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

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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[1]

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

1. Introduction

This chapter introduces the background for, the general approach for conducting the analyses described in, and the organization of this report.

1.1. Background

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. Corn ethanol's mandate started at 9 billion gallons in 2008, gradually increased to 15 billion gallons in 2015, and was held constant at that level through 2022.

With the exception of ethanol produced in certain grandfathered refineries, a biofuel must have a life-cycle greenhouse gas (GHG) profile at least 20 percent lower than that of the fossil fuel it replaces to qualify as a renewable fuel under the RFS2. Earlier studies by Searchinger et al. (2008) and Fargione et al. (2008) examined the effects of allocating billions of bushels of corn to ethanol production on supplies of corn and other commodities going to domestic and world food and feed markets.[2] These studies proposed that domestic and world commodity prices would rise and farmers in the United States and other regions would respond by bringing new lands into production. Bringing new land into commodity production results typically in CO_2 emissions and these emissions can be large if the former land use was native grassland, wetland, or forest. The domestic and international land effects described above are referred to as, respectively, "direct land-use change" and "indirect land-use change" (iLUC). GHG profiles of corn ethanol date back to the early 1990s, but those done prior to 2007 did not account for emissions related to iLUC. Searchinger et al. (2008) and Fargione et al. (2008) concluded that when emissions related to iLUC are accounted for, corn ethanol has a higher GHG profile than gasoline. More recently, researchers have reviewed the responses of farmers across the world to changes in corn demand. This study draws on these new findings, including Bruce Babcock and Zabid Iqbal's publication "Using Recent Land Use Changes to Validate Land Use Change Models". Babcock and Iqbal's study confirmed that the primary land-use change response by the world's farmers during the period 2004–2012 was to use

[2] The cap also reflected a practical constraint. For a various reasons, the ethanol content of gasoline sold in the Unites States for use in light trucks and automobiles is limited to 10 percent (a product called E10). This constraint is referred to as the "blend wall." The blend wall presents a challenge to expanding ethanol consumption because virtually all gasoline now sold in the United States is E10. In 2015, for example, the United States consumed about 140.4 billion gallons of gasoline (https://www.eia.gov/tools/faqs/faq.cfm?id=23&t=10). The blend wall thus limited domestic consumption of ethanol in transportation fuel to a little over 14 billion gallons.

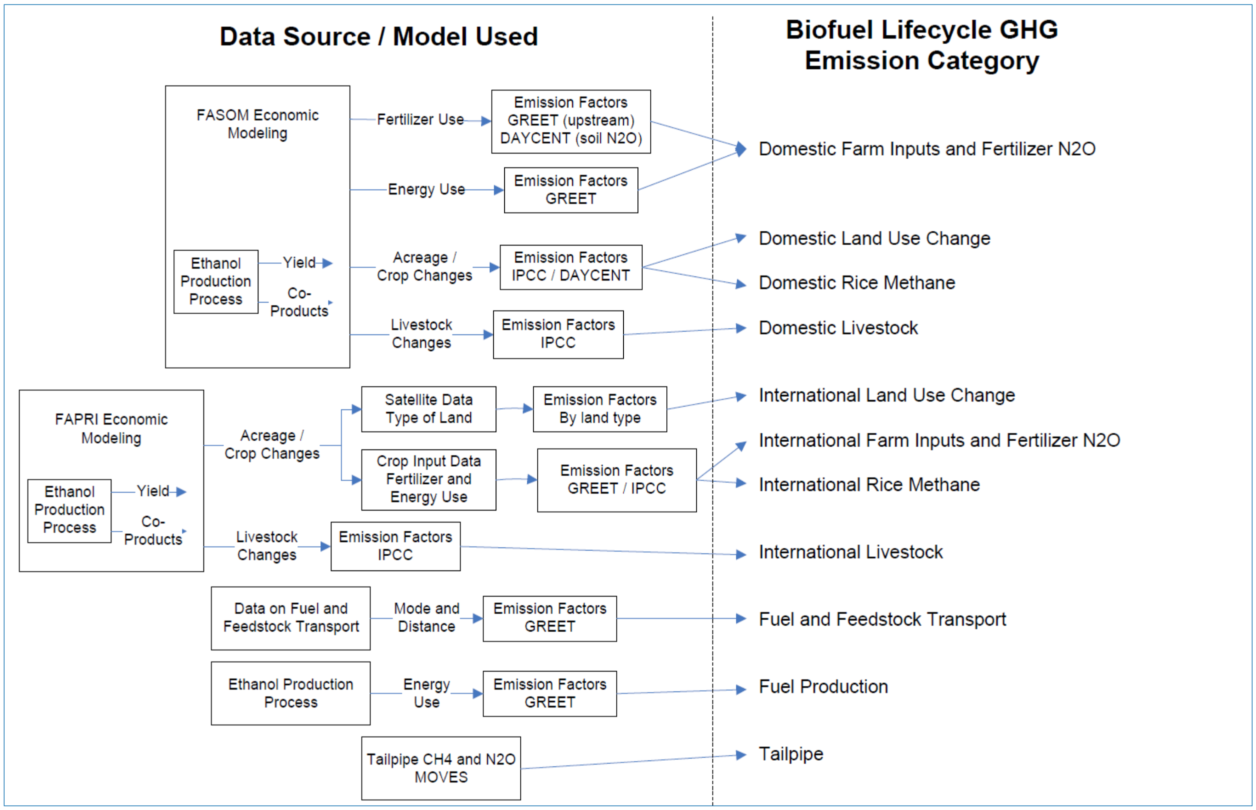
available land resources more efficiently rather than expanding land brought into production (Babcock and Iqbal, 2014). Farmers in Brazil, India, and China have increased double cropping, reduced unharvested planted area, reduced fallow land, and reduced temporary pasture in order to expand production.

The RFS2 directed the U.S. Environmental Protection Agency (EPA) to do a full life-cycle analysis (LCA) of greenhouse gas (GHG) emissions associated with the production of corn ethanol (as well as other biofuels) and explicitly specified that emissions related to iLUC be included. In 2010, EPA released this LCA as part of its Regulatory Impact Analysis (RIA) of the RFS2. 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[3]
4. Domestic livestock[4]
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. EPA evaluated the emissions and energy use associated with each emission category and the upstream components.

[3] Domestic rice methane is included to account for changes in land-use emissions based on the increased demand for biofuels and change in domestic rice acreage.
[4] Domestic livestock is included to account for the change in livestock production as costs for feed changes due to corn ethanol production.



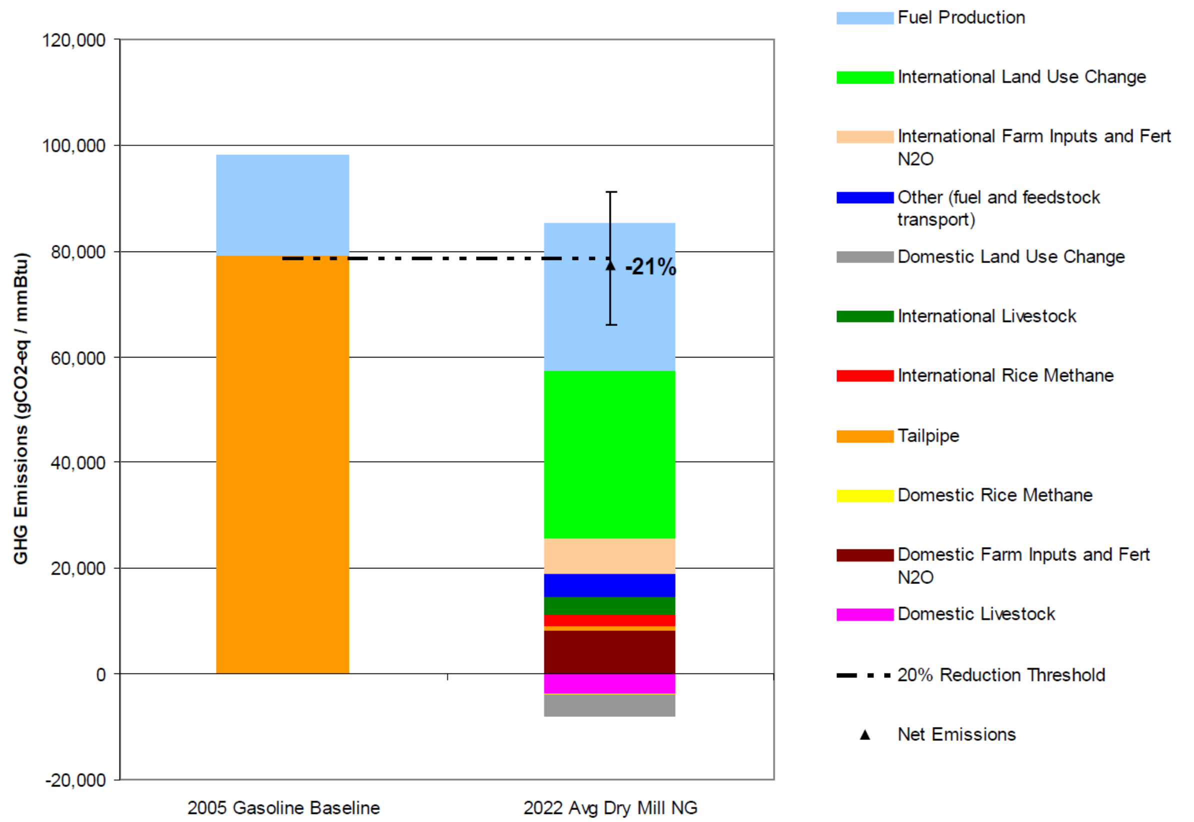
Source: EPA, 2010a.

Figure 1-1: Summary of Data Sources and Models Used in the Development of the Eleven Emission Sources (Source: Figure 2.2-1 from EPA RIA)

Based on the EPA RIA, EPA concluded that in 2022, the GHG emissions associated with production of a unit of corn-based ethanol from a state-of-the-art natural gas powered refinery would be about 21 percent lower than the emissions from an energy equivalent quantity of an "average" gasoline in 2005.[5] Figure 1-2 shows the EPA RIA emissions profiles for corn ethanol and the average gallon of gasoline.

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

Figure 2.6-2. Results for a New Natural Gas Fired Corn Ethanol Plant by Lifecycle Stage Average 2022 plant: natural gas, 63% dry, 37% wet DGS (w/ fractionation)



Source: EPA, 2010a.

Figure 1-2: Summary of LCA emission Factors Showing the Relative Contributions Across the 11 Emission Categories (Source: Figure 2.6-2 from EPA RIA)

Figure 1-2 shows that for corn ethanol—dry mill-natural gas plants—the largest sources of emissions were international land-use change, fuel production, and domestic farm inputs and fertilizer N_2O. The figure shows the 95 percent confidence interval from the study's uncertainty assessment for the corn ethanol scenario. The largest source of emissions within international land-use change are the conversion of land from pasture to cropland and the land-use change that were projected to occur in Brazil's Amazon region. These international land-use change contributions are important areas of focus for the updates conducted as part of this study. However, as discussed later other non-land use contributions are also important.

The EPA RIA is one of the most comprehensive modeling frameworks 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—that indicates that for many of the emission categories in the EPA RIA, the actual emissions pathways that have developed since 2010 differ significantly from those projected in the EPA RIA. The primary purpose of this report is to consider a more complete set of information now available related to the life-cycle emissions for corn-based ethanol and based on this information, assess its current (i.e., in 2014) GHG emissions profile.

This report also develops two projected emissions profiles for corn ethanol in 2022 (the last year of the RFS2). Starting with the current emissions profile, the first projection, labeled the business-as-usual (BAU) scenario, assumes that recent trends observed in corn inputs and per-acre 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. The second projection, labeled the Building-Blocks scenario, adds to the BAU the assumption that refineries adopt a set of currently available GHG reducing technologies and practices in corn production, transportation, and co-products. The Building-Blocks scenario can be viewed as a best-case assessment of corn ethanol's potential to mitigate GHG emissions given currently available technologies and production practices.

1.2. General Approach

Since 2010, the EPA RIA's estimated GHG mitigation value for corn ethanol, 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 the LCA developed in this report is designed so that comparisons of its results with those in the EPA 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 EPA 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 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. Based on a 2007 projection of ethanol production (i.e., before the RFS2) done by the Department of Energy's Energy Information Agency (EIA) without an RFS in place and the 15 billion gallon cap on corn ethanol in the RFS2, EPA projected that the RFS2 would increase corn ethanol production by 3.03 billion gallons in 2014 and 2.6 billion gallons in 2022 over the baseline EIA projection.[6] We used the 3.03 billion gallon increase in ethanol production to assess the contribution of most of the emission categories in the

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

current GHG profile and the 2.6 billion gallon increase in the two projected profiles for 2022. The only exception was the land-use change emission categories. Modeling of indirect land-use change (where the United States land-use change results were used for the domestic land-use impact) in the RIA and the results utilized in this study are based on the changes in land use to successfully meet the requirements of the RFS (15 billion gallons) with 2004 as the baseline year (when ethanol production was 3.4 billion gallons). The emission impacts in these two categories are quantified based on an ethanol production increase of 11.59 billion gallons (i.e., 15 billion gallons minus 11.59 billion gallons). Table 1-1 shows the values specific to the 2022 assumptions for corn ethanol.

