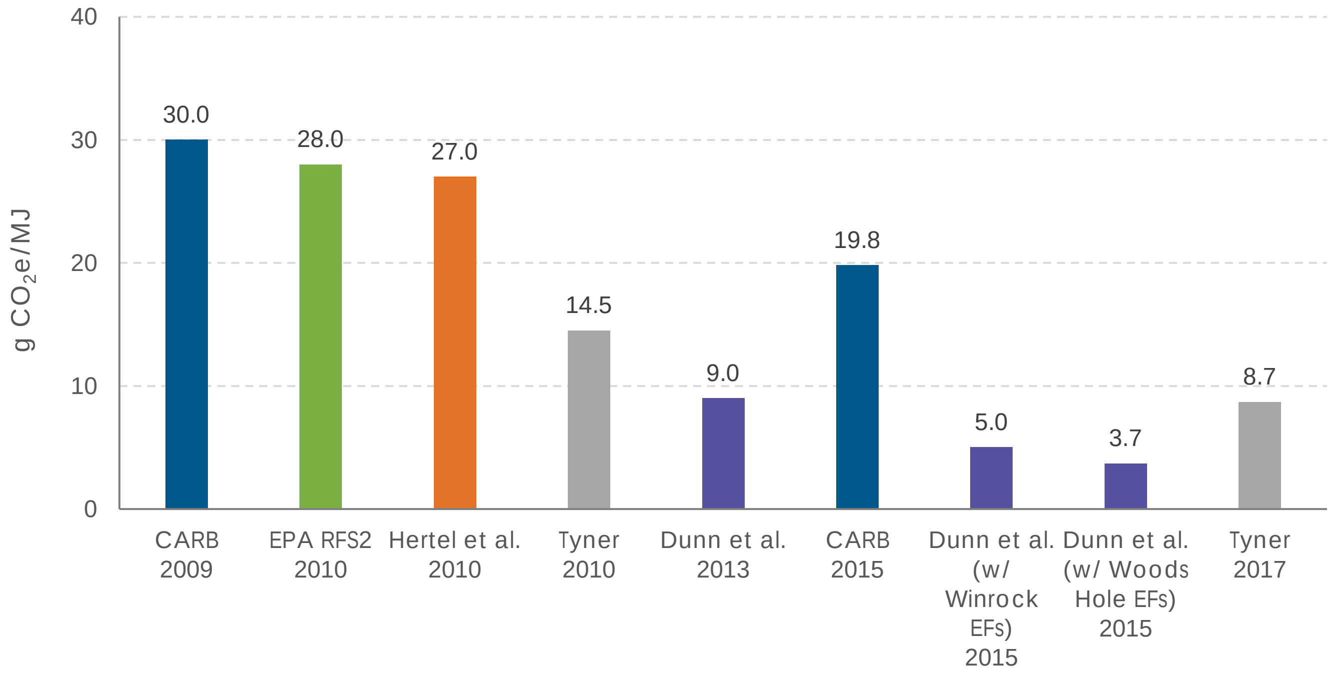


Source: EPA, 2010a

While FAPRI-CARD can assess how much new land will shift into commodity production in response to a global commodity market shock, it cannot distinguish the types of land that shift. The FAPRI projected changes in regional land areas used for commodity production (crops and livestock) were analyzed by Winrock International (WI) to determine the types of land, and the quantities of each land type, that would be affected. WI's methodology drew on MODIS satellite data covering the period 2001 to 2007 (Friedl, 2009; MODIS, n.d.) and expert opinion to quantify, by region, conversions and reversions of land to commodity production from forest land, from grassland, and from cropland-pasture.

Since 2010, a variety of new studies have assessed the iLUC impacts associated with the corn ethanol mandates in the RFS and RFS2 (e.g., Dunn et al., 2014; Taheripour and Tyner, 2013; Dunn et al., 2013; Babcock and Iqbal, 2014; and CARB, 2015). These studies employ data, modeling capabilities, and other information that were not available for the RIA. Results for studies that assess the iLUC emissions associated with the corn ethanol mandates in the RFS and/or the RFS2 are shown in Figure 2-5. Viewed collectively, three results stand out.

Figure 2-5: Comparison of International Land-use Change Emissions Related to Increases in U.S. Corn Ethanol Production - Various Sources



First, studies done after 2010 all find a significantly lower iLUC, and thus lower iLUC related emissions, in response to increases in corn ethanol production than was projected in the RIA. Second, across studies, estimates of corn ethanol driven iLUC emissions trend down over time. Finally, three research groups (CARB, Dunn et al., and Tyner) have looked at the issue more than once. For each group, iLUC

related emissions are significantly lower in their second analysis than in their first. These findings show that as we have learned more about the linkages between U.S. corn ethanol production and iLUC, and incorporated this improved understanding into economic models, the strength of corn ethanol production as a driver of iLUC has significantly and continuously decreased. Given that the RIA projected emissions path for iLUC is flat from 2015 onward, the new research strongly indicates that actual iLUC emissions related to corn ethanol are much lower than was projected in the RIA.

One reason the RIA over-estimated the global land-use response to increasing U.S. corn ethanol production is that, except in Brazil where some increases in double cropping were allowed, world agriculture's response to increasing commodity prices was generally limited to the extensive margin (i.e., bringing new land into production). While commodity production data show that the world's farmers did respond to high global and domestic commodity prices during the period 2004-2012 by increasing production, Babcock and Iqbal (2014) show that most of this increase was the result of the world's farmers making changes at the intensive margin (e.g., increasing the use of double and triple cropping, increasing irrigation, and reducing lands in idle uses).

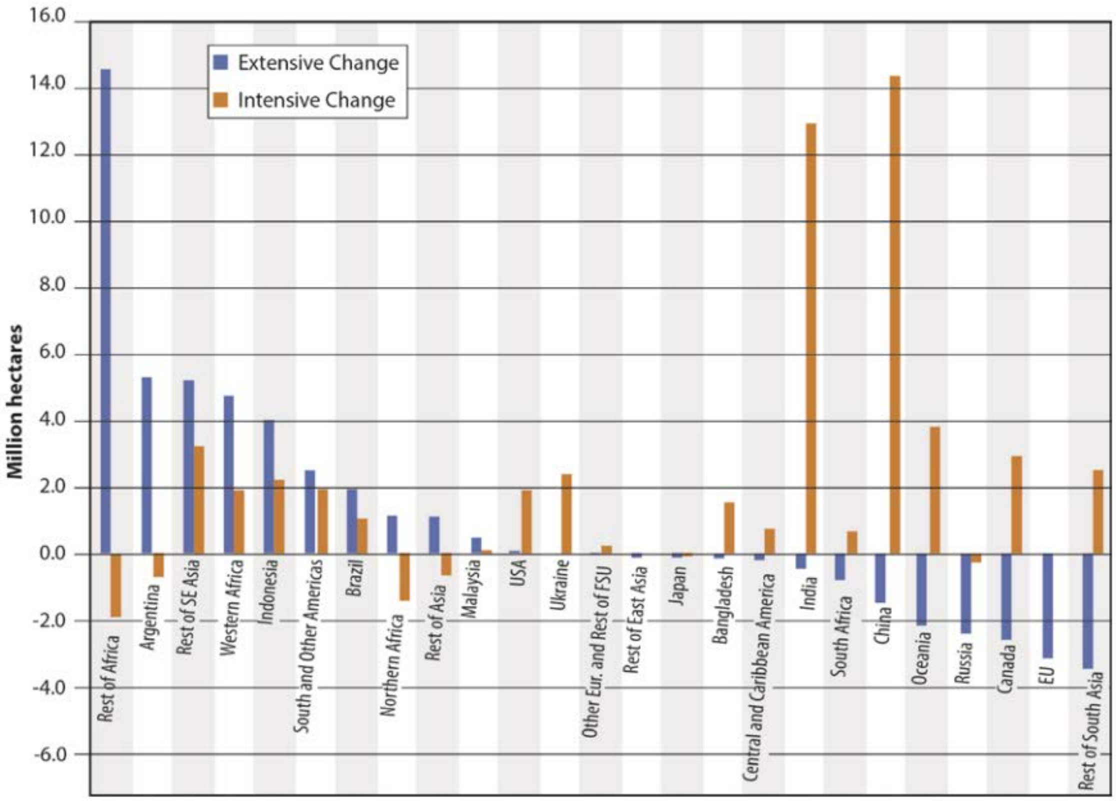
Using data from the Statistics Division of FAO (FAOSTAT) for the periods 2004–2006 and 2010–2012, Babcock and Iqbal (2014) analyzed intensive and extensive margin changes in harvested area by country/region in order to determine how much land use change was attributable to land expansion versus using existing cropland more intensely (primarily, by increased use of double cropping and reduction in idle cropland). Figure 2-6 shows their results by country/region.

Figure 2-6 makes clear the potential to overestimate LUC, and LUC related emissions, if an analysis limits agriculture's response to increasing commodity prices (or to other market shocks) to bringing new land into production. Focusing on three important agricultural regions, Babcock and Iqbal find that:

- For Brazil, 76 percent of the increase in harvested acres was due to increased use of double cropped land.
- All of India's increase in harvested acres should be attributed to reducing idle land (67 percent) and increased use of double cropping (34 percent).
- In China, from 2010 to2012, harvested acres increased but cultivated acres decreased. Hence, all of the increase in harvested was from intensification.

Overall, Babcock and Iqbal concluded that the RIA had significantly overstated the magnitude of iLUC attributable to increases in U.S. corn ethanol production.

Figure 2-6: Extensive and Intensive Land-use Changes: 2004–2006 to 2010–2012 from FAOSTAT



Source: Babcock and Iqbal, 2014.

Based on the country/region specific intensification adjustments described in Babcock and Iqbal (2014), (including the three noted above), ICF created a modified 2013 GTAP land-use change data set that incorporates the impact of intensification. Table 2-35 shows the both the 2013 GTAP and the intensification adjusted 2013 GTAP iLUC values for changes in forest, grassland, and cropland pasture for Brazil, India, China, Sub-Sahara Africa, and Indonesia.

Table 2-35: Comparison of GTAP 2013 Change in Hectares and GTAP 2013 Adjusted with Data from Babcock and Iqbal (2014)

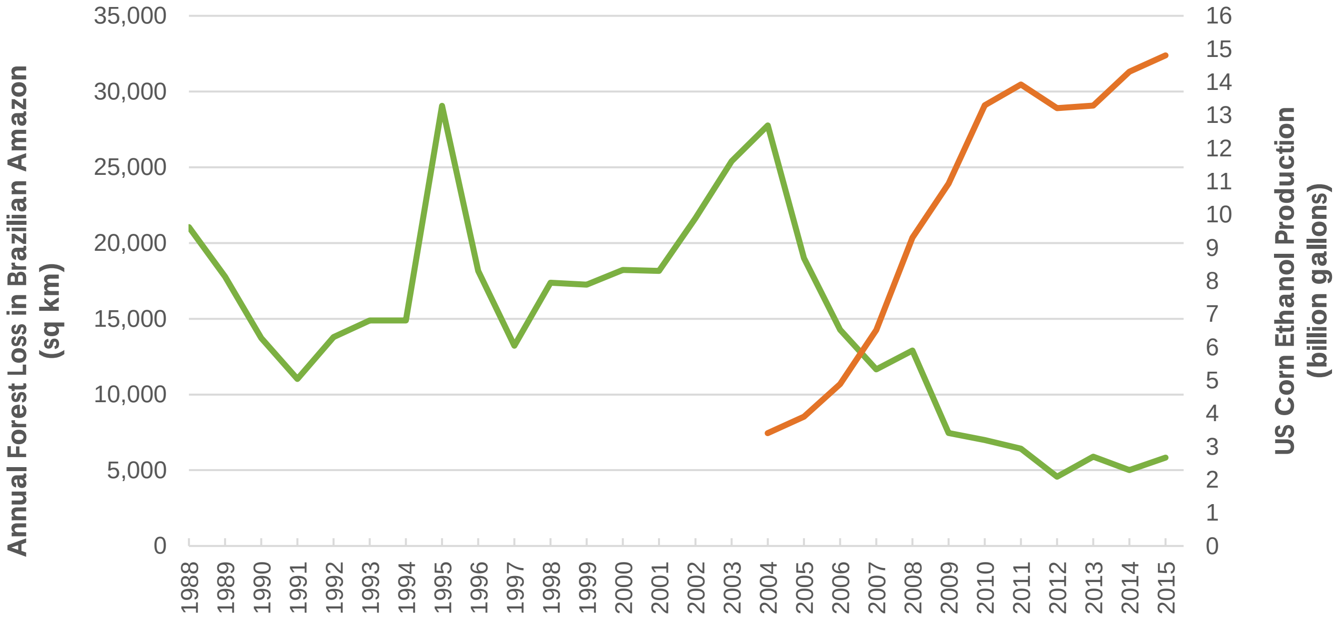
Country	Land Type	GTAP 2013	GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data
Brazil	Forest	62,448	14,988
	Grassland	−219,140	−52,594
	Cropland-Pasture	−213,930	−51,343
India	Forest	−7,004	0
	Grassland	−3,539	0

Country	Land Type	GTAP 2013	GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data
	Cropland-Pasture	0	0
China	Forest	−1,692	−1,193
	Grassland	−86,841	−61,240
	Cropland-Pasture	0	0
Sub-Saharan Africa	Forest	−167,148	−2,256
	Grassland	−294,788	−3,980
	Cropland-Pasture	0	0
Indonesia	Forest	892	446
	Grassland	−2,974	−1,487
	Cropland-Pasture	0	0

Source: Dunn et al. 2014a; Babcock and Iqbal 2014.

Finally, in the RIA, Brazil’s Amazon region accounts for about five percent of all iLUC related to the RFS2 corn ethanol mandate (see Table 2-34), but also, due to its high carbon intensity, about 40 percent of iLUC related emissions (see Table 2-36). If increases in U.S. corn ethanol production actually drive additional deforestation in Brazil’s Amazon, we would expect to see a direct correlation between the two over the period 2004 – 2015; that is, when annual U.S. corn ethanol production increased from 3.4 billion gallons to 14.8 billion gallons. As shown in in Figure 2-7, this correlation is not apparent in comparing data on of annual deforestation rates in Brazil’s Amazon for 2004-2015 with annual U.S. corn ethanol production over the period. In fact, U.S. corn ethanol production increased four-fold while annual deforestation rates in Brazil’s Amazon region decreased over 75 percent. While it is possible that deforestation rates in Brazil’s Amazon region could have dropped even further if U.S. corn ethanol production had remained at its 2004 level, this is not evident from the data. At a minimum, Figure 2-7 shows there were other factors affecting deforestation rates in Brazil’s Amazon from 2004 to 2015 besides increasing U.S. corn ethanol production.

Figure 2-7: Comparison of Brazilian Deforestation (sq. km) and U.S. Corn Ethanol Production (billion gallons) by Year



Sources: Deforestation from the Brazilian National Institute of Space Research (Butler, 2014); U.S. corn ethanol production from the U.S. Energy Information Administration (EIA, 2015a).

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

As noted, for the RIA, EPA used simulations of the FAPRI-CARD model to project total changes in land area used for commodity production by commodity (crops and livestock) and region. The land-cover types affected by conversions to commodity production and the location of those land conversions were determined by Winrock International using MODIS satellite data for the period 2001 to 2007 (MODIS; Friedl, 2009). The land conversion scenarios analyzed were the following:

- Annual Crops to/from Perennial Crops
- Pasture to/from Perennial Crops
- Pasture to/from Annual Crops
- Natural Ecosystems to/from Annual Crops
- Natural Ecosystems to/from Perennial Crops
- Natural Ecosystems to/from Pasture

Natural ecosystems included forests, grasslands, savannas, shrublands, wetlands, and barren land. For the RIA, Winrock assumed that the social, political, and economic forces that drove land-use change between 2001 and 2007 would remain the same through 2022. The Winrock emissions projections considered:

- Different types of land conversions were identified and analyzed with satellite data to show their current location and the likely land-cover types that would be affected by conversions.
- Forest Carbon emission factors that incorporated spatial, region-specific maps derived using adjusted biome-level Tier 1 default values from IPCC and supplemented with country-specific data sources (Ruesch and Gibbs, 2008).
- Fire for land clearing was assumed to occur in all countries except China and Argentina. These estimates were based on the area burnt, the mass of fuel used for combustion and the emission factor for dry matter (IPCC, 2006).
- Changes in soil carbon stocks on land converted to cropland were assessed based on Section 5.3.3.4 of the IPCC AFOLU section. The specific soil stock change factors used for land use, management, and inputs were multiplied by the reference carbon stocks. Following IPCC guidelines, the total difference in carbon stocks before and after conversion was averaged over 20 years (IPCC, 2006).
- To assess for foregone forest sequestration rates, forest sequestration rates were taken from the IPCC Tier 1 default values for native forests. Updated literature values were available for tropical intact old growth forests (0.49 t C/ha/yr) and temperate and boreal forests (3–4 t CO_2e/ha/yr.) (Lewis et al., 2009) (Myneni et al., 2001).
- All land reversion factors (except reversion to forest) were estimated as the reverse of the appropriate emission factors, and all increases in biomass stocks were assumed to occur in Year 1. Forest reversion factors were based on the assumption that biomass accumulates every year over a 30-year time period.
- Changes in pasture area resulting from livestock fluctuations were assessed in order to create a link between the livestock and land used for grazing. Regional pasture stocking rates determine the amount of land needed for pasture. Any unneeded pasture areas were considered available for cropland or to be returned to their natural state. The average stocking rates for each of the 54 FAPRI-CARD regions were determined based on FAO data (EPA, 2010a; Table 2.4-31.
- Winrock International emission factors for changes in agricultural land use were based on IPCC guidelines. The international land-use change GHG impacts were annualized over 30 years using a 0 percent discount rate.