Table 1-1: Assumptions for Corn Ethanol Volumes by 2022 (Source: EPA RIA)

Scenario	2022 Assumption for Corn Ethanol (billion gallons)
Fuel-Specific Scenario[a]	12.39[7]
Control Scenario[b]	15.00
Difference[c]	2.60

Source: AEO 2007; "Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx," "Inputs_Vol" tab.
[a] The Fuel-Specific—or Reference Case—(both labels are used in the RIA and analysis spreadsheets to represent the baseline conditions for each emission category), represents the business-as-usual case, and is the projected volume of corn ethanol that is likely to have occurred without the enactment of the Energy Independence and Security Act (EISA) of 2007. The projected volumes are based on the Energy Information Administration's (EIA's) Annual Energy Outlook (AEO) 2007 reference case projections (U. S. Department of Energy, Energy Information Administration, 2007). AEO 2007 was chosen because, unlike later versions of EIA's AEO, it did not include the impact of increased renewable fuel volumes under EISA and fuel economy improvements under the Corporate Average Fuel Economy (CAFE) standards as required in EISA.
[b] The Control Scenario represents the projected corn ethanol volume that might be used to comply with the EISA volume mandate. The RIA notes that although actual volumes and feedstocks will likely be different, EPA believes that the projections made are within the range of expected outcomes when the standards are met, and allow for an assessment of the potential impacts of the RFS2 rule.
[c] The Difference represents the volume difference between the business-as-usual projections and the anticipated volumes to comply with EISA.

While the analysis developed in this report draws extensively from the EPA RIA from 2010, it does not replicate the methodology developed by EPA at that time to evaluate lifecycle GHG emissions associated with corn ethanol for implementation of the Renewable Fuels Standard. As such, the results presented in this report are not directly comparable to the results included in EPA's RIA, nor does it alter the implementation of the RFS program. Here, ICF has considered the EPA RIA, observed industry trends since the implementation of the Renewable Fuels Standard, new research on lifecycle assessments, new data and other information that has become available since 2010—to reflect what has occurred (see Chapter 2).

[7] Note that this value is 12.29 in the report but 12.39 in the supporting spreadsheet calculations.

New information accounted for in this assessment includes new values that have been developed since 2010 for many of the GHG emissions 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).[8] 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 a large number of 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 gallon of ethanol (see Table 3-7). 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).

1.3. Organization of the Report

In the report that follows, Chapter 2 reviews the scientific papers, technical reports, data sets, and other information that has become available since 2010 and relate to current emission levels in each emission category.

[8] 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).

Chapter 3 develops current GHG emission values for each emission category included in the EPA RIA based on the literature review. Chapter 3 considers each emission category separately. For each emission category, the 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 3, Chapter 4 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, switch to biomass as a process fuel, and locating confined livestock operations in close proximity to refineries.

1.4. References: Introduction

Babcock, B.A. and Iqbal, Z., 2014. "Using Recent Land Use Changes to Validate Land Use Change Models". Staff Report 14-SR 109. Center for Agricultural and Rural Development: Iowa State University. http://www.card.iastate.edu/publications/dbs/pdffiles/14sr109.pdf

EPA. (2010, February). *U.S. Environmental Protection Agency: Renewable Fuel Standard (RFS2) Regulatory Impact Analysis.* Retrieved from http://www.epa.gov/oms/renewablefuels/420r10006.pdf

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. "Land Clearing and the Biofuel Carbon Debt." Science. Vol 319. 29 February: pp 1235-1238.

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Searchinger, T., R. Heimlich, R.A. Houghton, F. Dong, A. Elobeid, J. Fabiosa, S. Tokgoz, D. Hayes, and T. Yu. 2008. "Use of Cropland for Biofuels Increases Greenhouse Gases Through Emissions from Land-Use Change." Science. Vol 319. 29 February: pp 1238-1240.

U. S. Department of Energy, Energy Information Administration. (2007, February). *Annual Energy Outlook*. Retrieved from http://tonto.eia.doe.gov/ftproot/forecasting/0383(2007).pdf

2. Review of the Scientific Papers, Technical Reports, Data Sets, and Other Information that have Become Available Since 2010 and Relate to Current Emissions Levels in Each Emissions Category

This chapter reviews and synthesizes the 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 current emissions levels in the 11 source categories included in EPA's Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis (RIA). The review is organized by emission category with the exception of the domestic livestock with international livestock categories, which are dealt with in one section. For each emission category, a summary of the scientific papers, technical reports, data sets, and other information that has become available since 2010 is provided. Where applicable, information, data, and emission factors from the more recent literature is compared to corresponding information and data used in the RIA.[9] In addition, key issues identified in the available literature are summarized.

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 and international livestock
5. International land-use change
6. International farm inputs and fertilizer N_2O
7. International rice methane
8. Fuel and feedstock transport
9. Fuel production
10. Tailpipe

2.1. 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.

[9] Many of the inputs for the existing EPA emission estimates come from established data sources (e.g., the emission factors included in GREET) and other model outputs (e.g., FASOM, FAPRI, MOVES). We reviewed updated output datasets including emission factors from more recent versions of these models. For example, Argonne National Laboratory's GREET and Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) models were updated in 2015, so ICF was able to readily compare any updated emission factors against those used for the RIA.

The RIA uses estimates of domestic agricultural inputs for fertilizer, pesticides, and energy use from the Forestry and Agriculture Sector Optimization Model (FASOM) output. Since the release of the RFS2 RIA, additional empirical data are available to validate and/or update those inputs used in the analysis. 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.

2.1.1. 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.[10] Since 1990, NASS has surveyed U.S. farmers to collect information on the chemical ingredients they apply to agricultural commodities through fertilizers and pesticides. 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:

- Percentage acreage 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). Available annually for field crops.
- Percentage acreage 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. Selected items available for all commodity programs.

2.1.2. Domestic Farm Energy Use

Periodically, USDA produces an updated inventory of GHG emissions and carbon storage for the agriculture and forestry sectors. These reports are consistent with the annual emissions reporting done by EPA, but provide an enhanced view of the data regionally and by land use.

The report is 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*. The last USDA

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

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).

Empirical data with which to validate and/or update those inputs used (and emissions estimated) in the RFS2 RIA analysis is available from the underlying data source (and emission factors) used in the inventory.

> *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)*

2.1.3. Domestic Farm Nitrogen Application

As indicated in the recent literature (see Table 2-1), N application has increased from 137 to 143 pounds per acre from 2005 to 2010. However, yield per acre has increased during the same period, thereby resulting in a net decrease in N application per crop yield. In particular, as The Fertilizer Institute states:

> *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 slight decrease in fertilizer per bushel (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 impact of domestic nitrogen application.

Table 2-1: N Application for Corn

All Farms: TOTAL	Units	2010		2005	
		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.

2.1.4. Domestic Farm Inputs and Fertilizer N_2O Emission Factors

The RIA used Argonne National Laboratory's GREET_1.8c, released in 2009, to create emission factors for herbicides, pesticides, and nitrogen, phosphate, potash, and lime fertilizers. 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) the emission factors are presented below in Table 2-2.

Table 2-2: RIA Emission Factors for Domestic Farm Inputs and Fertilizer (Units: Emissions—grams per ton of nutrient; Energy Use—MMBtu per ton of nutrient)

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
CO	2,726	1,091	214	244	6,582	10,091
NO_x	2,274	6,206	1,103	781	23,188	29,312
PM10	436.1	1,468	137	544	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	21,979	17,007
CH_4	2,632	1,610	888	830	27,147	32,196
N_2O	1,481	16.68	9.12	7.762	216.3	281.7

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
CO_2	2,211,527	894,413	602,485	949,543	18,767,361	21,967,813
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: EPA, 2009b.

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 were taken from GREET and 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). Table 2-3 below shows the GREET data used in the RIA that includes the raw GREET emission factors multiplied by 1.1 found in the docket spreadsheet.

Table 2-3: RIA Emission Factors for Domestic Farm Inputs and Fertilizer (Units: Emissions—grams per ton of nutrient; Energy Use—MMBtu per ton of nutrient)

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
CO	6,288	1,387	470	287	10,386	15,864
NO_x	3,733	7,895	2,007	915.23	36,489	45,885
PM10	999	1,887	687	653	17,938	20,331
PM2.5	518	1,158	242	218	8,203	9,683
SO_x	1,957	70,105	1,465	1,039	34,420	26,672
CH_4	3,175	1,942	1,060	989	32,856	38,665
N_2O	1,794	19.71	10.43	8.78	253	327
CO_2	2,668,549	1,076,267	717,035	653,152	22,681,896	26,303,347
Coal Energy	2.81	2.77	2.98	2.97	55.64	68.30
Natural Gas Energy	40.68	6.13	2.34	2.31	71.54	84.33
Petroleum Energy	1.75	3.76	2.34	1.68	124.91	144.67

Source: EPA, 2009a.

Since the RIA was released, 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. The most recent release of GREET was October 2, 2015. Table 2-4 below shows the updated emission factors for herbicides, pesticides, and nitrogen, phosphate, potash, and lime fertilizers included in GREET 2015.

Table 2-4: Updated Emission Factors for Domestic Farm Inputs and Fertilizer (Units: Emissions—grams per ton of nutrient; Energy Use—MMBtu per ton of nutrient)

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
CO	6,542	2,197	460	19	12,516	20,673
NO_x	7,203	5,357	1,835	36	43,230	61,765
PM10	1,261	1,289	166	4	4,735	4,398
PM2.5	1,028	1,006	124	2	2,941	3,331
SO_x	16,417	55,843	1,146	6	51,568	20,634
CH_4	8,675	2,670	882	12	25,016	29,773
N_2O	1,818	25	9	0	317	321
CO_2	2,765,389	1,261,876	557,061	11,763	17,504,257	20,189,207
Coal Energy	2.08	2.35	2.11	0.01	39.10	47.76
Natural Gas Energy	46.09	11.95	2.54	0.02	74.87	89.99
Petroleum Energy	4.88	4.00	2.46	0.13	112.03	128.57

Source: Argonne National Laboratory, 2015.

With IPCC Fourth Assessment Report (AR4) Global Warming Potentials (GWPs) applied, a comparison of each set of emission factors (in g CO_2e/ton of nutrient) are presented below in Figure 2-1. The updated 2015 data shows an increase in the GHG impact of nitrogen and phosphate fertilizers but a decrease in the GHG impact of potash and lime fertilizers.

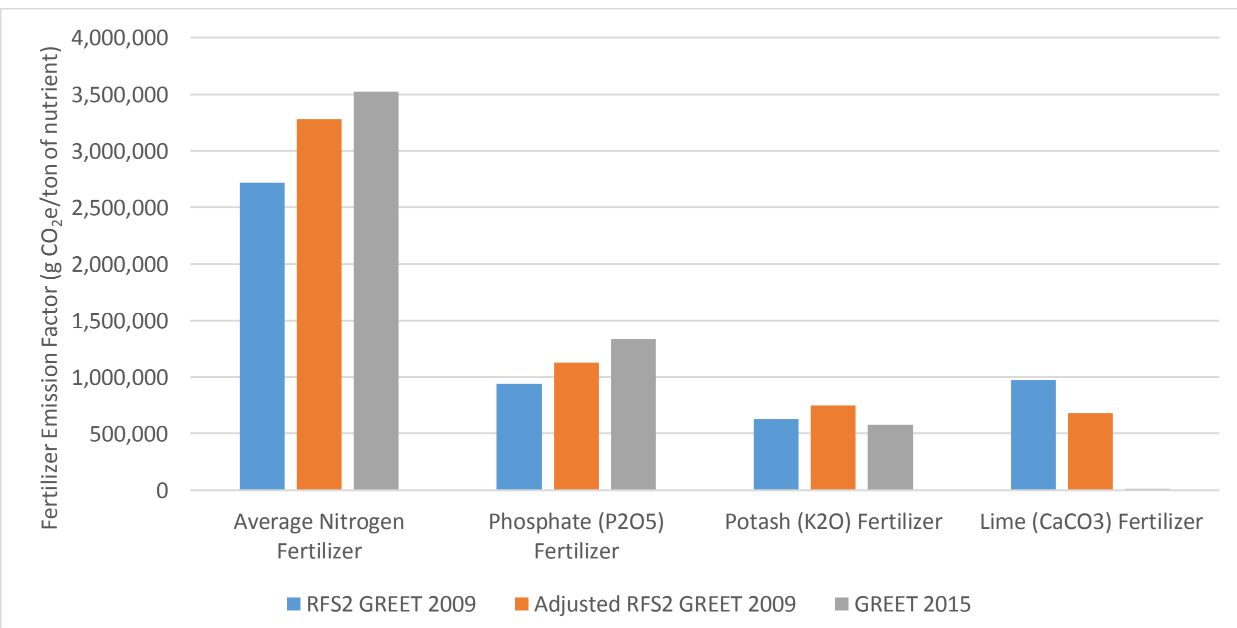

Figure 2-1: Comparison of Emission Factors for Fertilizers

As the tables show, there are significant differences in emissions and energy use between GREET1_2009 and GREET1_2015 for nitrogen fertilizer and lime.

For nitrogen fertilizer, between 2009 and 2015, Argonne adjusted energy use for nitrogen fertilizer manufacturing by increasing natural gas use across all nitrogen fertilizer types. For lime, energy use and emissions are significantly reduced from GREET_2009 to GREET_2015. The changes result from Argonne's correction of using crushed limestone in GREET_2015 from using lime in GREET_2009.

2.1.5. Domestic Farm Input and Fertilizer N_2O Management Practices

While the RIA includes comprehensive information on emission factors, it does not include the recent literature discussing an increase in crop and nutrient management strategies. These strategies have the potential to reduce the emissions from agriculture production, which could have a noticeable impact on domestic farm input and fertilizer N_2O emission calculations such as for the corn ethanol LCA. 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, and they give crops access to a larger percentage of applied fertilizer. This increased access to applied nitrogen improves the nitrogen use and reduces the nitrogen loss from crops, which decreases the resulting emissions from applied nitrogen-based fertilizers. More specifically, 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" (Trenkel, 2010). Maintaining the nitrogen in its ammonium form longer gives crops a more prolonged chance for nitrogen-uptake, therefore using the applied nitrogen more effectively and reducing emissions through nitrogen loss.