Table 2-34 and Figure 2-4 present the FAPRI-CARD projected changes in harvested cropland by commodity and country/region for the RFS2 corn ethanol mandate in 2022. The total change in international crop area harvested for 2022 was 789,000 hectares. International pasture area decreased by 446,000 hectares, which resulted in a decrease of 2.23 hectares/billion Btu (see: EPA, 2010a; Table 2.4-32).

Projected 2022 iLUC emissions by country and for the world (i.e., minus the United States) are shown in Table 2-36. The values in Table 2-36 reflect the annualized (over 30 years) amount of carbon dioxide emitted for each MMBtu of U.S. corn ethanol produced. Positive values indicate increases in emissions associated with net land use change.

Table 2-36: International Land-Use Change GHG Emission Impacts by Region, 2022 (kg CO_2e/MMBtu)

FAPRI-CARD Region	Corn Ethanol	FAPRI-CARD Region	Corn Ethanol
Algeria	0.02	Myanmar (Burma)	−0.06
Argentina	−0.31	Nigeria	0.76
Australia	0.52	Africa, Other	1.13
Bangladesh	−0.43	Asia, Other	0.12
Brazil: Amazon Biome	12.83	CIS, Other	−1.50
Brazil: Central-West Cerrados	4.09	Eastern Europe, Other	0.02
Brazil: Northeast Coast	0.41	Latin America, Other	0.49
Brazil: North-Northeast Cerrados	0.86	Middle East, Other	0.00
Brazil: South	1.93	Pakistan	−0.07
Brazil: Southeast	1.56	Paraguay	0.03
Canada	−0.04	Peru	−0.56
China	0.56	Philippines	1.25
New Zealand	0.05	Rest of World	1.04
Colombia	0.25	Russia	0.01
Cuba	0.05	South Africa	0.04
Egypt	−0.01	South Korea	0.00
EU	0.47	Taiwan	0.00
Guatemala	0.22	Thailand	0.22
India	0.84	Tunisia	0.02
Indonesia	3.34	Turkey	−0.10
Iran	0.09	Ukraine	−0.13
Iraq	0.01	Uruguay	−0.03
Ivory Coast	0.07	Uzbekistan	−0.47
Japan	1.22	Venezuela	−0.21
Malaysia	−0.11	Vietnam	0.23
Mexico	1.01	Western Africa	0.03
Morocco	0.04	**TOTAL**	**31.79**

Source: FAPRI-CARD output; "EPA_2010_RFS2_regulatory_impact_assessment.pdf" and EPA, 2010a (See Table 2.4-47 from EPA RIA).

Summed across countries and regions, EPA projected emissions for the International Land Use Change source category in 2022 at 31,790 g CO_2e/MMBtu.

ICF Methodology, Data Sources, and Results

Consistent with our treatment of the Domestic LUC source category, ICF evaluated the impacts of increases in U.S. corn ethanol production on international LUC using simulation results of the 2013 GTAP-BIO model available in ANL's CCLUB tool (Dunn et al., 2014). We also draw on the country/region land use intensification measures developed by Babcock and Iqbal (2014) and three sets iLUC emission factors that have been used to assess iLUC emissions since 2010.

GTAP-Bio is a computable general equilibrium model specifically tailored to estimate the land use impacts of market and policy shocks related to biofuels. Internationally, GTAP-Bio allows three land types to be used for biofuel production: forest, grassland, and cropland-pasture land. Relative to earlier versions of GTAP, in particular 2011 GTAP, GTAP-Bio has three important updates. First, the base year is 2004 (the year before the original RFS was implemented). Hence, simulations capture the complete set land-use changes related to RFS and RFS2 increases in U.S. corn ethanol production (i.e., 11.59 billion gallons a year). Second, GTAP-Bio has region specific land transformation elasticities. Land transformation elasticities reflect the ease of land moving from one state to another. A low value indicates limited ability to transition. In the 2011 GTAP model, there was only one land transformation elasticity for the world. Using two FAO land-cover datasets, Taheripour and Tyner (2013) developed region-specific elasticities for GTAP-Bio. Finally, GTAP-Bio has a cost structure that reflects the higher cost of converting forest to cropland relative to converting grassland.

International LUC results for 2011 GTAP are also available in ANL's CCLUB model (Dunn et al., 2014). Similar to the results for domestic LUC, the updates incorporated into GTAP-Bio result in significantly lower U.S. ethanol driven shifts of land into commodity production relative to 2011 GTAP. For example, GTAP-Bio results show 123,249 less forest hectares shifting in cropland than does the 2011 GTAP.

The complete set of 2013 GTAP-Bio international land use change results are shown in Table 2-37.

Table 2-37: GTAP Land-Use Change Output Generated by Taheripour and Tyner (2013)

Region	Forest (ha)	Grasslands (ha)	Cropland-Grassland (ha)
United States	−64,772	−92,617	−1,788,462
European Union 27	−14,718	−18,835	0
Brazil	62,449	−219,140	−213,930
Canada	−25,352	−14,759	0
Japan	−5,041	−146	0
China and Hong Kong	−1,692	−86,841	0
India	−7,005	−3,539	0
Central and Caribbean Americas	4,456	−9,854	0
South and Other Americas	68,910	−18,3325	0
East Asia	2,245	−3,763	0
Rest of South East Asia	−11,849	−2,528	0
Rest of South Asia	−3,099	−21,562	0
Russia	87,329	−145,276	0
Other East Europe and Rest of Former Soviet Union	−7,354	−21,478	0
Rest of European Countries	−240	−188	0
Middle Eastern and North Africa	168	−21,975	0
Sub-Saharan Africa	−167,148	−294,788	0
Oceania Countries	−543	−17,307	0
Totals	−82,369	−1,160,890	−2,002,393
International Total (w/o USA)	**−17,589**	**−1,068,278**	**−213,930**

Source: Dunn et al. 2014a.

As was noted in the Domestic LUC section, the increase in U.S. corn ethanol production considered in the RIA was 2.6 billion gallons per year; the increase considered in the 2013 GTAP-Bio simulation was 11.59 billion gallons. Hence, the ethanol driven changes in international land use are not directly comparable. To make the RIA and 2013 GTAP changes in iLUC more comparable, we convert them both to the metric, hectares per million gallons of additional ethanol. These values are shown in Table 2-38. For completeness, Table 2-38 also shows hectares per million gallons of additional ethanol for the 2013 GTAP iLUC adjusted with the intensification measures in Babcock and Iqbal (2014).

Table 2-38: Comparison of International Crop Area Change Between RIA and Proposed Data Million Gallons of Additional Ethanol Demand

	International Crop Area Change per Million Gallons (ha/million gallons)
RIA Corn Ethanol	303
GTAP 2013	112
GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data	45

Source: EPA, 2010a; Dunn et al., 2014a; Babcock and Iqbal, 2014.

To assess iLUC emissions associated with increases in U.S. corn ethanol production requires linking regional shifts of land into commodity production with a set of associated emissions factors. The RIA employs the emission coefficients developed by Winrock International (discussed above). A second set of emission factors are those developed by Woods Hole. The Woods Hole factors incorporate region- and biome-specific values for belowground carbon, biomass carbon, and carbon growth factors. The Winrock International and Wood Hole emission Factors are options in the ANL CCLUB model, but neither aligns exactly with the GTAP 2013 AEZ structure. Hence, using GTAP 2013 iLUC results with either set requires some aggregation of land conversions across land types and AEZs within each region.

A third set of iLUC emissions factors is available from the Low Carbon Fuel Standard Agro-ecological zones (AEZ) model (a GTAP model tailored to California) used by the California Air Resources Board (ARB) (CARB, 2015). The ARB AEZ emission factors are not included in the ANL CCLUB model but are completely consistent with the 2013 GTAP region-AEZs structure. This makes computing iLUC related emissions for GTAP 2013 simulation results relatively straight forward.

To our knowledge, there has not yet been a rigorous comparison of the three set of emissions factors discussed above. As a result, there is no established or emerging consensus regarding which, if any, is the most appropriate for our purposes. Hence, to assess the contribution of iLUC emissions to corn ethanol's GHG profile, we compute the average iLUC emissions for seven scenarios. Three scenarios are directly from CARB (2015) and Dunn et al., (2014). Four scenarios we construct using the regional iLUC impacts from Tahierpour and Tyner (2013), the ARB and Winrock emission factors, and the regional intensification data in Babcock and Iqbal (2014). Table 2-39 details the seven scenarios, their emission factors, and their iLUC emissions values. The emissions are annualized values over a 30-year period. We take the average annual iLUC emissions of these seven scenarios, specifically 9,082 g CO_2e/MMBtu, as our emissions value for the International Land Use Change source category. For completeness, Table 2-39 also shows the RIA iLUC emissions value. Figure 2-8 shows the same comparison of our seven scenarios graphically (although using the metric, g CO2$_e$/mega joule).

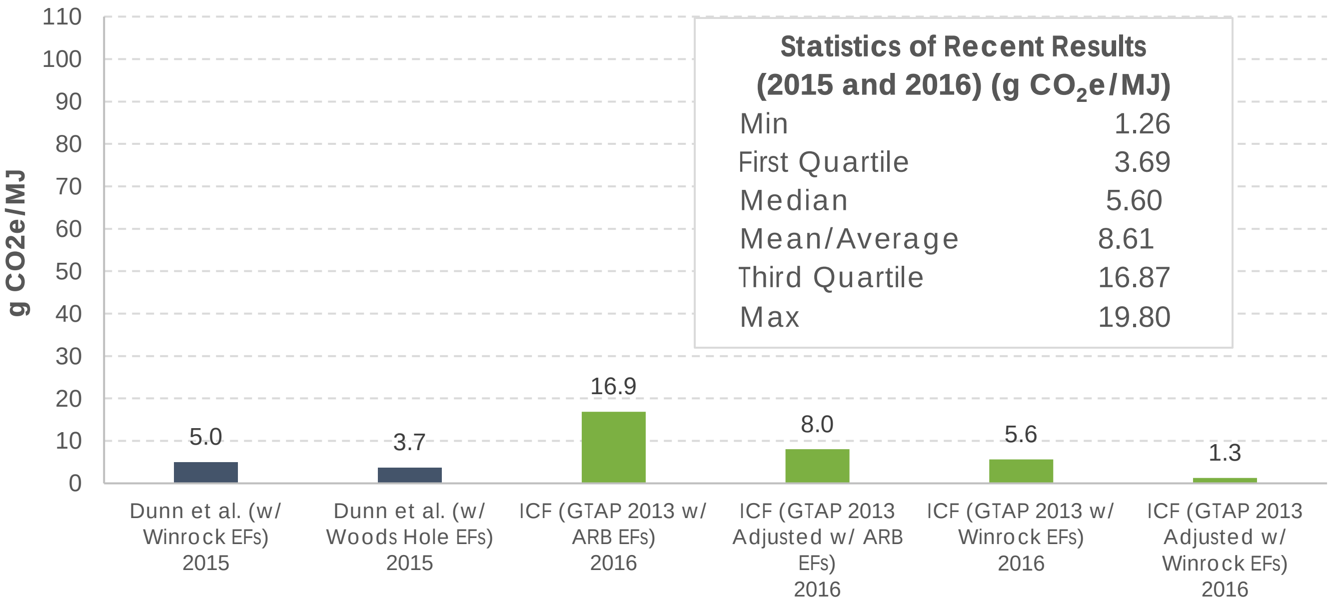
Table 2-39: International Land-Use Change Results by Scenario, Emission Factor Data Set and Annualized Emission Value

Scenario	Emission Factor Data Set	Emissions (g CO_2e/MMBtu)[3,4]
	EPA's RIA Analysis (2022)	
FAPRI-CARD	Winrock	31,790
	Scenarios Making up Composite iLUC Emissions Value used in this Analysis	
GTAP 2013	ARB LCFS AEZ Model	17,802
GTAP 2013 [2]	Winrock	5,913
GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data	ARB LCFS AEZ Model	8,464
GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data	Winrock	1,326
CARB 2015a	ARB LCFS AEZ Model	20,890
Dunn et al 2014a	Winrock	5,286
Dunn et al 2014a	Woods Hole	3,893

Source:

1. Dunn et al. and the 4 scenarios we construct use land conversion results published by Taheripour and Tyner (2013). CARB, modified some important factors and values within the GTAP-Bio model to produce their own unique land conversion results.
2. Emissions vary in these studies because within each region, Dunn et al. used a straight average of the individual country EFs, while we weight country's EFs by their share of regional arable land.
3. All studies assume emissions from land conversions occur over a 30-year period. The values in this column are annualized values for the 30-year emissions streams.
4. The RIA and 2013 GTAP-Bio consider different volume increases in corn ethanol production. Describing emissions in "g CO2e/MMBtu" puts all emissions in a comparable metric (see Domestic LUC discussion).

Figure 2-8: Literature and ICF Values for International Land-Use Change Due to U.S. Corn Ethanol Demand



Statistics of Recent Results (2015 and 2016) (g CO_2e/MJ)

Min	1.26
First Quartile	3.69
Median	5.60
Mean/Average	8.61
Third Quartile	16.87
Max	19.80

Limitations, Uncertainty, and Knowledge Gaps

Since 2010, a large body of evidence has emerged indicating that the RIA significantly over estimated the strength of increasing U.S. corn ethanol production on international land use change, as well as the related iLUC emissions. That said, economic iLUC assessments since 2010 have largely been done with versions of GTAP. Like all models, it has its limitations and the results presented here reflect those limitations. Additionally, emission factors are continuously being adjusted to reflect improve knowledge of soil science, cropping practices, livestock systems, atmospheric chemistry and process, and numerous other factors. Future advances in science and economic modeling capabilities should significantly improve our understanding of the relationship between biofuel production and land use change in general, and for corn ethanol in particular.

International Farm Inputs and Fertilizer N_2O

Literature Review Findings

This source category includes emissions related to changes in the use of chemical and energy inputs by farmers outside of the United States responding to changes in global commodity markets driven by increases in U.S. corn ethanol production. Two country-specific data sets exist for evaluating trends in international farm chemical inputs, especially nitrogen consumption:

- International Fertilizer Industry Association (IFA) Statistics[15]
- Food and Agriculture Organization of the United Nations (FAOSTAT)

Both of these sources have data on consumption by country. Table 2-40 presents IFA nitrogen consumption by region and Table 2-41 presents IFA data for a sample country, Brazil. As indicated in the tables, N consumption increased from 2010 to 2013 in most countries. Table 2-42 presents FAO data for Brazil for 2002 - 2013. As indicated in the tables, the level of detail and estimates differ between the data sources.

The FAO report entitled *World fertilizer trends and outlook to 2018* indicates that demand for total fertilizer nutrients will increase at 1.8 percent per year from 2014 to 2018 (FAO, 2015c, p. ix). FAO indicates that nitrogen inputs will increase at an annual growth rate of 1.4 percent.

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[15] The RIA was based on use of data provided in a report by the International Fertilizer Industry Association.

Table 2-40: Nitrogen Consumption by Region by Calendar Year as Provided by International Fertilizer Industry Association (metric tons of N)

Country	Product	2010	2011	2012	2013
Africa	Ammonia dir. applic.				
	Ammonium sulphate	121.6	99.7	69.0	104.6
	Urea	1,647.8	1,468.9	1,534.6	1,768.5
	Ammonium nitrate	562.7	594.9	575.5	545.4
	Calc.amm. nitrate	158.9	127.8	111.5	118.7
	Nitrogen solutions	0.1	0.1	0.1	0.2
	Other N straight				
	Ammonium phosphate (N)	170.3	164.8	207.5	211.3
	Other NP (N)				
	N K compound (N)			7.0	5.0
	N P K compound (N)	636.5	709.9	486.5	475.0
	Total N Straight	**2,491.1**	**2,473.0**	**2,425.8**	**2,537.4**
	Total N Compound	**782.8**	**843.7**	**882.4**	**691.3**
	Grand Total N	**3,297.9**	**3,166.1**	**2,984.7**	**3,228.7**
Developed Countries	Ammonia dir. applic.	3,647.9	4,192.1	4,189.8	4,147.0
	Ammonium sulphate	1,089.2	1,053.7	1,066.7	1,095.1
	Urea	7,456.8	7,879.0	8,245.7	8,440.6
	Ammonium nitrate	4,079.2	4,902.4	5,077.7	5,075.8
	Calc.amm. nitrate	2,752.7	2,830.4	2,868.8	2,777.1
	Nitrogen solutions	4,987.1	5,289.6	5,315.0	5,370.6
	Other N straight	893.3	945.3	967.7	959.0
	Ammonium phosphate (N)	1,340.5	1,399.6	1,473.3	1,494.9
	Other NP (N)	518.1	470.2	455.3	483.5
	N K compound (N)	49.0	145.5	153.8	154.6
	N P K compound (N)	3,808.8	3,212.0	3,193.6	3,343.8
	Total N Straight	**24,807.4**	**27,035.9**	**27,796.6**	**27,865.2**
	Total N Compound	**5,716.4**	**5,146.3**	**5,127.0**	**5,476.8**
	Grand Total N	**31,276.8**	**32,325.6**	**32,993.1**	**33,342.0**
Developing Countries	Ammonia dir. applic.	47.0	50.0	53.0	55.0
	Ammonium sulphate	2,323.4	2,349.7	2,507.9	2,365.2
	Urea	50,425.8	52,130.3	52,282.1	54,728.9
	Ammonium nitrate	1,526.3	1,741.0	1,669.5	1,657.1
	Calc.amm. nitrate	622.9	639.2	638.0	591.8
	Nitrogen solutions	198.5	196.9	181.6	216.6
	Other N straight	6,443.5	5,728.5	6,152.7	5,035.8
	Ammonium phosphate (N)	5,795.1	6,269.5	6,418.0	6,435.4

Country	Product	2010	2011	2012	2013
	Other NP (N)	1,400.9	1,822.4	1,410.4	1,515.1
	N K compound (N)	50.3	51.2	45.6	53.6
	N P K compound (N)	4,315.7	4,801.0	4,347.2	4,657.3
	Total N Straight	**61,587.4**	**63,319.7**	**62,615.0**	**64,650.4**
	Total N Compound	**11,538.0**	**12,913.1**	**12,911.9**	**12,661.4**
	Grand Total N	**73,244.9**	**75,531.4**	**75,565.7**	**77,126.3**
East Asia	Ammonia dir. applic.				
	Ammonium sulphate	1,217.0	1,212.6	1,389.1	1,201.8
	Urea	26,544.2	27,606.9	27,867.5	28,986.7
	Ammonium nitrate	28.7	36.6	39.2	37.9
	Calc.amm. nitrate	85.0	90.4	95.7	100.4
	Nitrogen solutions				6.6
	Other N straight	6,411.0	5,681.0	6,111.2	5,005.5
	Ammonium phosphate (N)	2,663.3	3,103.6	3,275.4	3,487.0
	Other NP (N)	240.0	266.0	155.0	326.0
	N K compound (N)	21.0	20.0	20.0	20.0
	N P K compound (N)	3,100.5	3,534.0	3,449.0	3,699.3
	Total N Straight	**34,285.9**	**34,927.5**	**34,460.1**	**35,338.9**
	Total N Compound	**6,024.8**	**6923.6**	**7,398.4**	**7,532.3**
	Grand Total N	**40,310.7**	**41,551.1**	**42,402.1**	**42,871.2**
Eastern Europe and Central Asia	Ammonia dir. applic.		80.0	152.8	200.0
	Ammonium sulphate	164.4	141.5	165.6	174.1
	Urea	577.8	754.9	683.2	677.9
	Ammonium nitrate	1 731.6	2 488.3	2 570.4	2 571.4
	Calc.amm. nitrate	10.4	55.6	66.5	55.5
	Nitrogen solutions	155.2	346.9	369.0	374.0
	Other N straight	5.0	53.3	44.0	5.0
	Ammonium phosphate (N)	109.9	113.1	131.7	128.9
	Other NP (N)	37.0	44.0	53.0	53.0
	N K compound (N)				
	N P K compound (N)	387.0	446.0	397.0	461.0
	Total N Straight	**2,644.4**	**3,916.8**	**4,189.7**	**4,057.9**
	Total N Compound	**533.9**	**606.1**	**493.7**	**642.9**
	Grand Total N	**3,828.3**	**4,523.6**	**4,628.2**	**4,700.8**
Latin America and the Caribbean	Ammonia dir. applic.	47.0	50.0	53.0	55.0
	Ammonium sulphate	797.5	883.2	879.6	871.8
	Urea	3,822.2	4,260.4	4,252.4	4,639.1
	Ammonium nitrate	585.2	780.4	654.4	659.8

Country	Product	2010	2011	2012	2013
	Calc.amm. nitrate	71.7	95.4	127.1	100.9
	Nitrogen solutions	198.4	196.8	181.5	209.8
	Other N straight	39.1	42.9	48.7	36.7
	Ammonium phosphate (N)	555.6	766.1	858.7	901.3
	Other NP (N)	10.0	10.0	72.9	2.0
	N K compound (N)	46.6	47.3	42.2	50.8
	N P K compound (N)	461.0	524.2	478.9	521.8
	Total N Straight	**5,561.1**	**6,295.1**	**6,235.0**	**6,573.1**
	Total N Compound	**1,073.2**	**1,347.6**	**1,455.0**	**1,475.9**
	Grand Total N	**6,729.8**	**7,408.4**	**7,509.1**	**7,863.5**

Source: IFI (2016).

Table 2-41: Consumption by Brazil by Calendar Year as Provided by International Fertilizer Industry Association (metric ton of N)

Product	2010	2011	2012	2013
Ammonia dir. applic.				
Ammonium sulphate	370.6	447.7	416.7	393.9
Urea	1,525.5	1,843.8	1,771.7	2,096.8
Ammonium nitrate	406.9	573.3	493.2	508.9
Calc.amm. nitrate	33.9	54.9	86.2	61.8
Nitrogen solutions				
Other N straight				
Ammonium phosphate (N)	201.5	404.4	465.1	519.5
Other NP (N)			70.9	
N K compound (N)	14.7	9.9		8.8
N P K compound (N)	206.4	280.3	271.5	294.3
Total N Straight	**2,336.9**	**2,919.7**	**2,767.8**	**3,061.4**
Total N Compound	**422.6**	**694.6**	**807.5**	**822.6**
Grand Total N	**2,855.0**	**3,366.0**	**3,435.0**	**3,698.5**

Table 2-42: Nitrogen Fertilizers Consumed (N Total Nutrients) in Brazil as Provided by Food and Agriculture Organization of the United Nations (metric ton of N)

Year	N total nutrients
2002	1,834,733
2003	2,407,558
2004	2,281,346
2005	2,072,214
2006	2,192,739
2007	2,948,784
2008	2,498,138
2009	3,145,930
2010	3,668,652
2011	4,418,196
2012	4,251,169
2013	3,953,800

Source: FAO (2016).

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

For the RIA, EPA used simulation results of the FAPRI-CARD model under the Control and the Corn Only Cases to project changes in harvested area and production by country and by crop. These acreage changes were combined with various international farm input use data as described below.

- **Fertilizer Application Rates**: The changes in crop area and production by crop type and country were assessed using FAPRI-CARD model simulations. Regional fertilizer consumption was taken from the IFA report, “Assessment of Fertilizer Use by Crop at the Global Level, 2006/07–2007/08.” The report covers 23 countries and 11 crop groups. For the RIA, EPA averaged the results from two reporting periods (2006/2007 and 2007/2008) (Heffer, 2009) to account for seasonal applications. Regional application rates were calculated by dividing IFA total consumption values by the FAOStat agricultural area data from the FAOStat database (FAO, 2009). The IFA report did not include lime use for corn and therefore this international input was omitted from the corn ethanol analysis.
- **Herbicide and Pesticide Application Rates**: Herbicide and pesticide activity data were obtained from the FAOStat data set for pesticide consumption. The data did not include China. Herbicide and pesticide activity data for China was provided by the U.S. Department of Agriculture’s (USDA) Economic Research Service (ERS) (FAO, 2009; USDA, 2009).

- **N_2O Emission Impacts**: International direct and indirect N_2O emissions from synthetic fertilizer application were calculated in the same manner as for the Domestic Farm Inputs source category.
- **Agricultural Energy Use**: International Energy Agency (IEA) data on total CO_2 emissions from agricultural electricity and fuel use by country were gathered for on-farm diesel, gasoline, and electricity use. The emissions associated with combustion were then calculated using IEA country-level GHG emission factors. The combustion emissions were then scaled up to represent the entire fuel life cycle emissions based on the ratio of combustion to life-cycle GHG emissions from U.S. electricity and fuel use provided by IEA (2015). The life-cycle emissions were then divided by the area of agricultural land in each country, from the FAOSTAT land area database (FAO, 2009). The emissions per land area were then multiplied by the country specific crop acreage changes from FAPRI-CARD to determine fuel-related emissions for corn ethanol.

Activity data for the international farm inputs analysis are shown in Table 2-43. The emission factors used for each source are provided in Table 2-44 and are based on GREET (EPA, 2009c).

Table 2-43: Changes in International Agricultural Inputs (Short Tons)

Input	2012	2017	2022
Total N	10,788	3,452	3,627
Total P_2O_5	15,165	11,815	9,495
Total K_2O	13,082	10,684	8,640
Herbicide	80	70	57
Pesticide	90	71	58

Source: FAPRI-CARD output, FAOStat, and ERS; "Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx," "Inputs_Ag" tab.

Table 2-44: Relative Change in International Fertillizer N_2O Emissions

		2012			2017			2022		
Emission Category	Units	Corn Only	Control Case	Difference	Corn Only	Control Case	Difference	Corn Only	Control Case	Difference
International Fertilizer Use	000 Tons CO_2e	73,282	73,565	−612.7	N/P	N/P	−935.1	N/P	N/P	−933

Source: FASOM output; "Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx," "Inputs_Ag" tab.
N/P = Not Provided.

The international change in agricultural energy use for corn ethanol in 2022 is 1.7 kg CO_2e/MMBtu (see: EPA, 2010a; Table 2.4-18).

The RIA projected 2022 emissions for the International Farm Input source category at 6,601 g CO2e/MMBtu in (see: EPA, 2010a; Table 2.4-25).

ICF Methodology, Data Sources, and Results

ICF assessed emissions for the International Farm Inputs and Fertilizer N_2O category based on the international acreage responses to increased U.S. corn ethanol production in the GTAP 2013 results available in ANL's CCLUB model (Dunn et al, 2014). Since the base year for the GTAP 2013 model is 2004, its iLUC results reflect the new land brought into commodity production outside the United States in response to the ethanol mandates in the original RFS and the RFS2. That is, the GTAP 2013 iLUC results reflect an increase of 11.59 billion gallons of U.S. corn ethanol. To make the 2013 GTAP iLUC numbers more directly comparable to the FAPRI-CARD values in the RIA, we convert both to new acres brought into commodity production per million gallon increase in U.S. corn ethanol. The GTAP 2013 and FAPRI-CARD values are, respectively, 277 and 748 acres per million gallons.

ICF based fertilizer, fungicide, insecticide, and herbicide application rates on the rates developed for the RIA. These application rates are based on data collected by the FAO and IEA and are compiled in FAO's FertiStat Database (EPA 2010b). ICF updated the herbicide and pesticide use data using current data available from FAO's FAOStat dataset for pesticide consumption (see Venezia et al. 2009). ICF combined the application rates into a weighted average by GTAP region. The weighting was based on the countries' percent contribution of arable land by region. The arable land area was taken from FAO.

Life-cycle emission factors for nitrogen, phosphate, potassium, calcium carbonate, and insecticide were based on the 2015 GREET model (ANL, 2015). Emission factors for herbicides and insecticides are from ecoinvent v2 found in SimaPro. These emission factors are cradle to farm gate and include the upstream emissions from the production of agricultural chemicals (Weidema et al. 2013).

The direct and indirect N_2O emission calculations are based on IPCC (2006) guidance. The guidance uses the nitrogen fertilizer application rates to assess the direct impacts including the N additions from fertilizer, and the N mineralized from mineral soil as a result of loss of soil carbon. The nitrogen fertilizer application rate is also used to calculate the indirect emissions from volatilization and leaching (IPCC, 2006).

Emissions associated with agricultural energy were calculated using the same methodology as the RIA. The RIA used IEA data on total CO_2 emissions from agricultural fuel combustion by country. These emissions were combined with agricultural electricity use by country. The total emissions were then scaled to represent the full life-cycle GHG emissions for each country. Finally, these emissions were divided by the FAOstat land area to derive a per acre GHG emission factor for each country (EPA 2010). The emission factors developed for the RIA were not updated because IEA no longer publicly releases country-specific emission factors. While the emission factors used in this analysis are the same as those in the RIA, they are multiplied by the change in acres data from

GTAP 2013. Table 2-45 shows the emission contributions from each of the international agricultural inputs.

Table 2-45: International Agricultural Input Emissions by Chemical and Application (g CO_2e/MMBtu)

Nitrogen Emissions	Direct and Indirect N_2O Emissions	Phosphate Emissions	Potassium Emissions	Fungicide Emissions	Insecticide Emissions	Herbicide Emissions	Energy Emissions	Total Emissions
289	1.71	87.3	82.4	1,574	0.64	1.34	181	**2,217**

These values are significantly lower than the RIA's estimates. The main driver of this difference is that relative to FAPRI-CARD results used in the RIA, the results of the GTAP 2013 simulation used in our analysis have a 63 percent reduction in new acres brought into production per million gallons increase in U.S. corn ethanol production. As shown in Table 2-45, ICF's emission value for the International Farm Inputs source category is 2,217 g CO_2e/MMBtu.

Limitations, Uncertainty, and Knowledge Gaps

One limitation of note is since EPA's development of the RIA, IEA no longer publicly publishes their annual *CO_2 Emissions From Fuel Combustion Highlights* report. Because of this, ICF was unable to use more recent emission factors for agricultural energy emissions.

International Rice Methane

Literature Review Findings

While rice is produced in all regions around the world, the majority of rice is produced and consumed in Asia (GRiSP, 2013). China, India, Indonesia, Bangladesh, and Vietnam account for about 65 percent of harvested rice acreage globally. Unlike U.S. rice production, which occurs under continuously flooded, shallow water conditions, additional regimes are used in other countries. The IPCC (2006) has developed emission factors for four categories of rice cropping regimes; specifically, irrigated, rainfed, upland, and deepwater. These factors are shown in Table 2-46. Globally, more than 90 percent of rice is grown under irrigation or on rainfed lowland rice fields (GRiSP, 2013).

Table 2-46: IPCC (2006) Default Global Rice Methane Emission Factors[a]

Rice Conditions		IPCC 2006 Scaling Factor
Irrigated	Continuously flooded	1.00
	Single aeration	0.60
	Multiple aeration	0.52
Rain-fed	Regular	0.28
	Drought-prone	0.25
	Flood-prone	-
Deep Water	Regular	0.31
Upland	Regular	-

[a] Relative to continuously flooded fields.

Between 2005 and 2014, the global harvested rice area increased marginally. Table 2-47 shows annual acres published by USDA and FAO for 2005 through 2012. For USDA and FAO, the increases over this period are, respectively, 16 million and 20 million acres (USDA ERS, 2015c; FAO, 2016a). Table 2-47 also shows FAO data on global CH$_4$ missions from rice cultivation for 2005- 2012. Reflecting the change in acres, there was a marginal increase in rice related CH$_4$ emissions over the period, from 492,539 to 521,991 GgCO$_2$e.