Precision agriculture refers to crop strategies that use field-specific data to optimize outputs. As Schimmelpfennig and Ebel (2011) describe in their paper on the recent adoption of precision agriculture, the term precision agriculture is used to designate crop practices that use "information gathered during field operations, from planting to harvest, to calibrate the application of inputs and economize on fuel use." These practices include 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.

Studies released since the implementation of RFS2 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.

Schimmelpfennig and Ebel (2011) describe an upward trend in use of precision agriculture, using data from the Agricultural Resource Management Survey (ARMS) of the USDA Economic Research Service (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 include up-to-date data from 2010, it would not have included changes in emissions data caused by these increasingly common practices.

Figure 2-2 shows the changing prevalence of corn acres treated with nitrogen (N) and the use of: (1) nitrogen inhibitors, (2) precision agriculture, (3) variable rate technology for any fertilizing, (4) variable rate technology (VRT) for nitrogen application specifically, and (5) guidance or AutoSteering systems (i.e. swath control). All of the nutrient management practices increased in use between 2005 and 2010, while the total number of corn acres treated with nitrogen declined only slightly. The average application rate of nitrogen did increase between 2005 and 2010, from 137 to 143 pounds per treated corn acre.

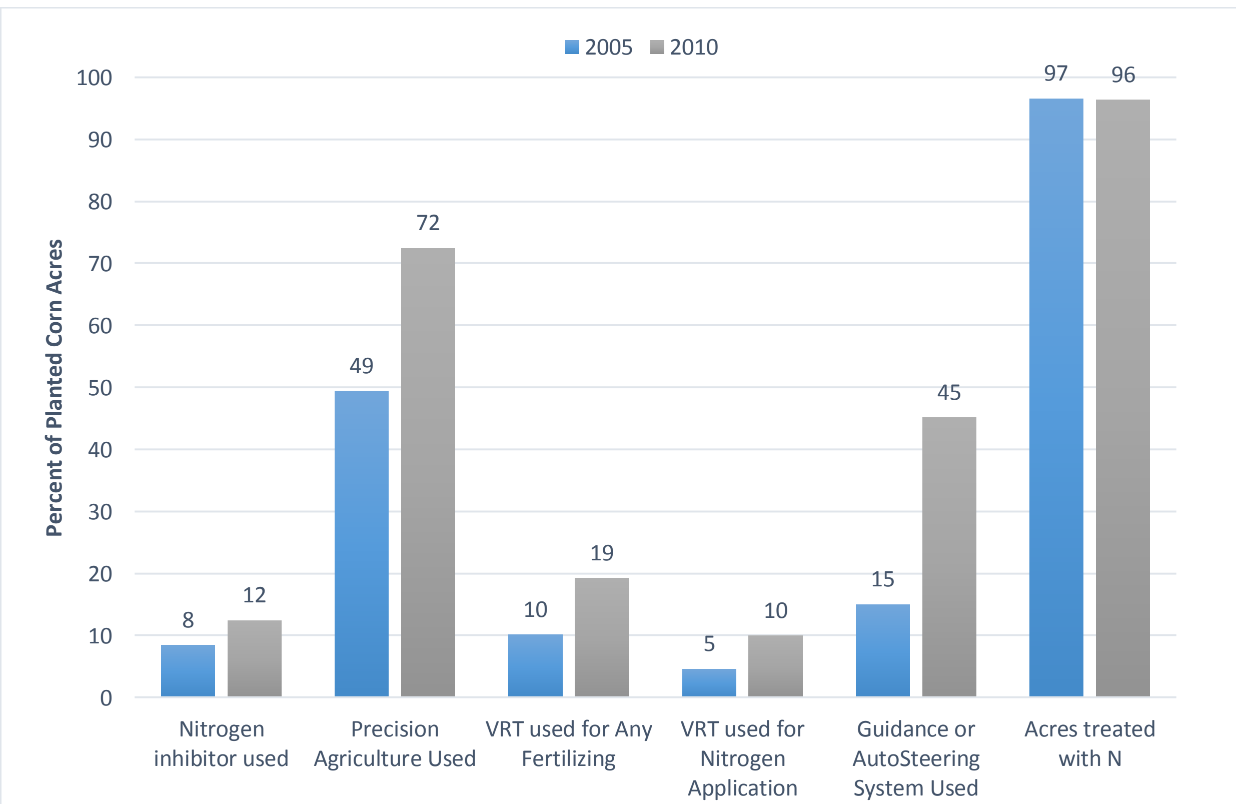

Figure 2-2: Changes in Corn Production Practices from 2005 to 2010

These practices are clearly increasing in use domestically, and given their positive reviews in the recent literature, they are likely to continue to increase. Practices such as use of nitrification inhibitors and precision agriculture could decrease both upstream and downstream emissions from agriculture and will play an important mitigation role in the sector. ICF recognizes that more recent data may be available including a report by the University of Nebraska (Castle et al. 2015).

2.1.6. References: Domestic Farm Inputs and Fertilizer N_2O

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2.2. Domestic Land-Use Change

USDA feed grains database provides useful information to determine actual land use for corn ethanol production. The database provides United States commodity market year annual information for:

- Corn Production
- Planted Acreage
- Corn Harvested Acreage
- Corn use in alcohol for fuel use

Current available information covers market years 1980 to 2015. Marketing years (MYs) span calendar years and often overlap both calendar years. For example, marketing year 2012 is interpreted as 2012/2013 and refers to the marketing year beginning September 1, 2012 and ending August 31, 2013. Annual values for the two most recent years (i.e., 2014 and 2015) are preliminary and/or forecasts (USDA ERS, 2015a).

The USDA National Agricultural Statistics Service corn production forecast has two components—acres to be harvested and expected yield per acre.

> *Every year a single survey is performed in June. The producers are asked to report the acreage, by crop, that has either being planted or that they intend to plant, and the acreage they expect to harvest as grain. Data from this survey are used to estimate, among other things, total acres planted to corn…regardless of the intended uses. Preliminary projections of acres to be harvested for grain are also made using these data. (USDA NASS, 1999)*

This information allows for the determination of historical average national corn yield, percentage of U.S. corn production allocated to ethanol, and differences between corn planted acreage and corn harvested acreage. Table 2-5 summarizes the data.

Table 2-5: U.S. Corn Crop Actual Performance

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	%
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	5,208.50	14,215.53	90.60	83.14	37%	171.0	92%
2015	5,200.00	13,653.51	88.38	80.66	38%	169.3	91%

Total U.S. corn harvested acreage exceeds the assumed acreage modelled in the Regulatory Impact Assessment (RIA) performed for RFS2 (EPA, 2010a). The RIA Base Yield Case assumes that in 2017 corn harvested acreage would be 78.72 million acres in the reference case and 83.59 million acres in the control (regulatory effects) case. The area was assumed to decrease later on in 2022 to 77.90 million acres in the reference case and 81.46 million acres in the control case (EPA, 2010b). USDA data shows that corn harvested acreage peaked in 2012 at a value of 87.37 million acres. Similarly, planted acreage peaked at 97.29 million acres. However, in 2012 production decreased considerably as crop yields decreased significantly (123.1 bu/acre) due to the exceptional drought that affected the Midwest and Great Plains. The USDA 2014 preliminary and 2015 forecasted figures indicate that since 2012, corn yields are expected to increase leading to a corn harvested acreage in 2015 (80.66 million of acres) that is below the RIA control case assumed for corn harvested acreage for 2017 and 2022 (i.e., 83.59 and 81.46 million acres, respectively). USDA long-term projections (USDA ERS, 2015a) (see Table 2-6) indicate that total U.S. harvested area will remain below RFS2 RIA assumed values for 2017, but exceed the RFS2 RIA assumed 2022 corn harvested area by over 0.5 million acres. Figure 2-3 shows U.S. Food and Agricultural Policy Research Institute (FAPRI) modelled values as opposed to FASOM values. The figure illustrates the trend expected in the RFS2 RIA compared to the actual and updated forecast of the performance of U.S corn crops.

Table 2-6: 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	5,150.00	13,940.00	90.00	82.40	37%	169.2	92%
2017	5,100.00	14,105.00	90.00	82.40	36%	171.2	92%
2018	5,075.00	14,270.00	90.00	82.40	36%	173.2	92%
2019	5,075.00	14,355.00	89.50	81.90	35%	175.3	92%
2020	5,075.00	14,520.00	89.50	81.90	35%	177.3	92%
2021	5,100.00	14,595.00	89.00	81.40	35%	179.3	91%
2022	5,125.00	14,760.00	89.00	81.40	35%	181.3	91%

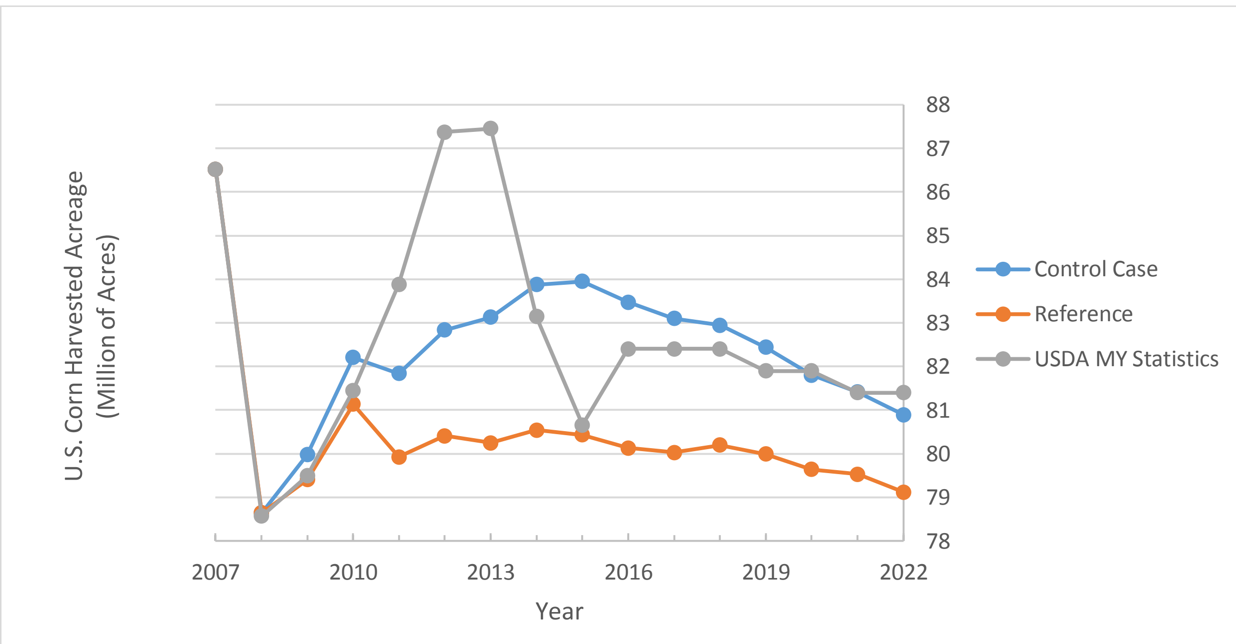

Figure 2-3: Comparison of Modelled Trend of U.S. Corn Harvested acreage to Actual and Recent Forecast (Sources: EPA (2010c), USDA ERS (2015b), and USDA (2015a))

USDA commodity market year annual information indicates that a high percentage of corn production has been allocated to ethanol during 2010 to 2012 (e.g., 43 percent in 2012 compared with the RIA assumed 41 percent in 2022). A potential reason for the high allocation value in those years is the low crop yields and an initial over production of corn fuel ethanol compared to the assumed values in the control case of the RIA. In the coming years, corn allocation to supply RFS2 fuel ethanol needs would potentially increase if low crop yields occur. In order to analyze this effect we compared the key assumptions the RIA used to analyze impact of the RFS2 fuel volumes on the U.S. and international agricultural sectors (Table 2-7) with actual U.S. corn ethanol production data (Table 2-8) and USDA actual and forecasted corn production data (Table 2-5 and Table 2-6).

Table 2-7 shows some discrepancies and/or non-harmonization among the production forecast parameters assumed for the RIA among sources. For the purposes of our analysis, FASOM results for 2022 are evaluated.

Table 2-7: RFS2 RIA Corn Ethanol Production Forecast Parameters for Control Base Yield Case as Documented by Several Sources

Data Source	Fuel Volume/Year (Billion Gallons/Year)					
	15 billion gallons in 2017			15 billion gallons in 2022		
	RFS2 RIA[a]	FASOM Results[b]	FASOM GHG Analysis[c]	RFS2 RIA[a]	FASOM Results[b]	FASOM GHG Analysis[c]
Harvested Acreage (million acres)	n.a.	84	88	81	81	87
Corn Production (million bushles)	n.a.	14,586	14,117	---	15,079	16,831
Yield (bu/acre)	170	175	173[d]/183[e]	180	185	184[1]/194[2]
Corn Allocation to Ethanol	n.a.	n.a.	n.a.	41%	37%[2]	n.a
Ethanol Conversion (gallons/bushel)	n.a.	2.69 (2.71 dry mill & 2.50 wet mill)	2.69	2.85 (2.85 dry mill & 2.63 wet mill)	2.69 (2.71 dry mill & 2.50 wet mill)	2.69

Notes: [d] Reported; [e] Estimated by ICF based on area, production, and conversion reported.
Source: [a] EPA (2010a); [b] Beach and McCarl (2010); [c] EPA (2010d).