Table 2-47: Global Harvested Rice Area and CH$_4$ Emissions, 2005-2012

Year	USDA Rice Yearbook[a] (million acres)	FAO[b] (million acres)	Emissions from Rice Cultivation (FAO) (Gg CO2e)[b]
2005	380.56	382.99	492,539
2006	382.02	384.46	495,469
2007	382.27	383.12	495,065
2008	390.67	395.36	509,146
2009	384.89	390.76	508,672
2010	390.89	398.31	517,627
2011	396.05	402.29	520,008
2012	390.92	401.10	521,991

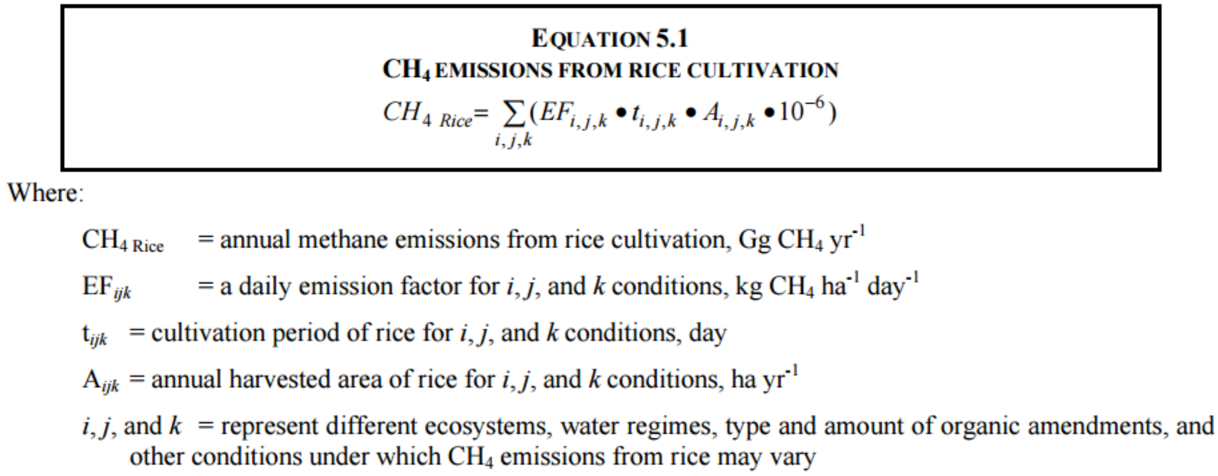
[a] USDA ERS (2015). [b] FAO (2016a).

EPA RIA and ICF Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

To project RFS2 corn ethanol mandate driven changes in international rice emissions in 2022, EPA followed the default IPCC (2006) equation shown in the box below. Changes in international rice production and area harvested, were obtained from simulation results of the FAPRI-CARD model under the Control and

the Corn Only Cases. Country-level and global projections of changes in rice production and area harvested developed from these simulations are shown in Table 2-48. The country changes in rice acres were then multiplied by IPCC default emission factors for irrigated, rainfed lowland, upland, and deepwater rice based on the percentage of each cropping regime used in the country (IPCC, 2006) Each country-regime-emissions combination was then multiplied by its cultivation season length (i.e., planting to harvest). The rice cultivation season lengths were based on data from the International Rice Research Institute (IRRI) (IRRI, 2008).



EQUATION 5.1

CH_4 EMISSIONS FROM RICE CULTIVATION

$$CH_{4\ Rice} = \sum_{i,j,k} \left(EF_{i,j,k} \bullet t_{i,j,k} \bullet A_{i,j,k} \bullet 10^{-6} \right)$$

Where:

$CH_{4\ Rice}$ = annual methane emissions from rice cultivation, Gg CH_4 yr^{-1}

EF_{ijk} = a daily emission factor for *i*, *j*, and *k* conditions, kg CH_4 ha^{-1} day^{-1}

t_{ijk} = cultivation period of rice for *i*, *j*, and *k* conditions, day

A_{ijk} = annual harvested area of rice for *i*, *j*, and *k* conditions, ha yr^{-1}

i, *j*, and *k* = represent different ecosystems, water regimes, type and amount of organic amendments, and other conditions under which CH_4 emissions from rice may vary

Internationally, the change in rice area harvested in 2022 as a result of the RFS2 corn ethanol mandate was projected at 144,110 acres (58,320 hectares) and the associated change in 2022 methane emissions was assessed at 19,918 Mg CH_4. This converted 2,089 g CO_2e/MMBtu, which was the value reported in the RIA for the International Rice Methane source category (see: EPA, 2010a; Table 2.4-25).

ICF Methodology, Data Sources, and Results

International Rice Methane is a relatively small source category in corn ethanol's GHG profile and very little new information has become available since 2010 to suggest a need to change the RIA methodology for assessing the RFS2 driven changes in: 1) country-specific and aggregate international rice acres; or 2) country-specific and aggregate international rice related CH_4 emissions (these are all shown in Table 2-48). Hence, to assess emissions for this source category, we start with the RIA's value for the RFS2 driven changes in world rice emissions (i.e., 19,918 Mg CH_4). We multiply this value by the AR4 CH_4 GWP to get the CO_2 equivalent. We then divide the CO_2 equivalent by 2.6 billion (i.e., the RFS2 related increase in U.S. corn ethanol production in 2022) to get an equivalent emissions value per gallon of ethanol. We convert this to g CO_2e/MMBtu using the heating value 76,330 Btu/gallon. The ICF value for the international rice methane emissions is 2,483 g CO_2e/MMBtu.

Table 2-48: 2022 International Rice Acreage, Emission Factors, and Associated GHG Emissions with Corn Ethanol Expansion

	2022 Difference Between Corn Only and Control Cases			
Country	**1,000s Hectares**	**1,000s Acres**	**kg CH_4/acre/yr**	**2022 Mg CH_4**
Argentina	0.09	0.23	71.02	16.01
Australia	0.08	0.19	106.13	19.82
Bangladesh	-16.74	-41.36	56.77	-2,248
Brazil	-7.34	-18.14	37.04	-671.8
China	-77.58	-191.70	72.49	-13,896
Colombia	2.43	5.99	56.37	337.8
Cuba	0.82	2.04	122.15	248.8
EU	0.09	0.22	91.82	20.03
Guatemala	0.08	0.19	84.47	16.43
India	-10.97	-27.11	119.55	-3,241
Indonesia	5.14	12.69	137.02	1,738
Iran	0.51	1.26	47.35	59.76
Iraq	0.72	1.77	63.13	111.7
Ivory Coast	1.64	4.05	11.41	46.22
Japan	55.54	137.25	107.13	14,705
Mexico	0.00	0.01	63.13	0.61
Morocco	0.03	0.07	84.47	5.69
Nigeria	0.37	0.91	32.67	29.72
Other Countries	57.91	143.10	84.47	12,088
Pakistan	3.35	8.27	107.13	886.0
Peru	2.04	5.05	84.47	426.81
Philippines	11.35	28.05	119.44	3,350
ROW	22.58	55.80	82.53	4,605
Russia	0.95	2.35	84.47	198.5
South Korea	0.14	0.35	76.60	27.02
Taiwan	-0.01	-0.02	126.26	-3.06
Thailand	2.56	6.33	93.80	593.7
Turkey	0.02	0.05	55.24	2.49
Ukraine	0.12	0.30	84.47	25.28
Uruguay	0.53	1.32	90.61	119.2
Uzbekistan	0.33	0.82	84.47	69.53
Venezuela	1.26	3.12	84.47	264.0
Vietnam	0.10	0.24	124.61	30.48
Western Africa	0.17	0.41	84.47	34.63
TOTAL	**58.31**	**144.11**	**N/A**	**19,918**

Limitations, Uncertainty, and Knowledge Gaps

The international rice methane analysis was limited by the need to rely on changes in acreage and emission factors developed for the RIA assessment. As noted in the literature review, since 2010, updates to emission factors for rice production have only been developed for a small set of rice-producing countries. As more become available, future research should utilize these new emission factors.

Fuel and Feedstock Transport

Literature Review Findings

CO_2 emissions from combusting gasoline and diesel fuels occur in transporting corn from farm to refinery, ethanol from refinery to retail station, and co-products from refinery to end users. While this category accounts for 5-6 percent of ethanol’s GHG profile, transportation vehicles and systems have become more fuel and GHG efficient since 2010 (Cai et al., 2015).

For the RIA, EPA obtained emission factors for rail, barge, and truck from the 2009 GREET model. The 2015 GREET model substantially expands the capabilities of the model’s truck transportation LCA. This expansion includes five varieties of diesel and gasoline freight vehicles. Beyond traditional fossil fuel vehicles, the update includes alternative fuel vehicles for hybrid and hydraulic technologies (e.g., biodiesel, dimethyl ether, renewable diesel, compressed natural gas, liquefied natural gas, liquefied petroleum gases, ethanol, and electricity) (Cai et al., 2015).

Outside of GREET, researchers have developed economic input-output LCA (EIO-LCA) methodologies to determine new life-cycle freight emission factors for rail, barge, truck, and air (Nealer et al., 2012). The study also assessed transportation through fossil fuel pipelines. While pipeline infrastructure for transporting of biofuels is currently minimal, recent research suggests that existing fossil fuel pipelines could be retrofitted to transport biofuels. Depending on the electricity mix used for pumping, research indicates significant potential GHG emissions savings from transporting biofuels through pipelines (Strogen et al. 2013).

EPA RIA and Current Condition GHG Emissions Value

EPA Methodology, Data Sources, and Results

The RIA includes the GHG impacts of transporting corn from the field to the refinery and the impacts of transporting the ethanol and co-products (e.g., DGS) from the refinery to the final user. The 2009 GREET model was used as the basis for assessing emissions related to transporting corn between the farm and ethanol plant. The model assumes a default truck transportation of 10 miles from farm to stacks (i.e., collection point) and 40 miles from stacks to plant. For the DGS, the

percentage shipped by mode assumptions are shown in Table 2-49 and were based on data provided by USDA, the Association of American Railroads, Army Corps of Engineers, Commodity Freight Statistics, and industry estimates. Transportation distances by mode for DGS were based on default 2009 GREET values for other commodities shipped by those transportation modes. The RIA did not consider transportation requirements for corn oil.

Table 2-49: Transportation Distance and Mode Assumptions for DGS (per ton)

Quantity of DGS (Percentage of DGS)	Mode of Transportation	Distance (miles)
14%	Rail	800
2%	Barge	520
86%	Truck	50

Source: GREET model and USDA; “EPA_2010_RFS2_regulatory_impact_assessment.pdf”.

To model the transportation of corn ethanol from the production or import facility to the petroleum blending terminal, an Oak Ridge National Laboratory study was used for distances and mode. These parameters are shown in Table 2-50 (Das, 2010). For each mode of transportation, the GREET default assumptions and emission factors were used. These emission factors are shown in Table 2-51.

Table 2-50: Transportation Distance and Mode Assumptions for Corn Ethanol

Quantity of Corn Ethanol (Percentage of Corn Ethanol)	Mode of Transportation	Distance (miles)
77%	Rail	629
12%	Barge	336
17%	Truck	68
83%	Local Truck [a]	6.5

Source: GREET; model and Oak Ridge National Laboratory; “EPA_2010_RFS2_regulatory_impact_assessment.pdf”

[a] This mode of transportation is an additional transportation leg experienced by 83 percent of corn ethanol.

Table 2-51: Emission Factors Used for Fuel and Feedstock Transport

Fuel/ Feedstock	per Bushel of Corn	per Short Ton of DGS
Emission	**Grams/bushel**	**Grams/ton**
CO	0.15	4.04
NO_x	0.46	12.03
PM10	0.049	1.56
PM2.5	0.024	0.71
SO_x	0.12	3.87
CH_4	0	0

Fuel/ Feedstock	**per Bushel of Corn**	**per Short Ton of DGS**
N_2O	0.53	17.86
CO_2	0.013	0.41
CO_2e	469	15,867
Energy	**Btu/bushel**	**Btu/ton**
Coal Energy	485	16,369
Natural Gas Energy	163.2	5,205
Petroleum Energy	313.6	10,021

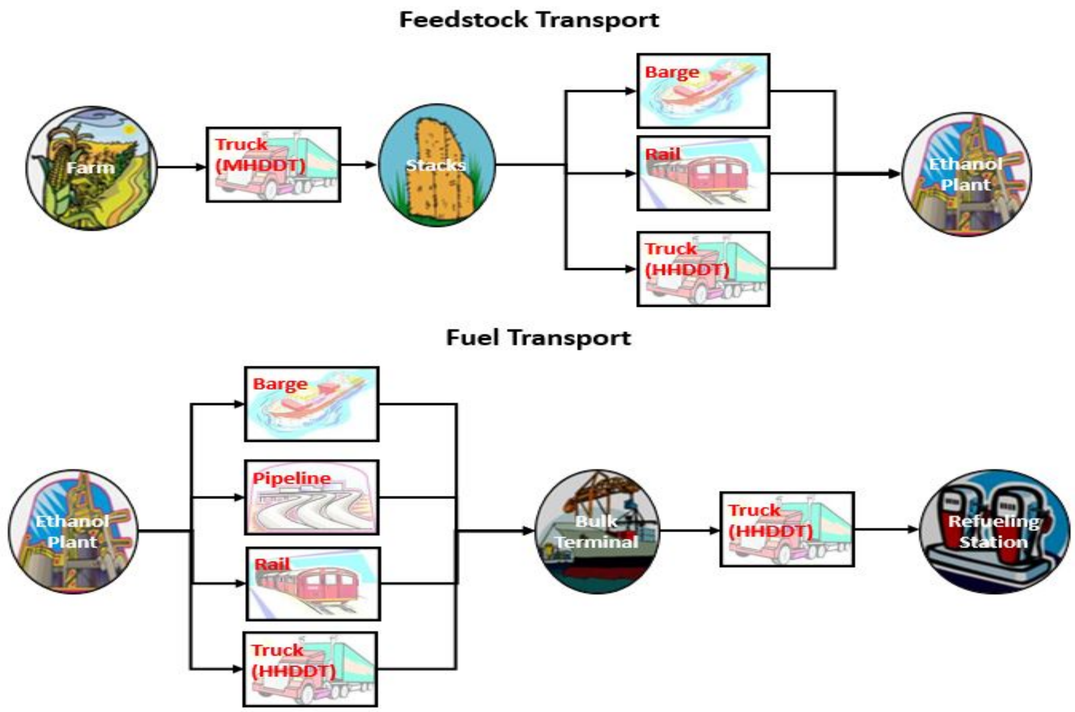
Source: GREET; "Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx," "Emission Factors" tab.

For the Fuel and Feedstock source category, the RIA projected emissions at 4,265 g CO_2e/MMBtu in 2022.

ICF Methodology, Data Sources, and Results

While Fuel and Feedstock Transportation is a relatively small source category, transportation systems are dynamic and, since 2010, have become more fuel efficient. In assessing emissions for this source category, ICF followed a similar approach as the RIA but utilized more recent data on modes of transportation, emission factors, and other information. Figure 2-9 shows the stages involved in fuel and feedstock transportation in the 2015 GREET model.

Figure 2-9: GREET Process Maps for Fuel and Feedstock Transportation



Source: GREET, 2015; HHDDT denotes heavy heavy-duty diesel trucks and MHDDT denotes medium heavy-duty diesel trucks

Our analysis also uses the 2015 GREET standard inputs for fuel and feedstock modes, distances, and emission factors. The analysis models corn oil transportation by extracting GREET's per mass GHG emission factor for transportation of the co-product. DGS transport is modeled using the EPA's mode and distance assumptions with emission factors from Nealer et al. (2012). Table 2-52 shows the assumptions in mode and distance for transportation used in our analysis. Both the RIA and ICF analysis assume no ethanol is transported through pipelines.

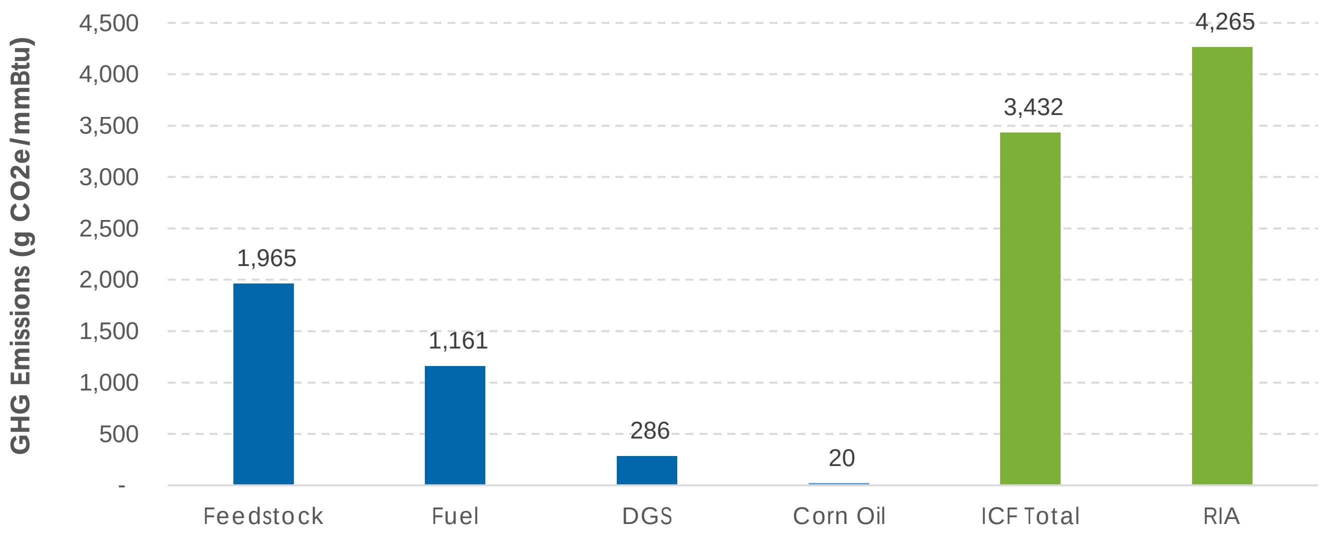
Table 2-52: Mode and Distance Assumptions

	Farm to Stacks		Stacks to Plant		Plant to Terminal		Terminal to Refueling Station		DGS	
Mode	% of Total Shipped	Distance (mi)	% of Total Shipped	Distance (mi)	% of Total Shipped	Distance (mi)	% of Total Shipped	Distance (mi)	% of Total Shipped	Distance (mi)
Barge	0%	0	0%	0	13%	520	0%	0	0.02	520
Rail	0%	0	0%	0	79%	800	0%	0	0.12	800
Truck	100%	10	100%	40	8%	80	100%	30	0.86	50

Source: GREET, 2015.

Figure 2-10 shows ICF's results for fuel and feedstock transportation emissions, in total and separated by input, product, and co-product. The RIA total is also included for comparison. The final DGS transportation result shown in Figure 2-10 is a weighted average of dry and wet DGS based on the expected yields for the "representative" industry refinery discussed in the Fuel Production section. Our emissions value for Fuel and Feedstock Transport is 3,432 g CO_2e/MMBtu.

Figure 2-10: Fuel and Feedstock Transportation Emissions



Limitations, Uncertainty, and Knowledge Gaps

A more complete assessment could collect supply-chain data from farms and corn ethanol plants to gain a better representation of the exact modes and transportation distances being used. This dataset could be compared to the assumptions used by EPA, GREET, and our analysis to assess if these estimates are accurate. However, major efforts to improve the accuracy of fuel and feedstock transportation emissions will likely only have a small effect on the total corn ethanol GHG profile because Fuel and Feedstock Transport is a relatively small source category.

Fuel Production

Literature Review Findings

Recent LCA literature has shown that corn ethanol production accounts for over 40 percent of total corn ethanol life-cycle GHG emissions (Wang et al., 2012). Since 2010, advances in production technologies, the introduction of new co-products, and refinements of LCA methodologies offer significant opportunities for reductions in the GHG intensity of refinery operations relative to the plant in the RIA.

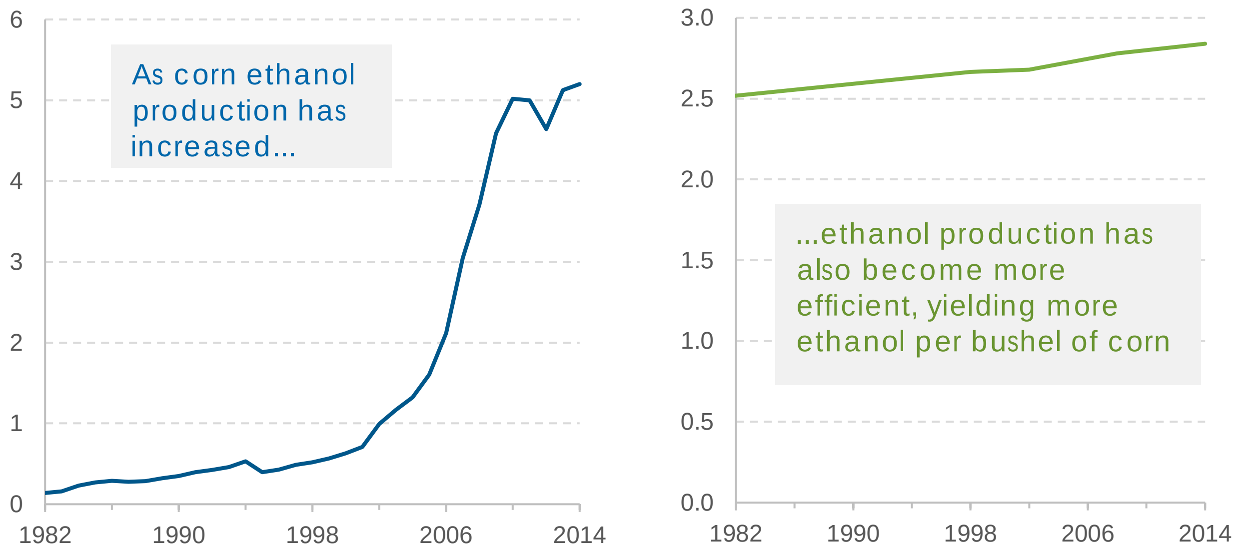
Table 2-53 shows the GHG emissions from corn ethanol production facilities reported under the EPA Greenhouse Gas Reporting Program (GHGRP) and corn ethanol production from the U.S. Energy Information Administration (EIA). Ethanol production facilities are required to report emissions under the GHGRP if they meet the reporting threshold of 25,000 metric tons of CO_2 equivalent per year for all emissions sources covered in program (40 CFR Part 98). Refinery emissions are primarily from on-site fuel combustion from both fossil and biogenic fuel sources. The GHGRP and EIA data show that the total national GHG intensity of ethanol refineries declined 4 percent between 2010 and 2014.

Table 2-53: GHG Intensity for Corn Ethanol Production Facilities

	Year				
Datum	**2010**	**2011**	**2012**	**2013**	**2014**
Number of Facilities [a]	161	163	166	170	175
CO_2 Emissions (metric tons)	17,600,254	18,151,600	17,182,627	17,063,166	18,265,090
CH_4 Emissions (metric tons)	17,450	14,689	17,771	11,866	20,801
N_2O Emissions (metric tons)	80,960	20,182	159,205	17,166	27,561
Total Emissions (metric tons CO_2e)	*17,698,648*	*18,186,453*	*17,359,574*	*17,092,175*	*18,313,426*
Ethanol Production (million gallons)	13,298	13,929	13,218	13,293	14,313
GHG Intensity (metric tons CO_2e per million gallons)	1,331	1,306	1,313	1,286	1,279
Change from 2010 GHG Intensity (%)	0%	−2%	−1%	−3%	−4%

In addition, corn ethanol yields continue to improve. Figure 2-11 shows that as corn ethanol production has grown, the industry has become more efficient, using fewer bushels of corn to produce a gallon of ethanol. Several factors contribute to the yield increases from a bushel of corn. Increased scale has allowed producers to incorporate better process technology, such as finer grinding of corn to increase starch conversion and improved temperature control of fermentation to optimize yeast productivity. The growth of the corn ethanol industry has enabled the development of better enzymes and yeast strains for improved output per bushel of corn.[16]

Figure 2-11: Ethanol Industry Corn Utilization and Average Yield, 1982–2014



Source: EIA, 2015b

The 2009 GREET model used in the RIA has been updated several times since 2009 and includes new co-products, production pathways, and co-product allocation methods. ANL researchers estimated current corn ethanol production using natural gas contributed 30 g CO_2e/MJ to the fuel's well-to-wheels GHG intensity (Wang et al., 2012). This estimate is similar to the value projected for 2022 by the EPA (2010) report. The ANL report acknowledged that major energy efficiency improvements could be made to the system if corn and corn stover processes were combined, utilizing combined heat and power (CHP) from the corn stover process.

The same research team produced a refined LCA of corn ethanol that detailed the benefits of dried distillers grain (DGS) and corn oil recovery in ethanol production (Wang et al., 2015). The study applied four different allocation techniques in determining the variations in effects of the co-products on the final GHG intensity: marginal energy allocation, hybrid market-value allocation,

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[16] See EIA's Today in Energy, May 13, 2015. Available online at: http://www.eia.gov/todayinenergy/detail.cfm?id=21212.

process-level allocation, and soy biodiesel displacement. This methodology estimated the life-cycle GHG intensity of corn ethanol production to range between 15–20 g CO_2e/MJ, a 33–50 percent reduction from the RIA, depending on the co-product handling method used. For the marginal and displacement methods, ethanol production values are similar to Wang et al. (2012), but a DGS displacement credit reduces the life-cycle emissions. The hybrid-market and process-level allocation methods do not use a displacement credit and allocate a share of the production burden to the DGS co-product.

Boland and Unnasch (LCA, 2014) projected significant reductions in life-cycle corn ethanol GHG intensity, using the RIA report as a baseline. This study assessed a corn and corn stover ethanol production pathway with 10 variations in fuel and co-products. The dry mill production variations using natural gas ranged from 20–35 g CO_2e/MJ. Substituting biomass in place of natural gas resulted in 10 g CO_2e/MJ, a 67 percent reduction from the RIA. The study projected these GHG intensities to decline by 8–20 percent from 2012–2022 due to efficiency improvements.

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

A study from the University of Illinois was the basis for calculating the emissions associated with fuel production. The amount of corn used for ethanol production was modeled by FASOM (Mueller, 2007). It was assumed that pure ethanol yields were 2.71 gallons per bushel at dry mill plants and 2.5 gallons per bushel for wet mill plants. Plants were modeled based on the type of plant and type of fuel used. Because drying DGS is energy intensive, the plants were also categorized by their co-products (wet versus dry DGS). The energy use for dry mill plants was based on the ASPEN model[17] from USDA. Future plant energy consumption was projected based on what would be built to meet increased ethanol production. Energy use by plant type, technology type, and process fuel are shown in Table 2-54. Upstream emission factors for process fuels were based on the 2009 GREET. These factors are shown in Table 2-55.

Table 2-54: 2022 Energy Use at Ethanol Plants with CHP (Btu/gallon)

Plant Type	Technology	Natural Gas Use	Coal Use	Biomass Use	Purchased Electricity
Corn Ethanol—Dry Mill-Natural Gas	Base Plant (dry DDGS)	28,660	N/A	N/A	2,251
	w/ CHP (dry DDGS)	30,898	N/A	N/A	512
	w/ CHP and Fractionation (dry DDGS)	25,854	N/A	N/A	1,512
	w/ CHP, Fractionation, and Membrane Separation (dry DDGS)	21,354	N/A	N/A	1,682

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[17] ASPEN is a model developed by Aspen Technology to analyze manufacturing plant operations, including ethanol plants. https://www.aspentech.com/

Plant Type	Technology	Natural Gas Use	Coal Use	Biomass Use	Purchased Electricity
	w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (dry DDGS)	16,568	N/A	N/A	1,682
	Base Plant (wet DGS)	17,081	N/A	N/A	2,251
	w/ CHP (wet DGS)	19,320	N/A	N/A	512
	w/ CHP and Fractionation (wet DGS)	17,285	N/A	N/A	1,512
	w/ CHP, Fractionation and Membrane Separation (wet DGS)	12,785	N/A	N/A	1,682
	w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (wet DGS)	9,932	N/A	N/A	1,682
Corn Ethanol—Dry Mill-Coal	Base Plant (dry DGS)	N/A	35,824	N/A	2,694
	w/ CHP (dry DGS)	N/A	39,407	N/A	205
	w/ CHP and Fractionation (dry DGS)	N/A	33,102	N/A	986
	w/ CHP, Fractionation, and Membrane Separation (dry DGS)	N/A	27,477	N/A	1,191
	w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (dry DGS)	N/A	21,495	N/A	1,191
	Base Plant (wet DGS)	N/A	21,351	N/A	2,694
	w/ CHP (wet DGS)	N/A	24,934	N/A	205
	w/ CHP and Fractionation (wet DGS)	N/A	22,390	N/A	986
	w/ CHP, Fractionation, and Membrane Separation (wet DGS)	N/A	16,766	N/A	1,191
	w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (wet DGS)	N/A	13,200	N/A	1,191
Corn Ethanol—Dry Mill-Biomass	2022 Base Plant (dry DGS)	N/A	N/A	35,824	2,694
	2022 Base Plant w/ CHP (dry DGS)	N/A	N/A	39,407	205
	2022 Base Plant w/ CHP and Fractionation (dry DGS)	N/A	N/A	33,102	986
	2022 Base Plant w/ CHP, Fractionation and Membrane Separation (dry DGS)	N/A	N/A	27,477	1,191
	2022 Base Plant w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (dry DGS)	N/A	N/A	21,495	1,191
	2022 Base Plant (wet DGS)	N/A	N/A	21,351	2,694
	2022 Base Plant w/ CHP (wet DGS)	N/A	N/A	24,934	205
	2022 Base Plant w/ CHP and Fractionation (wet DGS)	N/A	N/A	22,390	986
	2022 Base Plant w/ CHP, Fractionation and Membrane Separation (wet DGS)	N/A	N/A	16,766	1,191
	2022 Base Plant w/ CHP, Fractionation, Membrane Separation, and Raw Starch Hydrolysis (wet DGS)	N/A	N/A	13,200	1,191
Corn Ethanol—Wet Mill	Plant with Natural Gas	45,950	N/A	N/A	N/A
	Plant with Coal	N/A	45,950	N/A	N/A
	Plant with Biomass	N/A	N/A	45,950	N/A

Source: University of Illinois; "EPA_2010_RFS2_regulatory_impact_assessment.pdf".
N/A = Not Applicable.

Table 2-55: Upstream Emission Factors for Fuels and Electricity

	Liquefied Petroleum Gas (commercial boiler)	Coal Used in Biofuel Plants (industrial boiler)	Biofuel Used in Biofuel Plants (small industrial boiler)	Diesel Fuel (average of commercial boiler, stationary engine, and turbine)	Natural Gas: Biofuel Plant Use (50/50 mix of large and small industrial boiler)	U.S. Average Electricity Production
Emissions (g/MMBtu)						
VOC	1.89	2.068	5.341	16.725	1.987	19.682
CO	10.8	76.185	76.8	84.937	22.621	58.457
NO_x	84.619	120	110	225.535	38.5	239.631
PM10	2.43	85	12.661	32.996	3.083	289.622
PM2.5	2.43	45	6.331	29.04	3.083	76.28
SO_x	0	130	4.1	0.543	0.269	527.218
CH_4	1.08	4	3.834	1.848	1.1	296
N_2O	4.86	1	11	1.463	1.1	3.117
CO_2	67,380.833	107,318.59	N/A	77,973.126	58,818	219,707
CO_2e	68,910	107,712	3,490	78,465	59,182	226,889
Energy Consumption (Btu/MMBtu)						
Coal Energy	N/A	1,000,000	N/A	N/A	N/A	1,630,541
Natural Gas Energy	600,000	N/A	N/A	N/A	1,000,000	553,053
Petroleum Energy	400,000	N/A	N/A	1,000,000	N/A	115,046

Source: GREET; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Emission Factors” tab.
N/A = Not Applicable.

For the RIA, EPA assumed a typical new corn ethanol refinery in 2022 will be a dry mill plant using natural gas as its process fuel. It will also have a fractionation technology to extract corn oil and will produce a composite DGS coproduct that is 63 percent dry and 37 percent wet. Fuel Production emissions for this refinery were assessed at 28,000 g CO_2e/MMBtu in 2022.

ICF Methodology and Results

Corn-ethanol production has experienced considerable growth since 2010. From 2009–2014, U.S. fuel ethanol production increased by 40 percent, reaching over 14 billion gallons annually (EIA 2013, EIA 2015). There are currently 14 newly proposed and under-construction production plants, which will add over 850 million gallons per year to U.S. capacity (Ethanol Producer Magazine 2016).