The U.S. Energy Information Administration (EIA) published the trend on monthly total ethanol fuel production and consumption from 1981 to 2014 (EIA, 2015). Using this information, in terms of corn market years, the actual and most recent forecast for ethanol conversion can be estimated as illustrated in Table 2-8.

Table 2-8: U.S. Ethanol Production and Ethanol Conversion 2007 to 2014

Year	National Agricultural Statistics Service and U.S. Energy Information Administration Data			ICF Analysis
	Ethanol Production Calendar Year	Corn Use in Fuel Ethanol Market Year	Ethanol Production Market Year	Ethanol Conversion
	Millions of Gallons	Million bushels	Millions of Gallons	(gallons/bushel)
2007	6,521	3,049.21	8,367	2.74

Year	National Agricultural Statistics Service and U.S. Energy Information Administration Data			ICF Analysis
	Ethanol Production Calendar Year	Corn Use in Fuel Ethanol Market Year	Ethanol Production Market Year	Ethanol Conversion
	Millions of Gallons	Million bushels	Millions of Gallons	(gallons/bushel)
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

According to these data, since 2007 the average ethanol yield is 2.76 gallons/bushel. Moving forward a similar average yield could be expected. It means that the production of 15 billion gallons of corn ethanol would require around 5,435 million bushels of corn. The preliminary data for 2014 indicate that recently the yield could have improved for ethanol production (2.81 gallons/bushel or a 1.8 percent improvement over the average yield). These data indicate that actual national average ethanol conversion yield is slightly higher than the average national yield assumed in the FASOM model runs. FASOM assumes a potential contribution to ethanol production of dry mill versus wet mill ethanol facilities of 91 percent and 9 percent, respectively, with ethanol yields of 2.71 gallons/bushel and 2.50 gallons/bushel for dry mill and well mill processes, respectively (Beach and McCarl, 2010). As a result, FASOM GHG emissions estimates uses a weighted ethanol conversion factor of 2.69 gallons/bushel for the control case in both 2017 and 2022 (EPA, 2010d). Based on FASOM documentation, if the industry average conversion of 2.76 gallons/bushel is achieved in 2017 and 2022, it could be expected that the number of bushels (and domestic land-use all else equal) to be 2.5 percent lower compared to the estimated values in FASOM for the RIA analysis.

Table 2-9 shows that U.S. corn ethanol production aligns with expected production under the RIA. In the last four years, an average annual 6 percent net overproduction occurred when compared to the control case due to major production volume in the early days (2010–2011) of the RFS2.

On the other hand, assumed land-use impacts may be slightly affected by corn crop yield. USDA long-term projections (Table 2-6) anticipate that corn yield will not reach the assumed crop yield in the Base Yield Scenario in 2017 (175 bu/acre) or in 2022 (185 bu/acre). The difference implies that under USDA crop yields, production of bushels per acre would be 2.2 percent lower potentially resulting in land use for corn ethanol in 2022 (all else equal) being 2.2 percent higher than estimated in the RFS2 RIA Base Yield Scenario. Improvement on ethanol conversion yields could be offset by reduction on crop yield.

Table 2-9: U.S. Ethanol Production and Ethanol Conversion 2007 to 2014

Year	EIA Ethanol Production Calendar Year	Control Case Ethanol Production	Deviation
	Billions of Gallons	Billions of Gallons	
2010	13.30	11.24	15%
2011	13.93	12.07	13%
2012	13.22	12.83	3%
2013	13.29	13.42	−1%
2014	14.31	14.09	2%

2.2.1. Emission Factors Comparison

Straight comparison of land-use change (LUC) emission factors determined by Winrock, Woods Hole, and ARB LCFS AEZ models is limited. The factors are created under different set of parameters that may vary by the user and impact the final value of carbon estimated for a particular LUC. In order to compare the impacts that the use of different emissions factors would have on the GHG emissions estimates for the RFS2 RIA, the emission factors for each country/region have been documented in a consistent unit of measurement (i.e., Mg C/ha).

Table 2-10 compares forest LUC emission factors and illustrates that results vary among countries/regions. For the most part, Woods Hole and ARB LCFS AEZ factors are higher than the Winrock factors, and, hence, their use would provide the highest emission estimates. Total impact depends on the LUC area estimated for each country/regions. In the case of domestic emissions, Winrock emission factors are an approximate middle point between the three different emission factor categories. In the case of international emissions using LUCs estimates by the Global Trade Analysis Project (GTAP) included in the FAPRI model, the highest GHG emissions estimates in forest LUC would result from the use of Woods Hole emission factors. Use of the Winrock and ARB LCFS AEZ model emission factors would provide 35 percent and 24 percent lower emission estimates, respectively.

Table 2-10: Comparison of Winrock, Woods Hole, and ARB LCFS AEZ Model LUC Emission Factors for Forestry (Note: * indicates the highest emission factors among sources)

Country/Region	Winrock	Woods Hole	ARB LCFS AEZ model Country Weighted factor by FAPRI GTAP Area
	Mg C/ha	Mg C/ha	Mg C/ha
United States	125	151.9*	112.50
EU27	107	131.4*	101.41
Brazil	131*	124.9	-
Canada	77	108.2	123.80*
Japan	92	188.2*	133.35
CHIHKG	70	188.2*	154.03
India	100	131.4	196.21*

Country/Region	Winrock	Woods Hole	ARB LCFS AEZ model Country Weighted factor by FAPRI GTAP Area
	Mg C/ha	Mg C/ha	Mg C/ha
C_C_Amer	111	131.4	-
S_o_Amer	87	108.2	-
E_Asia	67	188.2*	86.97
Mala_Indo	219*	188.2	-
R_SE_Asia	143	188.2	228.05*
R_S_Asia	117*	114.9	204.31
Russia	66	151.9*	-
Oth_CEE_CIS	110	151.9*	99.66
R_Europe	85	99.7	107.24*
MEAS_Nafr	95	85.4	112.49*
S_S_Afr	74	108.2	219.70*
Oceania	134	151.9	157.68*

Table 2-11 compares grassland LUC emission factors. In a similar manner to the forestry emission factors, one methodology does not consistently overestimate or underestimate emission factors compared to the other alternatives. Deviations are specific to each country/region. However, in the case of domestic emissions due to grassland LUC, the Winrock emission factor provides the lower emission estimates per unit of area. In the case of international emissions using LUCs estimates by GTAP included in the FAPRI model, the highest GHG emissions estimates in grassland land-use change would result from the use of Woods Hole and ARB AEZ model emission factors. Winrock emission estimates would be 79 percent lower than those obtained in the use of Woods Hole or ARB LCFS AEZ emission factors.

Table 2-11: Comparison of Winrock, Woods Hole, and ARB LCFS AEZ Model LUC Emission Factors for Grasslands (Note: * indicates the highest emission factors among sources)

Country/Region	Winrock	Woods Hole	ARB LCFS AEZ model Country Weighted factor by FAPRI GTAP Area
	Mg C/ha	Mg C/ha	Mg C/ha
United States	11	30.0*	26.79
EU27	21	20.5	73.66*
Brazil	31	46.5*	35.11
Canada	16	28.5	33.44*
Japan	21	54.3	87.25*
CHIHKG	21	54.3*	29.77
India	21	20.5	25.77*
C_C_Amer	29	20.5	69.72*
S_o_Amer	20	28.5	58.47*
E_Asia	15	54.3*	25.93
Mala_Indo	67*	54.3	42.26
R_SE_Asia	28	54.3*	34.78

Country/Region	Winrock	Woods Hole	ARB LCFS AEZ model Country Weighted factor by FAPRI GTAP Area
	Mg C/ha	Mg C/ha	Mg C/ha
R_S_Asia	19	57.3*	22.03
Russia	13	54.3*	35.12
Oth_CEE_CIS	12	54.3*	31.41
R_Europe	13	18.1	34.73*
MEAS_Nafr	17	12.1	21.96*
S_S_Afr	19	28.5	30.20*
Oceania	16	54.3*	25.25

Table 2-12 indicates that only Winrock provides a complete set of emission factors for all different countries/regions in the category of Cropland Pasture. Wood Hole does not provide emission factors under this category and ARB provides only two data points.

Table 2-12: Comparison of Winrock, Wood Hole, and ARB LCFS AEZ Model LUC Emission Factors for Cropland Pasture

Country/Region	Winrock	ARB LCFS AEZ model Country Weighted factor by FAPRI GTAP Area
	Mg C/ha	Mg C/ha
United States	38	14.69
EU27	39	-
Brazil	58	2.11
Canada	32	-
Japan	38	-
CHIHKG	36	-
India	41	-
C_C_Amer	49	-
S_o_Amer	36	-
E_Asia	28	-
Mala_Indo	105	-
R_SE_Asia	58	-
R_S_Asia	43	-
Russia	26	-
Oth_CEE_CIS	32	-
R_Europe	26	-
MEAS_Nafr	36	-
S_S_Afr	33	-
Oceania	45	-

Notice that the variability in emission factors for a specific region highlights the significant impact that economic modeling has on LUC emission estimates.

> *Varying input parameter to the economic model can alter the magnitude and location of projected land conversion* (Plevin et al., 2015).

When using GTAP-BIO-ADV and AEZ-EF models, eleven parameters account for 80 percent of total variance on corn ethanol ILUC emission intensities (57 parameters contribute the remaining 20 percent);

> *the crop yield elasticity with respect to price is by far the most important parameter contributing with nearly 50% in the variance of corn ethanol ILUC emission intensities…Overall, economic model parameters dominate in the top 5 parameters (contributing over 65% of total variance) and the top contributors of `3rd tier` importance came from the emission factor model* (Plevin et al., 2015).

The next sections detail LUC emission factors by source.

2.2.2. Winrock Emission Factors

For the RIA, Winrock International conducted an analysis of historical land-use trends using MODIS satellite imagery from 2001 and 2004. The analysis indicates which land-use types decreased or increased at the country level during this time period. Winrock calculated the GHG emissions resulting from this projected land-use change by compiling world wide data on carbon stock of different land types. Winrock emission factors account for changes in above and below-ground biomass carbon stocks, changes in soils carbon stocks, lost forest sequestration, land clearing with firing, and emissions from rice cultivation. Winrock followed Intergovernmental Panel on Climate Change (IPCC) (2006) guidelines when calculating the change in carbon stocks resulting from the projected land-use changes (ICF International, 2009).

Table 2-13: Winrock LUC GHG Emission Factors for United States in Units of CO_2e/hectare

Conversion	Conversion	Conversion	Reversion	Reversion	Reversion
Forest	Grassland	Cropland Pasture	Crop	Crop	Crop
Crop	Crop	Crop	Forest	Grassland	Cropland Pasture
Mg CO_2e/ha	Mg CO_2e/ha	Mg CO_2e/ha	Mg CO_2e/ha	Mg CO_2e/ha	Mg CO_2e/ha
458	41	138	−237	−41	−138

Source: Winrock emission factors as cited in Dunn et al., 2014, cells J79:O83

Table 2-14: Winrock LUC GHG Emission Factors for United States in Units of C/hectare

Conversion	Conversion	Conversion	Reversion	Reversion	Reversion
Forest	Grassland	Cropland Pasture	Crop	Crop	Crop
Crop	Crop	Crop	Forest	Grassland	Cropland Pasture
Mg C/ha	Mg C/ha	Mg C/ha	Mg C/ha	Mg C/ha	Mg C/ha
125	11	38	−65	−11	−38

Source: Winrock emission factors as cited in Dunn et al., 2014, cells D79:I83

Table 2-15: Winrock LUC GHG Emission Factors—International

Country/Region	Conversion Forest Crop Mg C/ha	Conversion Grassland Crop Mg C/ha	Conversion Cropland Pasture Crop Mg C/ha	Reversion Crop Forest Mg C/ha	Reversion Crop Grassland Mg C/ha	Reversion Crop Cropland Pasture Mg C/ha
EU27	107	21	39	−29	−21	−39
Brazil	131	31	58	−111	−30	−54
Canada	77	16	32	−42	−16	−32
Japan	92	21	38	−85	−21	−38
CHIHKG	70	21	36	−72	−21	−36
India	100	21	41	−73	−21	−39
C_C_Amer	111	29	49	−94	−29	−47
S_o_Amer	87	20	36	−72	−20	−35
E_Asia	67	15	28	−59	−15	−27
Mala_Indo	219	67	105	−165	−36	−71
R_SE_Asia	143	28	58	−119	−28	−54
R_S_Asia	117	19	43	−81	−19	−41
Russia	66	13	26	−36	−13	−26
Oth_CEE_CIS	110	12	32	−62	−12	−32
R_Europe	85	13	26	−52	−13	−26
MEAS_Nafr	95	17	36	−82	−17	−35
S_S_Afr	74	19	33	−48	−18	−31
Oceania	134	16	45	−80	−16	-45

Source: Winrock emission factors as cited in Dunn et al., 2014, cells D90:I111

Winrock provides 30-year emission factors that are developed for three different periods following the land transition. For international emission factors Dunn et al. (2014)[11] summarize the method in the following equation:

$$EF_{30} = EF_1 + 19 \times EF_{2\text{–}19} + 10 \times \mathrm{EF}_{20\text{–}80}$$

where EF_{30} = GHG emissions 30 years after the transition [Mg CO_2e/ha]; EF_1 = GHG emissions in the first year after the transition [Mg CO_2e/ha]; $EF_{2\text{–}19}$ = GHG emissions in years 2 through 19 after the transition [Mg CO_2e/ha]; and $EF_{20\text{–}80}$ = GHG emissions in years 20 through 80 after the transition [Mg CO_2e/ha]. Complete details of the development of the Winrock emission factors are contained in Harris et al. (2009[12]).