With this growth have come improved process efficiencies and new co-products. These process upgrades have become drivers for a decreasing GHG-intensity of corn ethanol production. Production yields, measured in gallons of ethanol per bushel of corn, increased by 5 percent between 2006 and 2014. New enzymes and yeast strains have increased process efficiencies in starch conversion and fermentation (EIA 2015). Along with DGS, corn oil is now

recovered as a co-product, and 80 percent of dry grind mills are now capable of corn oil recovery (Wang, 2014). New state and federal programs, such as EPA's Efficient Producer Program and California's Low Carbon Fuel Standard, create incentives for innovative efforts that continue to lower the GHG emissions associated with refinery operations.

Our analysis uses more recent corn ethanol production data and emission factors available to estimate the current GHG intensity of production processes. Our analysis utilizes the corn ethanol pathways in the 2015 GREET model. We utilize several production processes in GREET to construct a refinery that is representative of current industry conditions. These processes include:

- Industry average—92 percent natural gas, 8 percent coal
- Dry mill—100 percent natural gas
- Dry mill—100 percent coal
- Dry mill—100 percent biomass (forest residue)
- Wet mill—72.5 percent natural gas, 27.5 percent coal

Table 2-56 shows the assumptions and inputs for each of these scenarios. The industry average and wet milling processes are the only ethanol pathways that include corn oil recovery. It should be noted that dry milling includes electricity consumption with the primary energy demands.

Table 2-56: Assumptions and Inputs for Fuel Production Modeling in GREET

Input Category	Dry Milling Plant w/o Corn Oil Extraction	Dry Milling Plant w/ Corn Oil Extraction	Wet Milling Plant
Total energy use for ethanol production (Btu/gallon)	26,856.00	26,421.11	47,409.00
Energy use: natural gas, coal, and biomass (Btu/gallon)	24,323.41	23,862.00	47,409.00
Electricity demand (kWh/gallon)	0.74	0.75	0.00
Co-Product Yield: Dry DGS to animal feed (Actual lb/gallon ethanol)	4.21	4.02	0.00
Co-Product Yield: Wet DGS to animal feed (Actual lb/gallon ethanol)	5.52	5.28	0.00
Co-Product Yield: CGM to animal feed (Actual lb/gallon ethanol)	0.00	0.00	1.35
Co-Product Yield: CGF to animal feed (Actual lb/gal ethanol)	0.00	0.00	5.86
Co-Product Yield: Corn Oil (Actual lb/gallon ethanol)	0.00	0.19	0.98
Ethanol Yield (gallon/bushel)	2.80	2.82	2.61

Source: GREET, 2015

Table 2-57 shows the results of the modeling for each of the scenarios described.

Table 2-57: Corn Ethanol Fuel Production Results (g CO_2e/MMBtu)

Model Scenario	Dry Mill w/o Corn Oil Extraction	Dry Mill w/ Corn Oil Extraction	Wet Mill Corn Ethanol
Industry Average	32,114	31,590	53,055
Dry Mill—100% Natural Gas	30,683	N/A	N/A
Dry Mill—100% Coal	51,450	N/A	N/A
Dry Mill—100% Biomass	10,570	N/A	N/A
Wet Mill	N/A	N/A	53,055

We construct our “representative” refinery as a plant that is 18 percent dry milling without corn oil extraction, 71 percent dry milling with corn oil extraction, and 11 percent wet milling. This plant uses a process fuel that is a weighted mix of natural gas and coal representative of what the industry uses as a whole. We assess Fuel Production emissions for our representative refinery at 34,518 g CO_2e/MMBtu. This is higher than the RIA value for Fuel Production emissions, which is primarily due to the RIA refinery using 100 percent natural gas for a process fuel and the ICF refinery using some coal.

Limitations, Uncertainty, and Knowledge Gaps

Our assessment relies on the detailed modeling efforts of others, which are based on more recent available data and emission factors. A more detailed assessment would compile process-level data from existing corn ethanol production facilities to create a representative dataset of current operations. This bottom up approach in LCA could allow for modeling of more variations (e.g., CHP), particularly in efficiency improvements not captured in existing models such as GREET. The GREET model utilized in this study also does not allow for corn oil extraction applications to scenarios outside the industry average. This limited our ability to model the effects of different primary energy sources on that specific process. Wet milling modeling also does not allow for variations in primary energy sources through GREET. Future work could include developing a comprehensive database of energy demands, process emissions, ethanol yields, and co-product recovery for a wide range of corn ethanol plants to generate a stronger assessment of the GHG intensity of current production practices.

Tailpipe

Literature Review Findings

About 19.64 pounds (8.91 kg) of carbon dioxide (CO_2) are produced from burning a gallon of gasoline that does not contain ethanol. Most of the retail gasoline now sold in the United States contains about 10 percent fuel ethanol (or E10) by volume. Burning a gallon of E10 produces about 17.68 pounds (8.02 kg) of CO_2 that is emitted from the fossil fuel content. If the CO_2 emissions from

ethanol combustion are considered, then about 18.95 pounds (8.60 kg) of CO_2 are produced when a gallon of E10 is combusted. About 12.73 pounds (5.77 kg) of CO_2 are produced when a gallon of pure ethanol is combusted.[18]

CO_2 emissions from combusting corn ethanol are assumed to be biogenic and offset by carbon uptake during new biomass growth. Hence, CO_2 emitted from the tailpipe following ethanol combustion is not included in either the EPA or ICF analyses. Combusting ethanol does emit CH_4 and N_2O. These emissions are included in the EPA and ICF analyses.

For the RIA LCA, EPA used the 2009 version of its motor vehicle emission simulator (MOVES) model to estimate CH_4 and N_2O emissions from gasoline and diesel vehicles (EPA, 2015b; EPA, 2010e).[19] MOVES emission factors are derived from federal GHG emission testing. EPA updated the MOVES model in 2010 and 2014. The 2010 update included multiple improvements for gasoline and diesel GHG emission rates for the following criteria (EPA, 2014b):

- Corporate Average Fuel Economy (CAFE) standards and projections for light duty vehicles from 2008–2016;
- Updated and projected energy usage rates for light and heavy-duty vehicles; and
- Improved methane emission calculations based on total fuel hydrocarbons.

The 2014 model further updated the gasoline/diesel emission factors to reflect changes in fuel economy data. While these updates allow for improved accuracy in LCA models, it should be noted that tailpipe emissions account for about 1 percent of total life-cycle GHG emissions from corn ethanol (EPA, 2010a).

EPA RIA and Current Condition GHG Emissions Value

EPA RIA Methodology, Data Sources, and Results

Based on results from its 2009 MOVES, EPA projected emissions for the tailpipe source category at 880 g CO_2e/MMBtu in 2022. The breakdown by gas is shown in Table 2-58.

Table 2-58: Emission Factors for Tailpipe Combustion

Fuel Type	CH_4 (g CO_2e/MMBtu)	N_2O (g CO_2e/MMBtu)
Ethanol	269	611

Source: EPA, 2010a.

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[18] See *How much carbon dioxide is produced by burning gasoline and diesel fuel?* Available online at: http://www.eia.gov/tools/faqs/faq.cfm?id=307&t=10.

[19] EPA's Motor Vehicle Emission Simulator (MOVES) model is an emission modeling system which estimates emissions for mobile sources covering a broad range of pollutants and allows multiple scale analysis.

ICF Methodology, Data Sources, and Results

Since 2010, new estimates of the CH_4 and N_2O emissions associated with combust ethanol have been published by the Washington Department of Ecology (WDE) (2016), the State of California GREET model (CA-GREET, 2015) , and the 2015 GREET model. These are shown in Table 2-59. While there are large variations in the results, all are less than the RIA value of 880 g CO_2e/MMBtu. We note that the emission factors for the two GREET models reflect E85 while the WDE value reflects pure ethanol (same as the RIA value). Given our reliance on 2015 GREET coefficients throughout this analysis, ICF selected the 2015 GREET emission value of 578 g CO_2e/MMBtu for the tailpipe source category.

Table 2-59: Ethanol Tailpipe Emissions

Source	g CH_4/MMBtu	g N_2O/MMBtu	g CO_2e/MMBtu
2015 GREET (used by Current Conditions)	2.01	1.77	578
CA-GREET 2.0 (CARB, 2015b)	2.45	1.85	613
Washington Department of Ecology (2016)	-	-	187
EPA RIA: 2022	8.97	2.31	880

Limitations, Uncertainty, and Knowledge Gaps

The RIA used the 2009 MOVES model to estimate the GHG emissions from vehicle ethanol combustion. Our analysis did not use the more recent (2015) EPA MOVES model for determining ethanol emissions. MOVES is the official model for state implementation plans (SIPs) and transportation conformity, as well as being the standard for determining tailpipe GHG emissions. MOVES bases emissions on instantaneous energy consumption and a continually-updated database to generate emission factors customized for regional, temporal, and other scenarios. Because of this highly-region-specific nature of MOVES, ICF used recent literature that focused on average emission factors. Future assessments could utilize the latest version of MOVES to better estimate ethanol tailpipe emissions. However, this added effort will likely have minimal effect as tailpipe emissions are the smallest emissions category in both the EPA RIA and ICF LCAs.

Aggregating Source Category GHG Emissions into a Current GHG Profile for U.S. Corn Ethanol

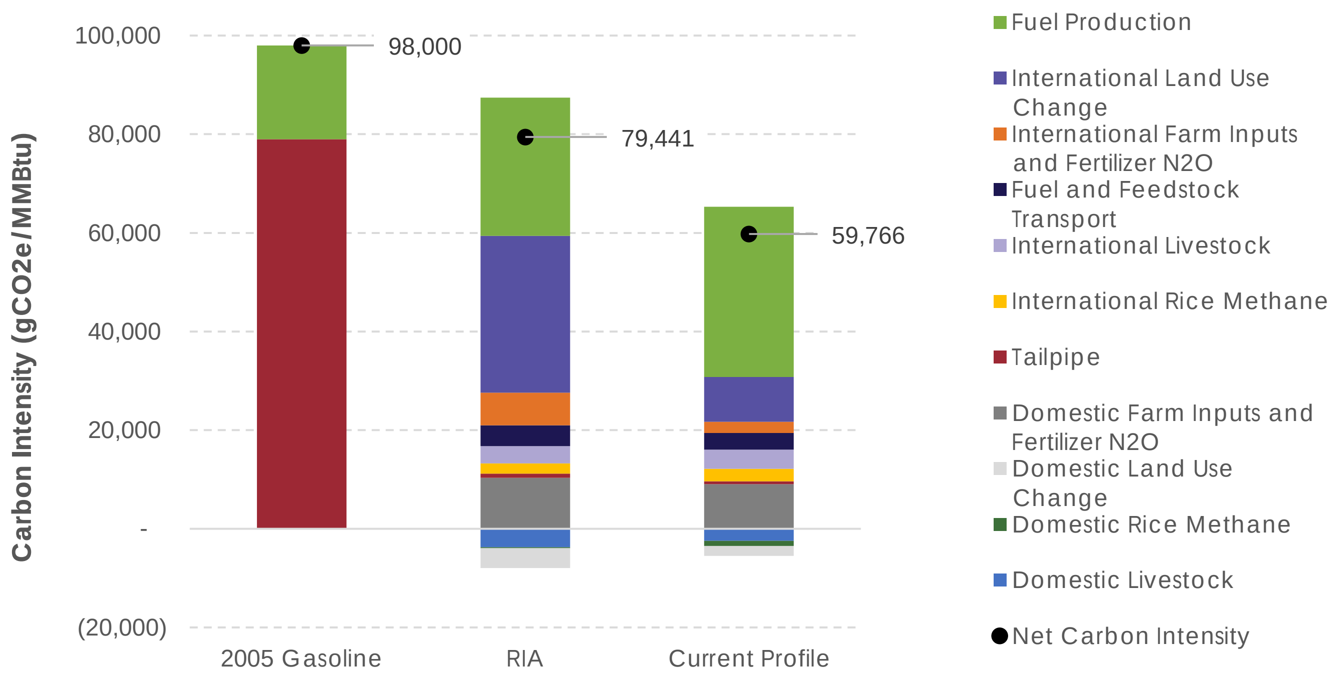
This section brings together the current emissions estimates developed for each of the eleven source categories into a current GHG LCA for U.S. corn ethanol. Most of the data, emissions factors, and global warming use to develop the ICF LCA span the 2010–2015 timeframe; most of the studies we draw on have publication dates from 2013 to 2015. This means our current GHG emissions profile does not reflect a specific year but rather a composite year representative of the mid-2010s.

This section also summaries the RIA LCA developed by EPA in 2010. While the RIA LCA was a 2010 projection of the GHG emissions associated with the production and combustion of corn ethanol refined in a new natural gas powered refinery in 2022, the RIA and ICF LCAs are comparable. First, the large majority of existing refineries use natural gas as a process fuel (i.e., the industry has already shifted away from coal-fired plants). Second, the annual RFS2 mandates for corn ethanol were just under 15 billion gallons in 2014 and 15 billion gallons thereafter. Additionally, actual U.S. corn ethanol production over the period 2014 to 2016 has been just under or just over 15 billion gallons (14.3, 14.8, and 15.3 billion gallons in, respectively, 2014, 2015, and 2016). Hence, the ethanol industry and refinery projected in the RIA changes very little between 2014 and 2022 and is very similar to the ethanol industry that actually exists now.

Figure 2-12 shows the RIA LCA of corn ethanol, the ICF Current Conditions LCA of corn ethanol, and the RIA LCA an average gallon of gasoline in 2005. The RIA LCA value for corn ethanol is 79,441 g CO_2e/MMBtu. Comparing this GHG profile with that of gasoline (98,000 g CO_2e/MMBtu), EPA concluded that the emissions associated with producing and combusting corn ethanol were 21.0 percent lower than the emissions associated with producing and combusting an energy equivalent quantity of gasoline. .

The ICF Current Conditions LCA value is 59,766 g CO_2e/MMBtu. This represents a 25 percent reduction in corn ethanol's GHG profile relative to the RIA, and a 39 percent emissions reduction relative to gasoline.

Figure 2-12: Comparison of EPA-RIA and ICF Carbon Intensities



Projected GHG Emissions Scenarios for Corn Ethanol in 2022: Business-As-Usual (BAU) and High Efficiency-High Conservation (HEHC)

Based on the current GHG emissions profile of corn ethanol developed in Chapter 2, this chapter develops two projected profiles for corn ethanol in 2022. The first projection, labeled the Business-as-Usual (BAU) scenario, considers a continuation through 2022 of observable trends in corn yields (per acre), process fuel switching toward natural gas, and fuel efficiency in trucking. Refineries do not actively try to reduce emissions in this scenario, so it can be viewed as the case where refineries take a passive approach to GHG mitigation. The second projection, labeled the High Efficiency-High Conservation (HEHC) scenario, adds a number of changes refineries could make in their value chain to further reduce the GHG intensity of corn ethanol. These management changes include contracting with farmers to grow corn using specific GHG mitigation technologies and practices (reduced tillage, cover crops, and nitrogen management), switching to biomass as a process fuel, and locating confined livestock operations in close proximity to refineries. The scenario can be viewed as the case where refineries are proactive with respect to GHG mitigation.

The remainder of the chapter is organized as follows:

- Key Parameters and BAU and HEHC Scenarios
- Domestic Farm Inputs and Fertilizer N_2O
- Domestic Land-Use Change
- Fuel Production
- Fuel and Feedstock Transportation
- Summary of the 2022 BAU and 2022 s Scenarios Results

Key Parameters and BAU and HEHC Scenarios

Table 3-1 summarizes the key variables ethanol producers can adjust under each scenario.

Table 3-1: Key Parameters and Scenarios Considered

Source Category	Key Parameter	2022 BAU Scenario	2022 HEHC Scenario
Domestic Farm Inputs and Fertilizer N_2O	▪ Yield increases ▪ Conservation technologies and practices: - Reduced tillage - Nutrient management - Cover crops	Yield increases	Yield increases + Conservation technologies and practices
Domestic Land-Use Change	▪ Tillage practices: - Conventional tillage - Reduced tillage	Conventional tillage	Reduced tillage
Fuel Production	▪ Increased corn to corn ethanol yield ▪ Process fuel switching (natural gas and/or biomass)	Process fuel switching to natural gas	Process fuel switching to biomass + Increased corn to corn ethanol yield
Fuel and Feedstock Transport	▪ Increased truck efficiency ▪ Fuel switching (natural gas, biodiesel, renewable diesel, renewable natural gas) ▪ Co-location of CAFOs (reduced transportation distances for DGS)	Increased truck efficiency w/ fuel switching to natural gas	Increased truck efficiency w/ fuel switching to natural gas or another lower carbon intensity fuel + Co-location of CAFOs

Domestic Farm Inputs and Fertilizer N_2O

The Domestic Farm Inputs and Fertilizer N_2O emissions category affects both projections. The BAU scenario includes a continuation of current increases in corn yields through 2022. The HEHC scenario incorporates farm adoption of reduced tillage, nitrogen management, and cover crop practices in corn production (on top of the increase in yields).