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[11] Dunn JB, Qin Z, Mueller S, Kwon H, Wander M, Wang M (2014) Carbon Calculator for Land Use Change from Biofuels Production (CCLUB), Users' Manual and Technical Documentation (No. ANL/ESD/12-5 Rev. 2). Argonne National Laboratory (ANL). Available at: https://greet.es.anl.gov/publications.

[12] Harris NL, Grimland S, Brown S (2009) Land use change and emission factors: Updates since proposed RFS rule. Report submitted to EPA, Available at Docket ID #EPA-HQ-OAR-2005- 0161-3163, www.regulations.gov

2.2.3. Woods Hole Emission Factors

Woods Hole emission factors include C-Release Weighted values by Ecosystem for Above Ground, Below Ground, and Annual Growth components. The emission factors (see Table 2-16 and Table 2-17) result from several assumptions:

- Above Ground emission factors are based on estimated areas for the six (6) different Ecosystem Subclasses, assumptions about the percentage of area in each ecosystem that is converted to biofuel feedstock production, an estimated carbon content in the vegetation for each Ecosystem Subclass, and the assumption that 75 percent of such carbon is released during conversion.
- Below Ground emission factors are based on the percentage of area in each ecosystem that is converted to biofuel feedstock production, an estimated carbon content in soil for each Ecosystem Subclass, and the assumption that 25 percent of such carbon is release during conversion.
- Annual Growth emission factors are based on the percentage of area in each ecosystem that is converted to biofuel feedstock production, and an estimated carbon sequestration value for each Ecosystem Subclass. Five (5) of the ecosystem subclasses would sequester carbon when mature. Computed final emission factor uses an assumption of 30 years for feedstock production (Foregone C-Sequestration Period). Similar to Winrock, these emission factors have been estimated using CCLUB to represent emission during a 30-year duration of biofuels production.

Table 2-16: Woods Hole C-Release Weighted by Ecosystem for United States

	Non-Soil Above Ground Biomass	Below Ground Biomass	Annual Growth/Foregone Sequestration	Emissions
	(Mg C/ha)	(Mg C/ha)	(Mg C/ha)	(Mg C/ha)
FORESTLAND	113.2	34.6	0.402	159.9
CROPLAND	0.0	0.0	0.000	0
GRASSLAND	10.0	20.0	0.000	30

Source: Woods Hole as cited in Dunn et al., 2014, cells I72, I74, I76, M72, M74, M76, R72, R74, R76.

Table 2-17: Woods Hole C-Release Weighted by Ecosystem in Forest Internationally

Region	Forest Below Ground	Forest Non-Soil	Forest Annual Growth	Forest Emissions
	$Mg\ C\ ha^{-1}$	$Mg\ C\ ha^{-1}$	$Mg\ C\ ha^{-1} yr^{-1}$	$Mg\ C\ ha^{-1}$
EU27	32.3	82.0	1.3	151.9
BRAZIL	23.8	102.2	0.2	131.4
CAN	48.7	74.0	0.1	124.9
JAPAN	23.4	74.8	0.3	108.2
CHIHKG	23.7	138.6	0.9	188.2

Region	Forest	Forest	Forest	Forest
	Below Ground	Non-Soil	Annual Growth	Emissions
	Mg C ha^{-1}	Mg C ha^{-1}	Mg C $ha^{-1}yr^{-1}$	Mg C ha^{-1}
INDIA	23.7	138.6	0.9	188.2
C_C_Amer	23.8	102.2	0.2	131.4
S_o_Amer	23.8	102.2	0.2	131.4
E_Asia	23.4	74.8	0.3	108.2
Mala_Indo	23.7	138.6	0.9	188.2
R_SE_Asia	23.7	138.6	0.9	188.2
R_S_Asia	23.7	138.6	0.9	188.2
Russia	42.0	65.0	0.3	114.9
Oth_CEE_CIS	32.3	82.0	1.3	151.9
R_Europe	32.3	82.0	1.3	151.9
MEAS_NAfr	22.2	54.9	0.8	99.7
S_S_AFR	31.6	51.9	0.1	85.4
Oceania	23.4	74.8	0.3	108.2

Table 2-18: Woods Hole C-Release Weighted by Ecosystem in Grassland Conversion Internationally

Region	Grassland	Grassland	Grassland	Grassland
	Below Ground	Non-Soil	Annual Growth	Emissions
	Mg C ha^{-1}	Mg C ha^{-1}	Mg C $ha^{-1}yr^{-1}$	Mg C ha^{-1}
EU27	47.3	7.0	0.00	54.3
BRAZIL	13.8	6.7	0.00	20.5
CAN	41.4	5.1	0.00	46.5
JAPAN	10.5	18.0	0.00	28.5
CHIHKG	47.3	7.0	0.00	54.3
INDIA	47.3	7.0	0.00	54.3
C_C_Amer	13.8	6.7	0.00	20.5
S_o_Amer	13.8	6.7	0.00	20.5
E_Asia	10.5	18.0	0.00	28.5
Mala_Indo	47.3	7.0	0.00	54.3
R_SE_Asia	47.3	7.0	0.00	54.3
R_S_Asia	47.3	7.0	0.00	54.3
Russia	47.3	10.0	0.00	57.3
Oth_CEE_CIS	47.3	7.0	0.0	54.3
R_Europe	47.3	7.0	0.00	54.3
MEAS_NAfr	14.3	3.8	0.00	18.1
S_S_AFR	7.5	4.6	0.00	12.1
Oceania	10.5	18.0	0.00	28.5

Source: Woods Hole as cited in Dunn et al., 2014, cells B73:T93.
Assumption: Input 6: Feedstock Production Years (Foregone C-Sequestration Period) = 30 years
Production Years (Foregone C-Sequestration Period) = 30 years

2.2.4. Air Resources Board Low-Carbon Fuel Standard Agro-Ecological Zone Model

The Air Resources Board (ARB) Low-Carbon Fuel Standard (LCFS) Agro-Ecological Zone (AEZ) model provides U.S. and international LUC emission factors for the conversion of forestry, pasture, cropland pasture, and annuals. The model emission factors are disaggregated by world region and agro-ecological zones (AEZs). The model is consistent with the 19 regions and 18 zones reported by GTAP-BIO (GTAP biofuels) model. As a result, the model combines matrices of carbon fluxes (Mg CO_2 $ha^{-1}yr^{-1}$) with matrices of changes in land use (ha) according to land-use category as projected by the GTAP-BIO model. The model also includes indexed carbon stock estimates (MgC ha^{-1}) for biomass and soil carbon by the GTAP AEZ and region. The model uses assumptions about carbon loss from soils, biomass, mode of conversion, quantity and species of carbonaceous, and other GHG emissions resulting from conversion and carbon remaining in harvested wood products and char, and foregone sequestration (CARB, 2015). The full analytic time horizon used in AEZ-EF model is 30 years (Plevin et al, 2015[13]).

Table 2-19 shows the emission factors for Forest to Annuals, Pasture to Annuals, and CroplandPasture to Annuals that can be compared to the emission factors developed by Winrock or Woods Hole. In order to do a comparison, the emission factors that are provided by region and AEZ should be converted into equivalent emission factors by country/region. The country/region equivalent emission factors are weighted based on LUC area in each AEZ estimated by GTAP. Table 2-20 shows the equivalent emission factors.

[13] Plevin et al.,2015. Carbon Accounting and Economic Model Uncertainty of Emissions from Biofuels-Induced Land Use Change. Environmental Science & Technology, 49(5). March 3, 2015. http://escholarship.org/uc/item/9wz1r8gf

Table 2-19: AEZ LUC Emission Factors Model v.52 (CO_2e/ha)

AEZ	United States	EU27	Brazil	Canada	Japan	ChiHkg	India	C_C_Amer	S_o_Amer	E_Asia	Mala_Indo	R_SE_Asia	R_S_Asia	Russia	Oth_CEE_CIS	Oth_Europe	ME_N_Afr	S_S_Afr	Oceania
Forestry-to-Annuals																			
1	0	0	380	0	0	0	278	338	465	0	0	0	250	0	0	0	523	505	436
2	0	0	403	0	0	0	503	734	551	0	0	0	0	0	0	0	495	505	459
3	0	0	502	0	0	0	696	715	487	0	0	0	643	0	0	0	390	483	711
4	0	524	637	0	0	141	778	1055	651	585	998	829	728	0	0	0	434	571	811
5	0	0	853	0	0	719	830	1075	765	583	1010	848	837	0	0	0	0	796	863
6	0	0	925	0	0	807	905	1013	915	603	1017	885	859	0	0	0	0	937	1076
7	376	0	0	243	0	287	181	773	344	193	0	0	241	257	261	0	492	390	310
8	411	262	0	361	0	292	325	799	349	218	0	0	416	314	352	0	449	384	454
9	439	325	0	505	371	364	477	525	445	235	0	0	453	325	358	111	412	415	458
10	441	372	564	466	501	519	507	732	556	330	0	584	576	384	369	398	434	382	486
11	419	401	442	501	544	558	600	756	608	338	0	653	621	380	326	354	0	399	496
12	398	399	636	0	395	571	670	860	714	341	0	677	657	206	397	0	0	491	586
13	243	197	0	293	0	211	561	0	461	225	0	0	437	195	202	113	0	0	0
14	255	212	0	369	0	202	434	0	578	227	0	0	457	198	193	181	0	0	0
15	291	376	0	429	344	208	489	0	587	220	0	580	585	215	203	399	0	0	404
16	395	281	0	567	0	226	584	0	755	0	0	709	663	243	233	375	0	0	516
17	0	0	0	0	0	197	0	0	817	0	0	0	0	0	0	0	0	0	641
18	0	0	0	0	0	0	0	0	722	0	0	0	0	0	0	0	0	0	0
Pasture-to-Annuals																			
1	0	0	78	0	0	0	49	72	83	0	0	0	62	0	0	0	69	59	67
2	0	0	68	0	0	0	82	177	139	0	0	0	0	0	0	0	73	66	77
3	0	0	92	0	0	0	88	174	105	0	0	0	89	0	0	0	84	90	90
4	0	154	124	0	0	29	106	442	202	114	140	121	125	0	0	0	99	117	119
5	0	0	123	0	0	202	132	313	224	108	140	126	139	0	0	0	0	186	85

AEZ	United States	EU27	Brazil	Canada	Japan	ChiHkg	India	C_C_Amer	S_o_Amer	E_Asia	Mala_Indo	R_SE_Asia	R_S_Asia	Russia	Oth_CEE_CIS	Oth_Europe	ME_N_Afr	S_S_Afr	Oceania
6	0	0	125	0	0	134	135	253	394	84	160	150	130	0	0	0	0	125	191
7	91	0	0	104	0	103	54	165	83	107	0	0	68	96	80	0	77	45	70
8	99	110	0	119	0	93	86	192	99	117	0	0	71	128	94	0	79	47	78
9	113	145	0	319	333	78	88	159	162	108	0	0	96	153	126	0	89	83	79
10	123	272	143	196	329	101	126	553	129	112	0	102	113	249	239	168	104	99	109
11	111	309	84	111	347	119	138	155	253	112	0	119	182	168	164	116	0	124	120
12	103	291	161	0	347	131	124	463	215	82	0	119	197	124	162	0	0	225	193
13	53	64	0	16	0	78	43	0	83	56	0	0	45	62	57	27	0	0	0
14	65	69	0	65	0	77	63	0	78	74	0	0	46	68	61	46	0	0	0
15	106	80	0	65	147	85	59	0	70	82	0	74	66	99	70	40	0	0	66
16	204	262	0	94	0	112	82	0	78	0	0	106	77	106	94	225	0	0	86
17	0	0	0	0	0	97	0	0	78	0	0	0	0	0	0	0	0	0	94
18	0	0	0	0	0	0	0	0	55	0	0	0	0	0	0	0	0	0	0
CroplandPasture-to-Annuals																			
1	0	0	39	0	0	0	25	36	42	0	0	0	31	0	0	0	34	29	34
2	0	0	34	0	0	0	41	89	70	0	0	0	0	0	0	0	36	33	38
3	0	0	46	0	0	0	44	87	52	0	0	0	45	0	0	0	42	45	45
4	0	77	62	0	0	15	53	221	101	57	70	61	63	0	0	0	49	59	60
5	0	0	62	0	0	101	66	156	112	54	70	63	70	0	0	0	0	93	42
6	0	0	63	0	0	67	68	126	197	42	80	75	65	0	0	0	0	63	96
7	45	0	0	52	0	51	27	83	42	53	0	0	34	48	40	0	38	23	35
8	50	55	0	60	0	47	43	96	49	58	0	0	35	64	47	0	40	24	39
9	56	72	0	159	167	39	44	79	81	54	0	0	48	76	63	0	45	42	39
10	62	136	72	98	164	51	63	277	65	56	0	51	56	124	119	84	52	50	54
11	56	155	42	56	173	59	69	78	127	56	0	60	91	84	82	58	0	62	60
12	52	145	80	0	173	66	62	232	108	41	0	60	98	62	81	0	0	112	96

AEZ	United States	EU27	Brazil	Canada	Japan	ChiHkg	India	C_C_Amer	S_o_Amer	E_Asia	Mala_Indo	R_SE_Asia	R_S_Asia	Russia	Oth_CEE_CIS	Oth_Europe	ME_N_Afr	S_S_Afr	Oceania
13	27	32	0	8	0	39	22	0	42	28	0	0	23	31	28	13	0	0	0
14	33	35	0	33	0	39	31	0	39	37	0	0	23	34	31	23	0	0	0
15	53	40	0	33	74	42	30	0	35	41	0	37	33	49	35	20	0	0	33
16	102	131	0	47	0	56	41	0	39	0	0	53	39	53	47	113	0	0	43
17	0	0	0	0	0	48	0	0	39	0	0	0	0	0	0	0	0	0	47
18	0	0	0	0	0	0	0	0	28	0	0	0	0	0	0	0	0	0	0

Source: Plevin, 2014.