Methodology: 2022 BAU Scenario

The BAU scenario for the Domestic Farm Inputs and Fertilizer N_2O emission category assumes that corn yields will increase 2 bushels per acre per year through 2022 (see Table 3-2). This assumption is based on USDA's long-term projections of U.S. corn production and corn acres harvested (USDA ERS, 2015a). Based on these projections, crop yields will increase from 169.2 bushels/acre in 2016 to 181.3 bushels/acre in 2022.

Table 3-2: USDA Corn Crop Long-Term Projections

Year	USDA National Agricultural Statistics Service Data				ICF Analysis		
	Corn Use In Fuel Ethanol	U.S. Corn Production	Corn Planted Acreage	Corn Harvested Acreage	Corn Allocation to Ethanol	Average Crop Yield	Harvested/ Planted Acreage
	Million bushels	Million bushels	Million acres	Million acres	%	bushels/ acre	%
2016	5,150	13,940	90.0	82.4	37%	169.2	92%
2017	5,100	14,105	90.0	82.4	36%	171.2	92%
2018	5,075	14,270	90.0	82.4	36%	173.2	92%
2019	5,075	14,355	89.5	81.9	35%	175.3	92%
2020	5,075	14,520	89.5	81.9	35%	177.3	92%
2021	5,100	14,595	89.0	81.4	35%	179.3	91%
2022	5,125	14,760	89.0	81.4	35%	181.3	91%

Source: USDA ERS, 2015a.

Methodology: 2022 HEHC Scenario

The HEHC scenario reflects the farm-level adoption of three conservation practice standards (CPSs) in the production of corn used to produce ethanol that USDA's Natural Resources Conservation Service (NRSC) have recognized as having GHG benefits. These are:

- CPS 345—Residue and Tillage Management, Reduced Till;
- CPS 590—Nutrient Management: Improved Nitrogen Fertilizer Management; and
- CPS 340—Cover Crops.

For each CPS, ICF adjusted the associated emission calculations used in the BAU scenario to reflect the GHG benefits of these practices.

CPS 345—Residue and Tillage Management, Reduced Tillage

The RIA and ICF current conditions LCAs both assume that corn is grown using conventional tillage practices. Reduced tillage decreases soil disturbance during field operations and leaves a large proportion of plant residues on the field. Based on USDA's COMET-Planner Report, this practice affects the soil carbon storage (see Domestic Land-Use Change section below) and nitrous oxide emissions from changes in the soil environment. It does not affect any changes in fertilizer application rates. [20]

To account for the adoption of reduced tillage in this analysis, ICF adjusted the fuel used for on-farm equipment and reduced the indirect N_2O emissions

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[20] http://comet-planner.nrel.colostate.edu/COMET-Planner_Report_Final.pdf

associated with conventional tillage. Diesel fuel use is assumed to be 7.74 gallons per corn-acre under conventional tillage, based on 2015 farm budget worksheets published by the University of Tennessee (2015). To model reduced tillage, ICF reduced the fuel used for chisel and disk machinery in the conventional tillage case by 50 percent. Fuel use and related CO_2 emissions for all other equipment used in no-till systems is the same as in conventional tillage systems (University of Tennessee, 2015). This results in a fuel consumption of 6.95 gallons per corn-acre. With respect to indirect N_2O emissions, the shift from conventional to reduced tillage reduces the volatilization rate of nitrogen fertilizer (Swan et al., n.d.) The COMET-Planner report attributes a 0.07 Mg CO_2e/acre/year reduction in emissions due to reduced tillage relative to conventional tillage. This value represents a 74.4 percent reduction in volatilization of N_2O emissions (here measured in kg N_2O/acre per kilogram of nitrogen applied).

CPS 590—Nutrient Management: Improved Nitrogen Fertilizer Management

CPS 590 assumes the adoption of new nitrogen fertilizer management techniques including reduced application rates from targeted nitrogen fertilizer applications and the use of nitrification inhibitors. The COMET-Planner report estimates that CPS 590 practices can reduce nitrogen application rates by 15 percent. This percent adjustment was made to the application rates in the HEHC scenario.

Nitrification inhibitors are applied to reduce the leaching or production of N_2O in the soil. The most common nitrification inhibitor used in the United States on corn acres is nitrapyrin. A report by the International Fertilizer Industry Association states that application rates of nitrapyrin range between 1.4–5.6 liters per hectare (Trenkel 2010). The assumed density is 1.582 grams/cm^3 (LookChem 2008). Based on these data, ICF assumed an application rate of 2.24 kg/acre. There are very few sources of publicly available life-cycle assessment data with which to quantify the upstream emissions for nitrification inhibitors. For the upstream production emissions, ICF used “Organophosphorus-compound” from the ecoinvent database (Weidema et al. 2013) as a proxy for nitrapyrin. The emissions per kilogram of product are in line with those found in Dow’s “Using LCA to Identify Options for Greenhouse Gas Emission Reductions in Australian Wheat Farming" (Helling et al. 2014).

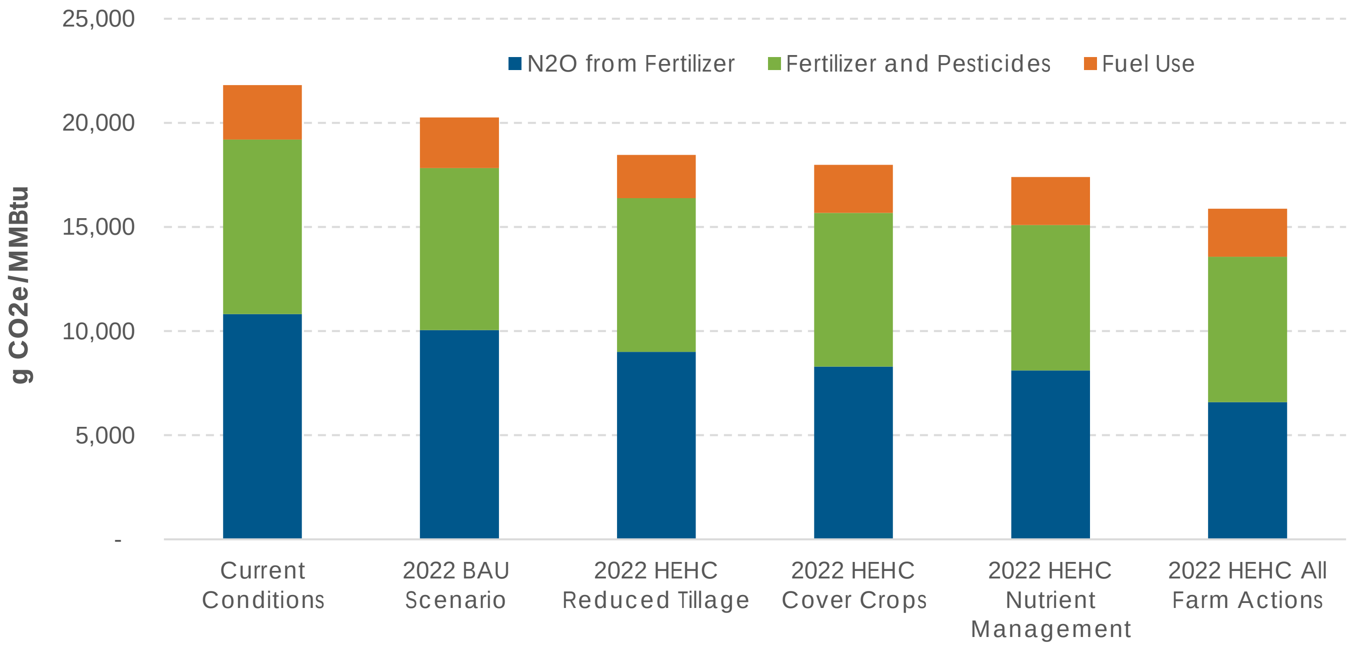
CPS 340—Cover Crops

Cover crops are planted in addition to seasonal crops to increase nitrogen and water-use efficiencies. The additional crop residues increase soil carbon levels (Swan et al., n.d.) and can reduce the indirect emissions of N_2O. Reductions of indirect N_2O emissions are due to decreases in the leaching rate of nitrogen fertilizer (Swan et al., n.d.). The COMET-Planner Report attributes a 0.05 Mg CO_2e/acre/year reduction in emissions due to cover crops. This value represents a 76.8 percent reduction in leaching N_2O emissions (here measured in kg N_2O/acre per kilogram of nitrogen applied).

Domestic Farm Inputs and Fertilizer N_2O Results

ICF quantified the emission reductions of a farm producing corn for ethanol in 2022 from implementing CPS 340, CPS 345, and CPS 590 in the COMET Planner individually and all three combined. Figure 3-1 shows the range of emissions from Current Conditions on the far left to the 2022 HEHC Scenario on the far right. Current conditions LCA emissions for this source category are 21,814 g CO_2e/MMBtu of ethanol. The 2022 BAU Scenario incorporates projected changes in annual corn yields through 2022 from the 2016 USDA Baseline resulting in emissions of 20,259 g CO_2e/MMBtu. In the 2022 HEHC Scenario, corn farmers simultaneously adopting the three CPSs. This results in emissions of 16,734 g CO_2e/MMBtu. The central three bars represent farmers adopting each CPS in isolation.

Figure 3-1: Range of Emissions for the Domestic Farm Inputs and Fertilizer N_2O Emission Category Based on Adoption of USDA Conservation Practice Standards



The values presented in Figure 3-1 do not include the ethanol co-product credit from DGS displacing corn, soybean meal, and urea in animal feed markets. To be consistent with the analysis in Chapter 2, ICF modified the GREET model inputs including corn yields, fertilizer application and nitrogen emission rates, and ethanol production technology (e.g., dry mill refining with corn oil extraction) for each of the scenarios to develop the unique co-product credit for each scenario. The co-product credits for the BAU and the HEHC scenarios were calculated by

modifying GREET to incorporate the farm inputs and fertilizer N_2O unique to each scenario. In the HEHC scenario, the ethanol yield from corn for Dry Mill ethanol refineries with corn oil extraction was increased from 2.8 gallon/bushel to 2.95 gallon/bushel. Utilizing the AR4 GWPs for CH_4 and N_2O, Table 3-3 shows the resulting DGS credit per MMBtu and the resulting total emissions impacts for the Domestic Farm Inputs and Fertilizer N_2O emission category.

Table 3-3: Domestic Farm Inputs and Fertilizer N_2O Emissions Including Ethanol Co-Product Credit

	Farming Inputs (g CO_2e/MMBtu)	Co-Product Credit (g CO_2e/MMBtu)	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	-	-	10,313
Current Conditions	21,814	−12,749	9,065
2022 BAU Scenario	20,259	−12,069	8,190
HEHC Scenario	15,883	−11,393	4,490

Limitations, Uncertainty, and Knowledge Gaps

The largest area of uncertainty are the upstream production emissions associated with the nitrification inhibitor Nitrapyrin. A proxy compound was used for these life-cycle emissions that is in line with the published literature. Also, GREET maintains a consistent DGS yield in pounds per gallon of ethanol. Therefore, it does not account for potential variations in DGS yield with either increasing or decreasing ethanol yield per bushel of corn. If the DGS yield changes, the DGS credit will also change.

Domestic Land-Use Change

The BAU and HEHC scenarios incorporate projections to 2022 for the following key variable that affects GHG emissions under the Domestic Land-Use Change source category:

- BAU: Continuation of conventional till practices by farms for producing corn for ethanol,
- HEHC: Adoption of reduced till practices by farms producing corn for ethanol.

Methodology

The methodology and results for determining total acreage change can be found in Chapter 2. Our projections use the same emission factors and acreage changes as the ICF current conditions LCA. Acreage changes are based on the 2013 corn ethanol production scenario in the GREET model's CCLUB (Dunn et al., 2014a). Using the 2013 production scenario assumes that total U.S. corn ethanol production will remain constant at 15 billion gallons annually through 2022 (11.59 billion gallons/year greater than 2004 production levels). The difference between

the BAU scenario and HEHC scenario is the continued adoption of conventional till in the BAU scenario and the adoption of reduced till in the HEHC scenario.

Domestic Land-Use Change Results

Table 3-4 shows the total GHG emission results for conventional (2022 BAU Scenario) and reduced till (2022 HEHC Scenario) for 100 cm soil depths.

Table 3-4: ICF Analysis Results for Reduced and Conventional Till Practices

Tillage Practice	Total Direct Emissions (Mg CO_2e)	Annualized Emissions (Mg CO_2e/year)	Direct Emissions (g CO_2e/gallon)	Direct Emissions (g CO_2e/MMBtu)
Conventional Till— 2022 BAU Scenario	−1,803,611	−155.6	−1.9	−2,038
Reduced Till— 2022 HEHC Scenario	−62,656,429	−2,088,548	−180.2	−2,359

Limitations, Uncertainty, and Knowledge Gaps

A switch from conventional to reduced tillage in corn production can reduce the GHG emissions associated with corn ethanol. This analysis is based on the assumption that corn grown for ethanol production will use reduced till. At the industry level, the total domestic land-use change benefits will depend on how many farmers the actually adopt reduced tillage.

Fuel Production

For the BAU and HEHC scenarios, ICF estimated emissions for the Fuel Production source category to reflect refinery shifts to less carbon intense process fuels. Relative to the current conditions LCA where refineries use a composite mix of natural gas and coal reflecting the industry today, the BAU scenario assumes refineries use only natural gas as the process fuel. In the HEHC scenario, refineries use only biomass as the process fuel. The HEHC scenario also includes an increase in the ethanol yield per bushel of corn.

Methodology

This assessment followed the ICF fuel production methodology with updates for ethanol production yield. This analysis focused on modeling variations in dry milling for the industry average in GREET with and without corn oil extraction. For the HEHC scenario, production yields were increased from 2.80 gallons/bushel to 2.93 gallons/bushel based on Energy Information Administration (EIA) data (EIA, 2015b) and GREET's projected dry milling with corn oil extraction's yield of 2.95 gallons/bushel.

The projections focus only on dry milling, as recent industry trends show an increasing shift towards dry milling. In 2013, dry mill plants comprised 83 percent of U.S. corn ethanol production facilities and grew in number by 90 percent from

2000–2013. No wet mill plants have been constructed in the United States since 2005, largely due to high capital costs for limited production capacity compared to dry mill plants (Life Cycle Associates, 2014).

Fuel Production Results

From the 2015 GREET model, Table 3-5 shows fuel production emissions for dry mill refineries by technology (i.e., with and without corn oils extraction), process fuel used, and ethanol yields per bushel of corn. For the BAU scenario, ICF assumes that by 2022, the representative refinery will use a dry mill technology with corn extraction and the process fuel will be natural gas. For the HEHC scenario, the representative refinery will have the same technology but will use biomass for the process fuel. The rows showing the technology-process fuel combinations selected for the BAU and HEHC refineries are highlighted in bold in Table 3-5. Projected 2022 emissions for the Fuel Production category are 31,006 g CO_2e/MMBtu emissions for the BAU scenario and 9,695 for the HEHC scenario.

Table 3-5: Fuel Production Emissions by Refinery Technology and Process Fuel

		Fuel Mix Share			Production Carbon Intensity	
Refinery type	**Production Yield (gallons/bushel)**	**Fuel Mix % NG**	**Fuel Mix % Coal**	**Fuel Mix % Biomass**	**g CO_2e/ MMBtu**	**g CO_2e/MJ**
Dry Mill w/o Extraction – Default	2.80	92%	8%	0%	32,374	30.7
Dry Mill w/ Extraction – Default	2.82	92%	8%	0%	31,844	30.2
Dry Mill w/o Extraction – Biomass	2.80	0%	0%	100%	9,694	9.2
Dry Mill w/ Extraction – Biomass	2.82	0%	0%	100%	9,594	9.1
Dry Mill w/o Extraction – NG	2.80	100%	0%	0%	31,520	29.9
2022 BAU Scenario: **Dry Mill w/ Extraction – NG**	**2.82**	**100%**	**0%**	**0%**	**31,006**	**29.4**
Dry Mill w/o Extraction – Default	2.93	92%	8%	0%	32,473	30.8
Dry Mill w/ Extraction – Default	2.95	92%	8%	0%	31,944	30.3
Dry Mill w/o Extraction – Biomass	2.93	0%	0%	100%	9,793	9.3
2022 HEHC Scenario: **Dry Mill w/ Extraction – Biomass**	**2.95**	**0%**	**0%**	**100%**	**9,695**	**9.2**
Dry Mill w/o Extraction - NG	2.93	100%	0%	0%	31,620	30.0
Dry Mill w/ Extraction - NG	2.95	100%	0%	0%	31,107	29.5

Limitations, Uncertainty, and Knowledge Gaps

The projections for fuel production yields are uncertain. Also, the categorization (i.e., waste, farmed) of the biomass could influence the carbon intensity of the corn ethanol pathway. For example, waste biomass has a lower carbon intensity than purposely farmed biomass.

Fuel and Feedstock Transportation

The ICF current conditions LCA used literature published since 2010 to update the RIA emissions associated with the transportation of corn to refineries and ethanol to distributors. In developing the BAU and HEHC scenarios, this analysis considers improved fuel efficiency in trucking, increased use of less carbon-intensive transportation fuels, and reduced co-product transportation requirements.

Methodology

The ICF current conditions LCA used default 2015 GREET transportation and distribution emission factors, mode allocations (i.e., barge, truck, or rail), and distance assumptions to generate current transportation related emissions estimates for corn ethanol. For this analysis the default 2015 GREET emissions are modified as follows:

- 2022 BAU Scenario—incorporates increased fuel economy in trucks and substitution of liquid natural gas (LNG) for diesel fuel heavy duty trucks; and
- 2022 HEHC Scenario—incorporates the BAU scenario modifications and eliminates emissions related to transporting dried distillers grains (due to the assumption that confined livestock operations are located in close proximity to ethanol plants).

Starting with 2015 GREET emission factors for LNG and renewable liquefied natural gas (RLNG) used in transportation by trucks, the improved truck fuel economy was assumed to be a 50 percent increase from the default GREET assumptions, where the baseline was 5.3 and 10.4 miles per diesel gallon for heavy heavy-duty diesel trucks (HHDDT) and medium heavy-duty diesel trucks (MHDDT), respectively. Table 3-6 shows the effects of these variations on emission factors for fuel and feedstock transportation segments. GREET assumes that MHDDTs are used for farm to stacks transport, and HHDDTs are used for all other transportation segments.

Table 3-6: Emission Factor Variations for Fuel and Feedstock Transportation Pathways

	g CO_2e/MMBtu of Fuel Transported		
Fuel and Technology	**Farm to Stacks**	**Stacks to Ethanol Plant**	**Ethanol Plant to Refueling Station**
Diesel	37.88	39.65	8.21
LNG w/ Improved Fuel Economy	21.28	25.28	5.02
Renewable LNG w/ Improved Fuel Economy	3.87	7.07	1.44

Our analysis also includes these fuel economy and new fuel variations in our assessment of corn oil transportation. Fuel types and fuel economies for rail and barge are the same as in the ICF current conditions LCA. Transportation distances and mode allocations, outside of the removed DDGS transportation for the HEHC scenario, are unchanged as well.

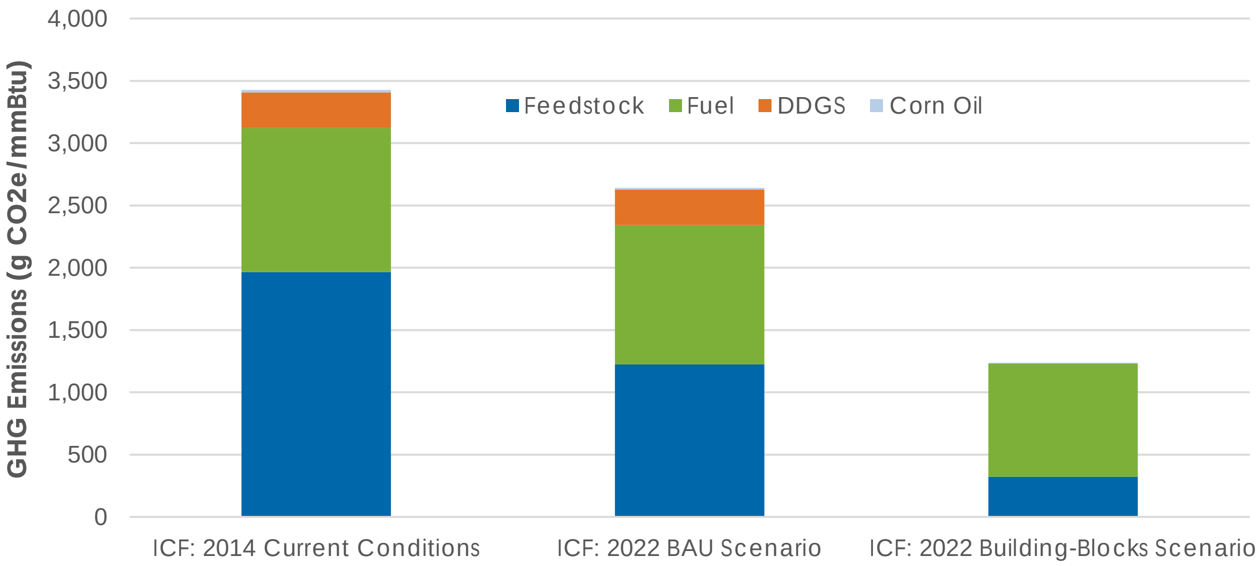
Fuel and Feedstock Transportation Results

Table 3-7 and Figure 3-2 show the emissions for the Fuel and Feedstock Transportation source category for the Current Conditions LCA and the BAU and the HEHC scenarios.

Table 3-7: Fuel and Feedstock Transportation Emissions for Current Conditions, 2022 BAU, and 2022 HEHC Scenarios

	g CO_2e/MMBtu				
Scenario	**Feedstock**	**Fuel**	**DDGS**	**Corn Oil**	**TOTAL**
Current Conditions	1,965	1,161	286	20	**3,432**
2022 BAU Scenario	1,224	1,118	286	13	**2,641**
2022 HEHC Scenario	322	910	N/A	6	**1,237**

Figure 3-2: Fuel and Feedstock Transportation Emissions by ICF Scenario



Note that the fuel transportation requirements have a greater effect as trucking emissions are reduced due to the high portion of rail and barge transportation used in the distribution of corn ethanol downstream of the production plant.

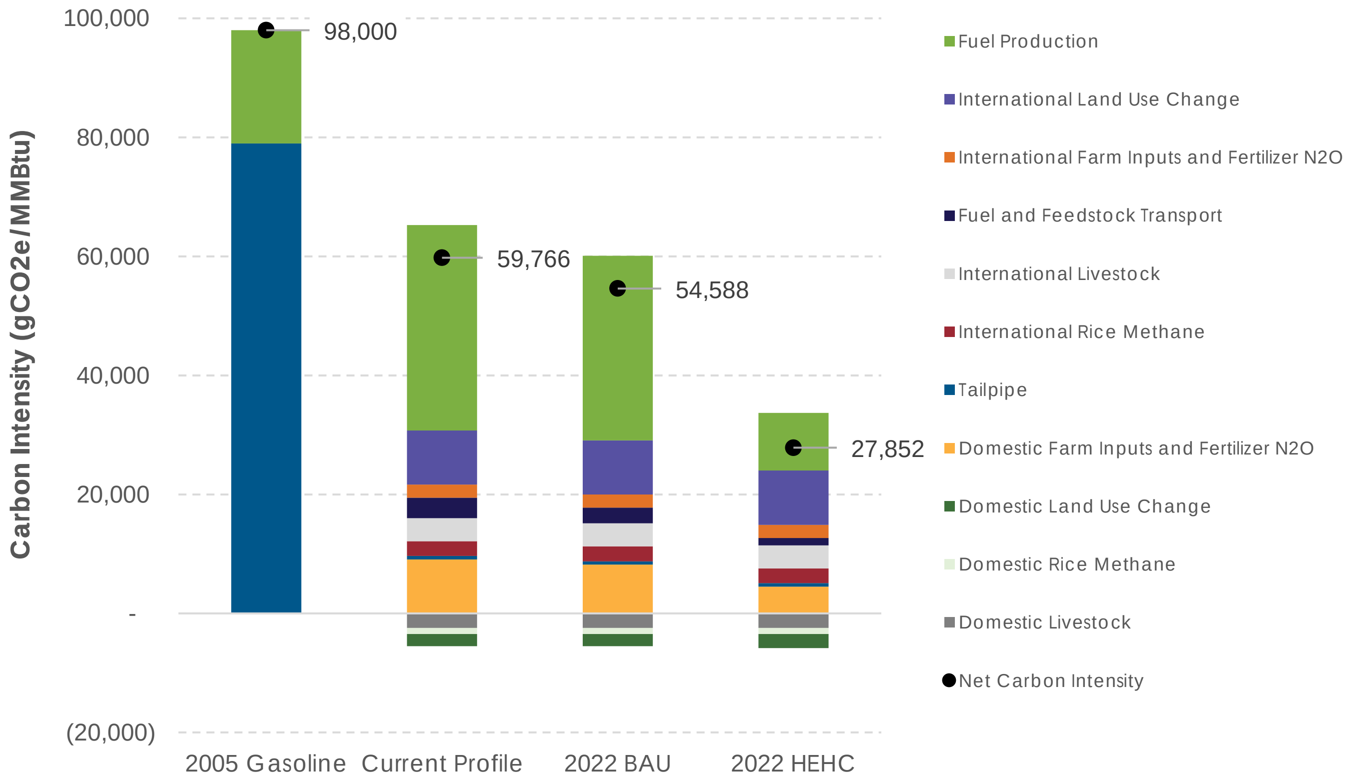
Limitations, Uncertainty, and Knowledge Gaps

This assessment focused on increasing truck fuel efficiency and trucking technology improvements. The emission results could differ if alternative fuels and efficiency gains for rail and barge transport and other fuel transportation modes (e.g., use of pipelines) had been considered. This assessment also used renewable LNG as an example for a non-fossil alternative fuel, but other fuel sources (e.g., biodiesel, renewable diesel) would likely create variations in the results. Finally, actual transportation and distribution mode allocations and associated distances in 2022 could vary significantly over supply chains than those in 2015 GREET. While these uncertainties could affect the emissions associated with the Fuel and Feedstock Transportation, this source category accounts for a very small share of the total life-cycle emissions of corn ethanol.

Summary of the 2022 BAU and 2022 HEHC Scenarios Results

Figure 3-3 shows the RIA GHG profile for a composite blend of gasolines sold in 2005, the RIA projected GHG profile for corn ethanol in 2022, our current GHG profile for corn ethanol, and our two projected GHG profiles for corn ethanol in 2022.

Figure 3-3: Full Life-Cycle Corn Ethanol GHG Results for the Current Conditions, 2022 BAU, and 2022 HEHC Scenarios



In the RIA, EPA quantified the LCA emissions associated with gasoline at 98,000 g CO2e/MMBtu. For corn ethanol, the RIA projected emissions in 2022 at 79,441 g CO2e/MMBtu. With some assumed gains in production and emissions efficiencies between 2010 and 2022, EPA projected the life-cycle GHG emissions of corn ethanol in 2022 at 21 percent lower than gasoline.

Our Current Conditions scenario assesses the life-cycle emissions of corn ethanol at 59,766 g CO$_2$e/MMBtu. This is a 39 percent reduction in GHG emissions relative to gasoline; almost twice the reduction developed in the RIA. This scenario assumes ethanol plants use a composite process fuel that reflects today's mix of natural gas and coal used by refineries. Hence, the 39 percent reduction is the industry-wide average GHG reduction for the corn ethanol relative to gasoline. Most refineries today use natural gas as a process fuel. Replacing the Fuel Production emissions in the Current Conditions scenario with the Fuel Productions emissions in the BAU scenario, indicates the GHG profile of corn ethanol produced in today's dry mill refineries that use natural gas as a process fuel is 42.6 percent lower than gasoline.

Our BAU scenario assumes a continuation through 2022 of current trends in average corn yields per hectare, process fuel switching from coal to natural gas, and increasing fuel efficiency in heavy-duty trucks. Based on these trends, we project life-cycle GHG emissions for corn ethanol in 2022 at 54,588 g CO$_2$e/MMBtu. This scenario indicates that even if the ethanol industry does not actively try to reduce emissions, the GHG profile of corn ethanol will continue to improve. By 2022, the emissions associated with producing and combusting corn ethanol will be, on average, 44.3 percent lower than the emissions associated with producing and combusting gasoline.

Our HEHC scenario assumes refineries takes steps in their value chain to reduce emissions associated with their ethanol. Refineries use sustainable biomass for the process fuel, contract with farmers to grow corn using low-emission practices and locate confined livestock operations near refineries. Projected emissions for corn ethanol in 2022 are 27,852 g CO$_2$e/MMBtu, which is a 71.6 percent reduction in GHG emissions relative to gasoline. The main source of emissions reductions is the shift to sustainable biomass as the process fuel. While it is not likely the ethanol industry as a whole will undertake these changes, it does highlight the emissions reductions that are technically possible with currently available technologies. Given appropriate incentives, some refineries will likely undertake these changes. The most likely source of such incentives are opportunities to participate in new or expanding markets for low-carbon transportation fuels in California and outside of the United States.

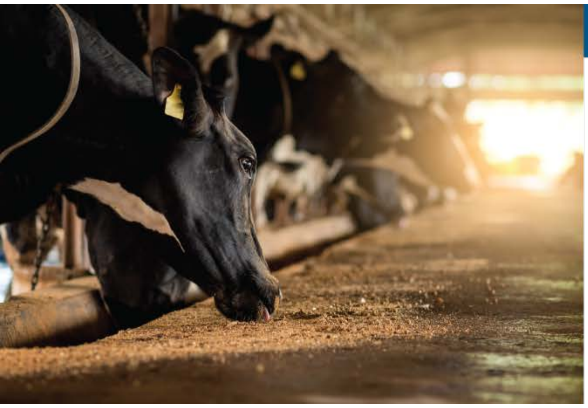
Finally, in the HEHC scenario refineries reduce emissions 4,021 gCO$_2$e/MMBtu by contracting with farmers grow corn using low-emissions technologies and practices. The practices considered are currently available and in use to some degree. Again, given appropriate incentives, refineries could use such contracts to reduce ethanol's current GHG profile. Subtracting 4,021g CO$_2$e/MMBtu from the current emissions levels of a 'representative' refinery results in an emissions profile 43.1 percent less than gasoline. Subtracting 4,021g CO$_2$e/MMBtu from the emissions of today's natural gas powered refineries results in an emissions profile 46.7 percent less than gasoline.

Summary

This report has analyzed the current GHG profile of U.S. corn ethanol and two projected emissions profiles for 2022. The starting point is the GHG life-cycle analysis (LCA) done by the U.S. Environmental Protection Agency (EPA) in 2010 for U.S. corn ethanol as part of its Regulatory Impact Analysis (RIA) for the Revised Renewable Fuel Standard (RFS2). In the RIA, EPA projected that in 2022, the life cycle emissions associated with ethanol would be 21 percent lower than those of an energy equivalent quantity of gasoline.

We assessed each of the 11 emissions categories in the 2010 EPA LCA in light of new data, technical papers, research studies and other information that have become available since 2010. Aggregated across the 11 categories, we found U.S. corn ethanol is developing along an emissions pathway significantly lower than what EPA projected in 2010. Our analysis indicates the current GHG profile of U.S. corn ethanol is, on average, 39 percent lower than gasoline. For natural gas powered refineries, this value is almost 43 percent lower. Finally, current trends in the ethanol industry and actions refineries could take to reduce emissions offer opportunities to lower the GHG profile of corn ethanol between 47.0 and 70.0 percent relative to gasoline.

This analysis is timely because many countries (e.g., Colombia, Japan, Brazil, Canada and the European Union) are now developing or revising their renewable energy policies. These policies typically require biofuel substitutes for gasoline to reduce GHG emissions by more than 21 percent. Our results could help position U.S. corn ethanol to compete in these new and growing markets.



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