Table 2-20: AEZ Model v.52 LUC Emission Factors Weighted by AEZ LUC Estimated by GTAP

AEZ Region	Forestry-to-Annuals	Pasture-to-Annuals	CroplandPasture-to-Annuals	Forestry-to-Annuals	Pasture-to-Annuals	CroplandPasture-to-Annuals
	Mg CO_2e/ha	Mg CO_2e/ha	Mg CO_2e/ha	Mg C/ ha	Mg C/ ha	Mg C/ ha
United States	412.52	98.24	53.86	112.50	26.79	14.69
EU27	371.82	270.09	-	101.41	73.66	-
BRAZIL	-	128.72	7.74	-	35.11	2.11
CAN	453.94	122.62	-	123.80	33.44	-
JAPAN	488.94	319.92	-	133.35	87.25	-
CHIHKG	564.78	109.16	-	154.03	29.77	-
INDIA	719.42	94.50	-	196.21	25.77	-
C_C_Amer	-	255.62	-	-	69.72	-
S_o_Amer	-	214.40	-	-	58.47	-
E_Asia	318.88	95.08	-	86.97	25.93	-
Mala_Indo	-	154.95	-	-	42.26	-
R_SE_Asia	836.18	127.51	-	228.05	34.78	-
R_S_Asia	749.15	80.77	-	204.31	22.03	-
Russia	-	128.78	-	-	35.12	-
Oth_CEE_CIS	365.43	115.15	-	99.66	31.41	-
Oth_Europe	393.22	127.34	-	107.24	34.73	-
MEAS_Nafr	412.46	80.51	-	112.49	21.96	-
S_S_Afr	805.55	110.74	-	219.70	30.20	-
Oceania	578.15	92.58	-	157.68	25.25	-

2.2.5. References: Domestic Land-Use Change

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2.3. Domestic Rice Methane

A review of the current literature shows that U.S. rice production and corresponding methane emissions have remained relatively constant between 1990 through 2013. Harvested acres of rice have fluctuated between ≈2.5 and 3.6 million acres, and emissions have fluctuated between 7.7 and 11.1 million metric tons CO_2 equivalent (MMT CO_2e) (USDA ERS, 2015; EPA, 2015). The RFS2 RIA FASOM has higher projections for future harvested rice acres than the current USDA Projections (USDA OCE, 2016). For example, both the Control Case and the Reference Case have higher predicted harvested acres of rice in 2012 (3.8 million acres for the Reference Case and 3.35 million acres for the Control Case) than were actually harvested in eight of the last nine years with 2010 as the only exception (USDA 2015).

Use of the RFS2 RIA emission factors for rice would under-estimate methane production from rice cultivation in most regions between 1990 and 2013 when compared to effective emission factors from the EPA Inventory (EPA, 2015). For example, the RFS2 RIA emission factor for the south central region (where approximately70 percent of all rice production occurs) is 2,249.20 kg CO_2e/acre compared to the effective Inventory emission factor which ranges from approximately 2,800 to 3,100 kg CO_2e/acre between 1990–2013. The total projected 2012 rice methane emissions from the RFS2 RIA are nearly double those of the EPA inventory despite the lower emission factors in the RFS2 RIA. The RFS2 RIA estimated 2012 emissions are 17.8 MMTons CO_2e for the Control Case and 18.41 MMT CO_2e for the Reference Case compared to 9.29 MMT CO_2e from the EPA inventory and 8.78 MMT CO_2e from the Food and Agriculture Organization of the United Nations (FAO). The RFS2 RIA values seem inexplicably high given the RFS2 RIA estimated acreage and the RFS2 RIA emission factors used. As the RFS2 RIA did not provide all of the necessary underlying data, we could not reproduce the RFS2 RIA total emissions to compare values to recent data.

2.3.1. Background on Methane from Rice Production

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 where drainage does not occur except by accident (EPA, 2015). 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 minor 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, 2015).

The amount of methane produced by rice cultivation is influenced by multiple factors (EPA, 2015; Garthorne-Hardy, 2013; Hussain et al., 2015), 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
- Soil type
- Rice cultivar
- Cultivation practices (e.g., tillage, seeding and weeding practices)

2.3.2. Number of crops per season (e.g., primary and ratoon crop) U.S. Rice Production Area

Rice is currently produced in seven states: Arkansas, California, Louisiana, Mississippi, Missouri, and Texas, and rice was produced in Oklahoma through 2007 (EPA, 2015; USDA ERS, 2015a). Figure 2-4 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).

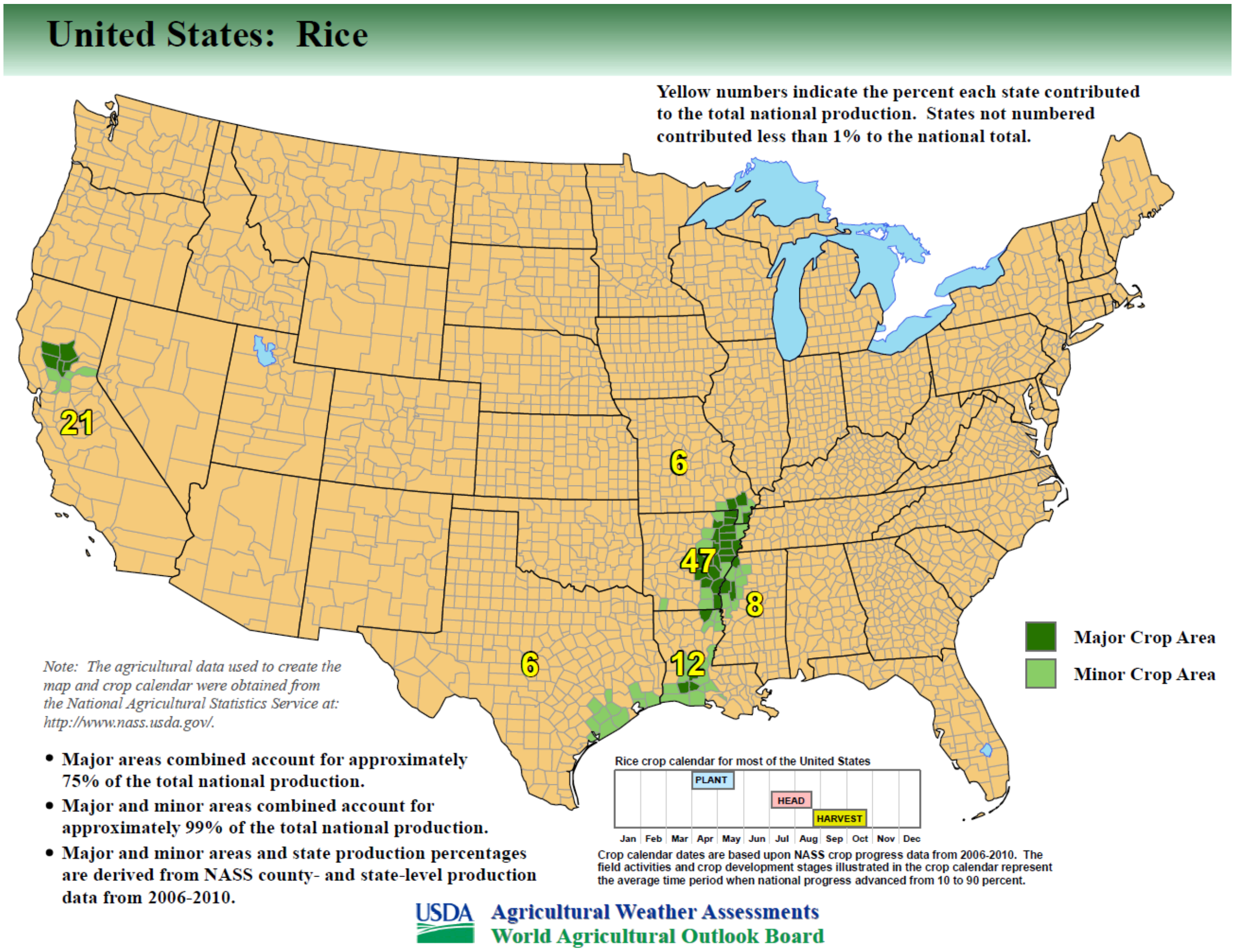

Figure 2-4: U.S. Map of Average 2006–2010 Major and Minor Rice Crop Areas

Figure 2-5 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 stat contributed to the total national production.

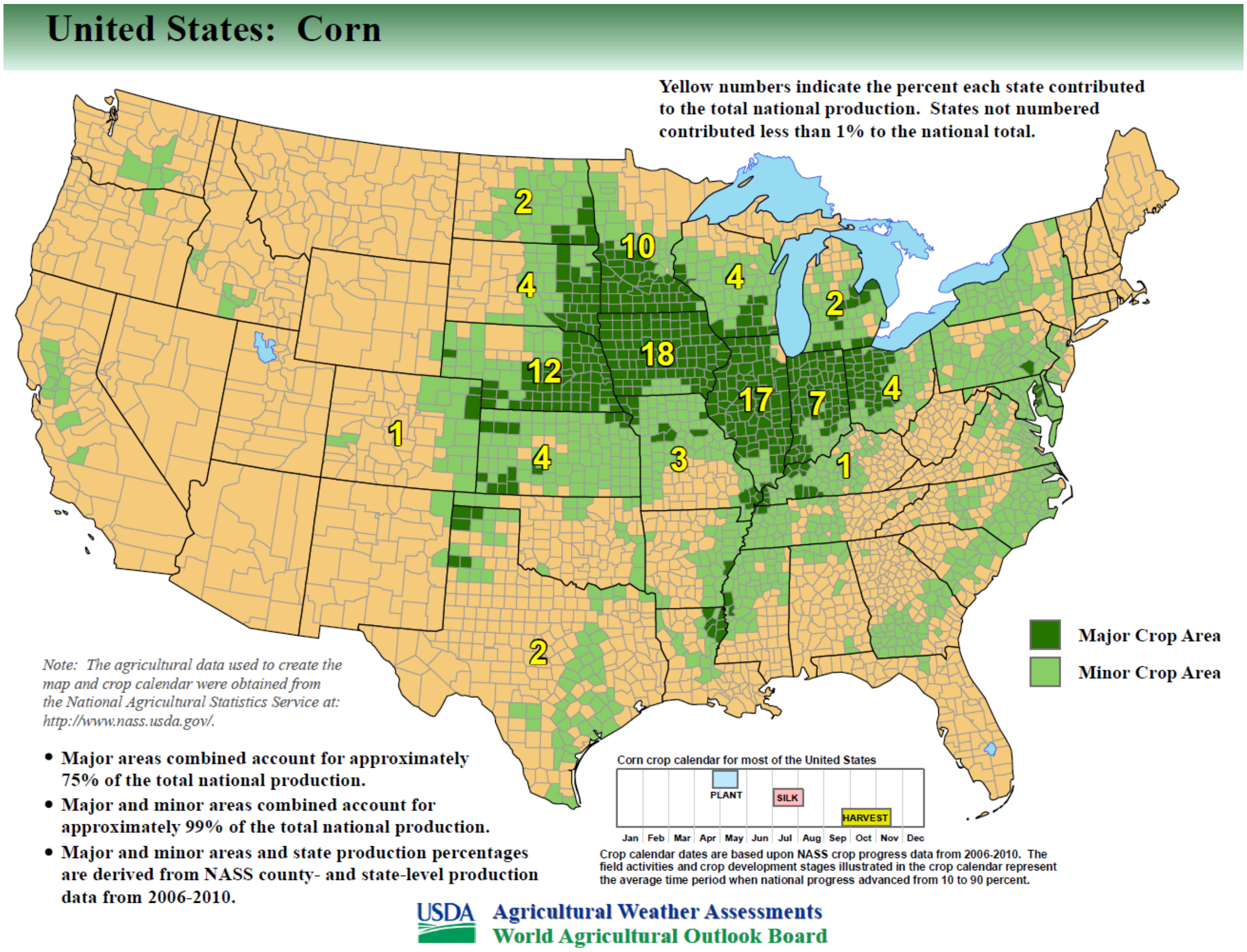

Figure 2-5: U.S. Map of Average 2006–2010 Major and Minor Corn Crop Areas

Comparison of 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 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).

Over the past 60 years, harvested rice acreage has fluctuated, but has shown an overall increase in area from 1,815,000 acres in 1959 to 2,919,000 acres in 2014 (USDA ERS, 2015b). In more recent years, rice acreage has remained relatively consistent fluctuating from 2,823,000 acres in 1990 to 3,615,000 acres in 2010 and back to 2,919,000 acres in 2014 (USDA ERS, 2015b). Table 2-21 presents acres of planted and harvested rice from 1990–2014 and projections of harvested rice for 2014–2023 from multiple sources, including the RIA (see table for more details on data sources). The same data are presented graphically in Figure 2-6. Harvested acres in the U.S. GHG inventory are consistently higher than harvested acres in the USDA Rice Yearbook over the entire time period (likely due to the inclusion of both the primary and the ratoon crop harvested acres in the U.S. inventory).

Table 2-21: 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 Reference Case[c]	Area Harvested USDA Projections[d]
1990	2.897	2.823	3.128	-	-	-
1991	2.884	2.781	3.071	-	-	-
1992	3.176	3.132	3.458	-	-	-
1993	2.920	2.833	3.111	-	-	-
1994	3.353	3.316	3.644	-	-	-
1995	3.121	3.093	3.391	-	-	-
1996	2.824	2.804	3.083	-	-	-
1997	3.125	3.103	3.382	-	-	-
1998	3.285	3.257	3.557	-	-	-
1999	3.531	3.512	3.801	-	-	-
2000	3.060	3.039	3.338	-	-	-
2001	3.334	3.314	3.564	-	-	-
2002	3.240	3.207	3.363	-	-	-
2003	3.022	2.997	3.223	-	-	-
2004	3.347	3.325	3.561	-	-	-
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	3.821	-
2013	2.490	2.469	2.776	-	-	-
2014	2.939	2.919	-	-	-	2.919
2015	-	-	-	-	-	2.570
2016	-	-	-	-	-	2.771
2017	-	-	-	3.722	4.032	2.796
2018	-	-	-	-	-	2.824
2019	-	-	-	-	-	2.824
2020	-	-	-	-	-	2.849
2021	-	-	-	-	-	2.858
2022	-	-	-	3.871	4.267	2.883
2023	-	-	-	-	-	2.883

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

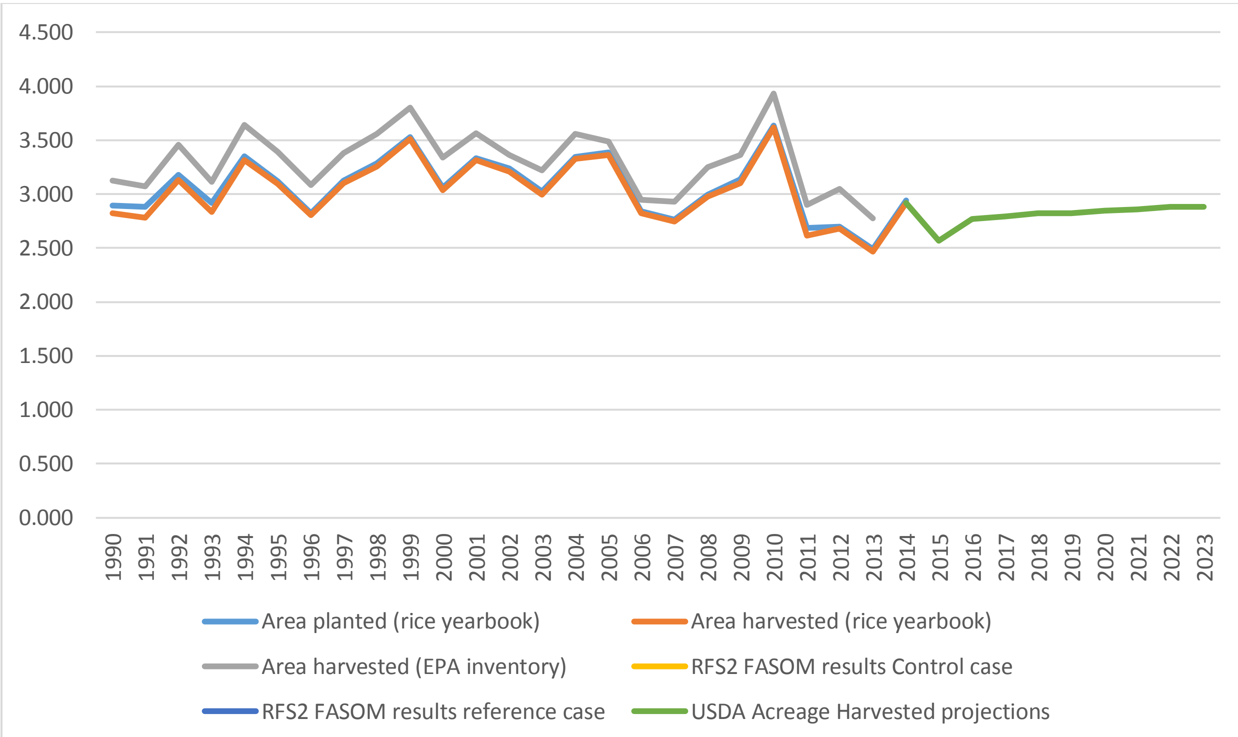

Figure 2-6: U.S. Planted and Harvested Rice (millions of acres)

2.3.3. U.S. Methane Emission Factors for Rice Production

For the RFS2 EIA, EPA used regional changes in rice cultivation area predicted by 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). The RFS2 RIA did not differentiate between primary and ratoon rice crops (the second rice crop grown in a season) and assumed that the reduction of rice acreage was the only method to reduce emissions related to rice cultivation.

In contrast, for inventories up to and including the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2011* (EPA, 2013) (during the period when the RFS2 RIA was developed), estimates for methane emissions from rice were based on the revised 1996 IPCC Guidelines[14] 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, 2014), subsequent inventories (EPA, 2015, EPA, 2016) updated the rice emission factors for specific regions. Table 2-22 presents the two sets of emission factors using the same regional break down as the RFS2 RIA used.

Table 2-22: Rice Methane Emission Factors from the Inventory of U.S. Greenhouse Gas Emissions and Sinks

Region	EPA Emission factors (1994–2013)		EPA emission factors (2014)	
	(kg CO_2e/acre/season or year)			
	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 RFS2 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 factor from the Inventory data we:

1. Put each rice producing state into the corresponding RFS2 RIA region category
2. Added up total emissions in that RFS2 RIA region annually from 1990–2013
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 RFS2 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 1990–2013 and RFS2 RIA emission factors is shown in Table 2-23. The RIA values are not annual values and, hence, are provided in the last row of the table.

[14] 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 2000).

Table 2-23: Comparison of Inventory (1990–2013) and RFS2 RIA (See Last Row) Effective Emissions Factors (kg CO_2e/acre)

Year	EPA Inventory Emission Factors by Region					
	South Central	Pacific Southwest	Southeast	Corn Belt	Southwest	United States
1990	2,815	2,149	4,230	2,399	3,963	2,910
1991	2,791	2,149	4,230	2,399	3,965	2,902
1992	2,814	2,149	4,230	2,399	3,968	2,902
1993	2,802	2,149	4,230	2,399	3,965	2,870
1994	2,801	2,149	4,230	2,399	3,965	2,873
1995	2,795	2,149	4,230	2,399	3,965	2,862
1996	2,823	2,149	4,230	2,399	3,968	2,870
1997	2,801	2,149	4,230	2,399	3,968	2,825
1998	2,799	2,149	4,230	2,399	3,968	2,841
1999	2,769	2,149	4,555	2,399	3,966	2,797
2000	2,857	2,149	3,994	2,399	4,226	2,859
2001	2,747	2,149	4,465	2,399	3,965	2,760
2002	2,585	2,149	4,321	2,399	3,879	2,625
2003	2,775	2,149	5,145	2,399	3,910	2,753
2004	2,753	2,149	4,792	2,399	3,821	2,731
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
RIA	2,249	1,783	N/A	1,826	4,375	N/A

The comparison of emission factors shows that the in general, the RFS2 RIA emission factors are lower than the effective emission factors for the inventory. Specifically the RFS2 RIA emission factors for the South Central, Pacific Southwest, and Corn Belt regions are lower than the effective inventory emission factors from 1990–2013. In contrast, the RFS2 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 RFS2 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 RFS2 RIA most likely underestimates total change in U.S. methane emissions from rice production due to the likely underestimation in the respective emission factors used for these regions.

2.3.4. Annual U.S. Methane Emissions from Rice Production

Similar to acreage harvested, annual methane emissions from rice production have fluctuated from 1990 through 2013, but have remained overall relatively constant. Emissions were 9.2 $MMTCO_2e$ in 1990 and 8.3 $MMTCO_2e$ in 2013 (EPA, 2015). The only RFS2 RIA methane emissions data for the Control Case or the Reference Case that we could find was for 2012 (EPA, 2009). Table 2-24 shows both EPA and FAO estimates for methane emissions from U.S. rice production from 1990–2013 and the the RFS2 RIA projection for 2012.

Table 2-24: Past and Projected Emissions from U.S. Rice Production ($MMTCO_2e$)

Year	Emissions from Rice Cultivation (U.S. Inventory)[a]	Emissions from Rice Cultivation (FAO data)[b]	Emissions from Rice Cultivation Control Case (RFS2 RIA data)[c]	Emissions from Rice Cultivation Reference Case (RFS2 RIA data)[c]
1990	9.16	9.26		
1991	9.01	9.12		
1992	10.14	10.27		
1993	9.03	9.29		
1994	10.57	10.87		
1995	9.81	10.14		
1996	8.94	9.19		
1997	9.63	10.17		
1998	10.19	10.68		
1999	10.71	11.52		
2000	9.62	9.96		
2001	9.89	10.87		
2002	8.88	10.52		
2003	8.91	9.83		
2004	9.77	10.9		
2005	8.95	11.03		
2006	7.7	9.25		
2007	7.99	9.01		
2008	9.26	9.76		
2009	9.44	10.17		
2010	11.1	11.85		
2011	8.47	8.58		
2012	9.29	8.78	17.8	18.41
2013	8.3	-		

[a] EPA (2015). (Includes both primary and ratoon acres.)
[b] FAO (2015a).
[c] EPA (2009).

The data show that FAO emissions projections[15] are slightly higher than EPA inventory data for all historic years except for 2012 where the FAO emissions projections are slightly lower than those from the EPA inventory. The total projected 2012 rice methane emissions from the RFS2 RIA are nearly double those of the EPA inventory and the FAO, despite the fact that the RFS2 RIA has lower emission factors than the EPA inventory. The RFS2 RIA estimated 2012 emissions are 17.8 MMT CO_2e for the Control Case and 18.41 MMT CO_2e for the Reference Case compared to 9.29 MMT CO_2e from the EPA inventory and 8.78 MMT CO_2e from the FAO. The RFS2 RIA values seem high given the RFS2 RIA estimated acreage and the RFS2 RIA emission factors used. However, as the RFS2 RIA did not provide all the data used to create the total emissions numbers, we cannot evaluate the underlying assumptions or data used to develop emission values used in the RFS2 RIA to compare values to updated data.

2.3.5. Conclusions

A review of the current literature shows that U.S. rice production and corresponding methane emissions have remained relatively constant between 1990 through 2013 despite the expansion in corn and corn ethanol production. Harvested acres of rice have fluctuated between approximately 2.5 and 3.6 million acres, and emissions have fluctuated between 7.7 and 11.1 $MMTCO_2e$ during this period (USDA ERS, 2015; EPA, 2015). In comparison with the EPA inventory data, the RFS2 RIA FASOM data overestimates harvested rice acreage in 2012 and underestimates rice emission factors in most regions, when compared to effective emissions factors from the EPA inventory between 1990 and 2013. However, the RFS2 RIA total projected 2012 rice methane emissions are nearly double those of the EPA inventory and the FAO, despite the lower emission factors in the RFS2 RIA.

2.3.6. References: Domestic Rice Methane

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2.4. Domestic and International Livestock

Aligned with EPA's final Regulatory Impact Analysis (RIA) (EPA, 2010a) for the revised Renewable Fuel Standard Program (RFS2), the Domestic and International Livestock emission categories includes emissions, both domestically and internationally, related to domestic corn ethanol production and livestock production systems. Internationally we summarize the literature related to emissions associated with livestock production systems in various regions with whom the United States has significant agricultural and energy trade. Impacts internationally are projected to vary by livestock and ethanol feedstock (corn, soy, sugarcane, and switchgrass).

Livestock production systems include practices that involve raising livestock for meat, eggs, dairy, and other products such as leather, fur, and wool. Farmers and other facility operators raise animals in either confined, semi-confined, or unconfined spaces. Literature incorporated into this review is mostly limited to considering variables related to corn ethanol production, such as changes in livestock production that affect the cultivation and use of corn, including use of corn-based feed (including distillers grains), land-use demands for domestic livestock production (range, feedlots, pasture), trends in typical animal mass (TAM), total population, and the amount of meat and dairy from each animal.

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).

2.4.1. Livestock Emission Sources

Although there are emissions associated with livestock production that are not directly emitted from livestock and their waste (such as due to transportation, animal feed production, or dairy/meat processing), this literature review focuses on the two primary sources of emissions from livestock included in the RFS2 RIA: enteric fermentation and manure management. Enteric fermentation produces methane ("enteric CH_4") and manure management practices result in emissions of CH_4 and nitrous oxide (N_2O).

2.4.1.1. 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 emissions are also produced by monogastric (non-ruminant, e.g., swine) livestock but at a magnitude much lower than for ruminant livestock.

Methane emissions from enteric fermentation depend on a combination of the following factors: predominant animal types, the quantity and quality of the diet, use of dietary additives, and the animals' activity data (e.g., work performed, pregnancy rates) (ICF International, 2013; Eve et al., 2014).

The literature also indicates that a significant component in determining enteric emissions is dietary composition, which consists of overall feed intake and feed 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 food 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; increasing dietary fat content; and additives can decrease enteric CH_4 emissions from cattle (ICF International, 2013; Eve et al., 2014; Gerber et al., 2013). Diets rich in biofuel crop residues like distillers grains can have a higher fat content, helping to reduce enteric emissions from cattle (Lemenager et al., 2006; Latour and Schinckel, 2007). Expansion of the ethanol industry led to increased demand for corn and an increased supply of co-products from the ethanol production processes (USDA, 2009). Ethanol co-products have the potential to serve as both an economic source of cattle feed (USDA, 2009) and a means to reduce enteric emissions. However, the inclusion of additives, such as ionophores, nitrates, and tannins, have unclear long-term benefits in terms of reducing enteric CH_4 emissions.

At least one study concludes that cattle consuming steam-flaked corn (SFC)-based diets produce less enteric CH_4 and preserve more energy than cattle that consume dry-rolled corn (DRC)-based diets. However, inclusion of wet distillers grains with solubles (WDGS) at 30 percent of feed composition has little effect on enteric CH_4 production and energy metabolism (Hales et al., 2012). Another study concludes that, compared with use of WDGS, using corn or wheat based DDGs in finishing cattle's diets reduced enteric CH_4 emissions by 1 percent and 0.8 percent, respectively (Wunerberg et al., 2013).

Cows in intensive dairy production systems are typically fed high ratios of forages to concentrates. Feed often includes corn silage, alfalfa/ grass silage, alfalfa hay, high-moisture corn, soybean meal, and sometimes commodity feeds (e.g., corn gluten and/or dried distillers grains (DDG)). Dairy cows are fed diets that support the relevant milk production stage (ICF International, 2013). Although dairy cows are fed high quality nutrition, linked to lower enteric CH_4 emissions than lower-quality nutrition, they have a much higher TAM than beef cattle in the United States (EPA, 2015).

2.4.1.2. Manure Management

Manure management is the collection, storage, transfer, and treatment of animal urine and feces (Eve et al., 2014). The anaerobic decomposition of manure results in CH_4 production and both direct and indirect pathways[16] results in N_2O emissions. Manure management systems include variations within the following categories: solid storage, slurry systems, lagoons, and spreading.

The amount of CH_4 and N_2O generated from manure management practices depends on the animal type, animal diet, and activity data. However, the primary determinant of manure management GHG emissions is the system used to manage manure (e.g., solid storage, anaerobic lagoons, ponds). The same quantity of manure will generate different CH_4 and N_2O emissions as the management practice defines the emission rate (ICF International, 2013; Eve et al., 2014; Gerber et al., 2013). Manure stored under anaerobic conditions produce a significant portion of all manure-related emissions (specifically, as CH_4), so covering anaerobic lagoons or utilizing other anaerobic digesters provides a good opportunity to reduce these emissions (ICF International, 2013; Gerber et al., 2013).

2.4.2. Domestic Livestock Emissions

Overall emissions from domestic livestock production are dominated by enteric CH_4, but manure management practices produce emissions that are still a significant component of total agricultural sector emissions. Enteric CH_4 is more closely linked to diet, and thus corn (and other grain) production, than are the GHGs produced by manure management. Manure management mitigation methods focus primarily on capturing existing emissions, rather than through dietary modification.

2.4.2.1. Domestic Livestock Enteric Fermentation 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). Enteric CH_4 is the primary GHG produced by dairy cows (on a per-head basis). However, there are more beef cattle than dairy cows in the United States, consequently, more overall enteric CH_4 is produced by beef cattle (ICF International, 2013).

The model used in the RFS2 RIA (FASOM) projects domestic enteric CH_4 emissions using 2001 average emissions per head according to the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2003* (EPA, 2005) and multiplying them by the projected change in populations. Therefore, emissions are based only on populations, trends for which are discussed in Section 2.4.2.3.

[16] Indirect routes for producing N_2O include: (1) the direct production of NH_3 and NO_x later reacting further to produce N_2O and (2) runoff and leaching of N from manure into groundwater, also eventually reacting further to produce N_2O (Eve et al., 2014; EPA, 2015).

The annual emission factors used in the RFS2 RIA and the observed emission factors in 2013 are provided in Table 2-25. The cattle emission factors cited in the RFS2 RIA date to 2001 (EPA, 2010a) and have since increased due to multiple factors: typical animal masses (TAMs) in the United States are increasing, dietary factors vary, and because the sub-populations of cattle (i.e., bulls, heifers, calves) and their feeding situations are constantly in flux.

Table 2-25: Enteric CH_4 Annual Emission Factors

Livestock Type	RFS2 RIA Emission Factor (kg CH_4/head)	2013 Emission Factor (kg CH_4/head), per EPA, 2015
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.

2.4.2.2. Domestic Livestock Manure Management Emissions

In 2015, manure management practices in the United States resulted in GHG emissions of 78.8 MMT CO_2e. Emissions from cattle alone totaled 48.1 MMT CO_2e, 64 percent as CH_4 and 36 percent as N_2O. Beef cattle, dairy cattle, and swine collectively account for more than 92 percent of all emissions related to manure management. The remaining 8 percent is attributed to poultry, sheep, horse, and goat production (EPA, 2015).

Similar to the method for estimating domestic enteric CH_4 emissions changes, the model used in the RFS2 RIA (FASOM) projects domestic emissions from manure management using 2001 average emissions per head according to the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2003* (EPA, 2005) and multiplying them by the projected change in populations.

The emission factors used in the RFS2 RIA and the observed emission factors in 2013 are provided in Table 2-26. Note that a number of the emission factors have increased, particularly those related to dairy.

Table 2-26: Domestic Manure Management Annual Emission Factors

Livestock Type	RFS2 RIA CH_4 Emission Factor (kg CH_4/head)[a]	2013 CH_4 Emission Factor (kg CH_4/head), per EPA, 2015[b]	RFS2 RIA N_2O Emission Factor (kg N_2O/head)[a]	2013 N_2O Emission Factor (kg N_2O/head), per EPA, 2015[b]
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 (2010);
[b] EPA (2015).

2.4.2.3. Domestic Livestock Emission Trends

Since 1990, domestic livestock GHG emissions have increased significantly overall. Enteric CH_4 emissions have increased only slightly (less than 1 percent). Although cattle populations have decreased over this time, these emissions have ticked upward due to an increase in emission factors per head, as discussed above. 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 operations (concentrated animal feeding operations or CAFOs), which are more emission-intensive than dry storage systems (EPA, 2015).

Emission factors for beef cattle have increased on a per-head basis. However, emissions per pound of beef produced have decreased (ICF International, 2013). An increase in TAM of more than 10 percent resulted in only a 6 percent increase in enteric CH_4 (EPA, 2012).

The recent literature indicates that the use of WDGS in feedlot diets has increased in the Southern Great Plains as a result of the growing ethanol industry. In the past few years, ethanol producers have benefited from improved margins for DDGs. Sales of DDGs now provide a significant portion of the total revenue received by ethanol facilities, offsetting almost one-third of the corn feedstock price. Increased demand for both wet and dry distillers grains as animal feed in the United States has caused an increase in the margins for the production of ethanol (EIA, 2014). Hales et al. (2013) conclude that enteric CH_4 production as a proportion of Gross Energy (GE) intake increases linearly with WDGS concentration. This relationship may increase enteric CH_4 emissions, but this is not yet documented as a trend with the overall increasing use of distillers grains.

The RFS2 RIA projects livestock population changes as a result of increased ethanol production by 2022. These projections are shown in Table 2-27. The most significant change is in poultry populations under all scenarios (–58.85 million head). Swine would see significant increases under only the corn stover ethanol and switchgrass ethanol scenarios (9.15 and 7.80 million head, respectively) (EPA, 2010a). The livestock populations are based on a baseline of the 1990–2003 average populations in the *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2003* (EPA, 2005).

Table 2-27: Change in Domestic Livestock Herd Size by Scenario, 2022

Livestock Type	Corn Ethanol		Soy-based Biodiesel		Corn Stover Ethanol		Switchgrass Ethanol	
	mmHead	% change	mmHead	% change	mmHead	% change	mmHead	% change
Dairy	−0.02	−0.31%	−0.01	−0.17%	0.00	−0.01%	−0.02	−0.36%
Beef	0.09	0.14%	−0.11	−0.18%	0.95	1.56%	0.21	0.34%
Poultry	−58.84	−0.79%	−58.84	−0.79%	−58.84	−0.79%	−58.84	−0.79%
Swine	−0.22	−0.17%	0.24	0.19%	9.15	7.27%	7.80	6.20%

Source: EPA, 2010a.

For purposes of comparison, we present below average annual U.S. populations between the 1990–2003 for dairy, beef, poultry, and swine, as well as the actual 2013 populations (EPA, 2015). The trend in swine population is consistent with projections for the corn stover and switchgrass ethanol scenarios in the RIA, while the trend for dairy cattle, slightly decreasing, is consistent across all scenarios except corn stover ethanol. In the RIA, significant declines in beef population were not projected in any scenario; however, in 2011 drought resulted in early slaughter of beef herds in the Southern Plains region, which represents a significant portion of all domestic beef cattle. Poultry population was projected to decrease in all scenarios. As of 2013, the population had increased significantly in comparison to the 1990–2003 baseline.

The RFS2 RIA estimates emissions based only on the projected change in livestock populations, using a per-head emission factor as described in Section 2.4.2.1. The control case livestock populations projections are not available to compare to the historical populations available from the *Inventory of U.S. Greenhouse Gas Emissions and Sinks* (see Table 2-28).

Table 2-28: Changes in Domestic Livestock Populations between the 1990–2003 Average Populations and 2013 Populations

Livestock Type	1990–2003 Average Population ('000 head)	2013 Population ('000 head)	% Change
Dairy	18,524	18,482	−0.23
Beef	85,515	75,705	−11.47
Poultry	1,867,488	2,043,855	+9.45
Swine	58,616	65,747	+12.17

Source: EPA, 2015.

2.4.3. International Livestock Emissions

Gerber et al. (2013) show that global GHG emissions from livestock production[17] are estimated at 3.4 metric gigaton CO_2e per year for the 2005 reference period. About 2.7 metric gigaton CO_2e of the sector's emissions are due to enteric fermentation, with the remainder due to manure management practices. 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).

2.4.3.1. International Livestock Enteric Fermentation Emissions

Enteric fermentation is the largest source of global livestock emissions (about 79 percent). Of the enteric CH_4 emissions, most of it 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

[17] 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).

American animal product imports, cattle enteric fermentation accounts for 68 percent of all CH_4 emissions from agriculture. Beef cattle are responsible for 82 percent of all enteric methane emissions in the country (Barioni, n.d.).

The RFS2 RIA models enteric CH_4 emissions with default emission factors for each region. Therefore, similar to the method for calculating domestic enteric CH_4 emissions, the trends are based only on livestock population projections, discussed in Section 2.4.3.3.

The enteric CH_4 emissions factors used in the RFS2 RIA are provided in Table 2-29.

Table 2-29: 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.

2.4.3.2. International Livestock Manure Management Emissions

Globally, manure management practices emit 0.7 MMT CO_2e per year (about 21 percent of global agricultural emissions).

The RFS2 RIA models CH_4 emissions from manure management with default regional factors and N_2O using IPCC's default emission factors for each region (IPCC, 2006). Therefore, similar to the method for calculating domestic emissions, the trends are based only on livestock population projections, discussed in Section 2.4.3.3.

The CH_4 emission factors used for international manure management practices in the RFS2 RIA are provided in Table 2-30.

Table 2-30: 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

2.4.3.3. Trends in Emissions from International Livestock Production

Literature analyzing the ongoing growth of corn-based ethanol production suggests that production of pork and poultry would be reduced in response to higher corn prices and increased utilization of corn by ethanol plants. A report by Elobeid et al. (2006) estimates the long-run potential for ethanol production by calculating the corn price at which the incentive to expand ethanol production (e.g., increase the blend wall) disappears.

More recent studies have examined the impact of the biofuel sector on livestock production. There is 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 a higher energy price, 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).

2.4.4. References: Domestic and International Livestock

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2.5. International Land-Use Change

The FAPRI-CARD model was used to determine the number of hectares that will change internationally (excluding the United States) based on the impact of RFS2. Based on a review of published literature, it seems that the land-use patterns that were anticipated, particularly in South America and Africa, have not materialized.

2.5.1. Activity Data Used in RFS2 RIA

Iowa State University and the Center for Agricultural and Rural Development developed and manage FAPRI-CARD's international module. The module is based on multi-market, partial-equilibrium, econometric, non-spatial models. It considers a number of factors including population and GDP growth; production and consumption trends; existing trade patterns; and both international and domestic pricing. The model evaluates grains, oilseeds, livestock, dairy products, sugar and biofuels (ethanol and biodiesel) across the 54 major producing countries and regions. The area harvested was determined for each of the countries and regions, however FAPRI-CARD does not predict what type of land will be affected only the number of acres. EPA's RFS2 RIA determined the type of land using GIS data. Results showed that the international crop area harvested changed by 789 thousand hectares for the Corn Ethanol scenario in 2022.

FAPRI-CARD determined the change in harvested hectares for 20 crops in 2022, as seen below in Figure 2-7. The RIA considers only the hectares associated with the "first crop". First crop is determined by subtracting the change in hectares from crops that would be planted for winter and spring harvest from the total hectares. The harvested hectares subtracted were for winter barley, corn safrinha, the second cropping of dry beans, winter wheat and hay. The first crop data was then separated into annual and perennial crops. Annual crops included all first crops except for palm and sugarcane hectares. Perennial crops were assumed to be palm and sugarcane harvested hectares. The change in hectares harvested for 2022 is shown in Table 2-31.

Table 2-31: FAPRI-CARD Change in Harvested Hectares (000s ha) in 2022 (EPA, 2010c)

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	FIRST CROP TOTAL
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**
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**

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	FIRST CROP TOTAL
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**
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**

The foreign hectare totals are the World total minus the United States' total. The changes in hectares from FAPRI-CARD shown in Table 2-31 are also presented in Figure 2-7.

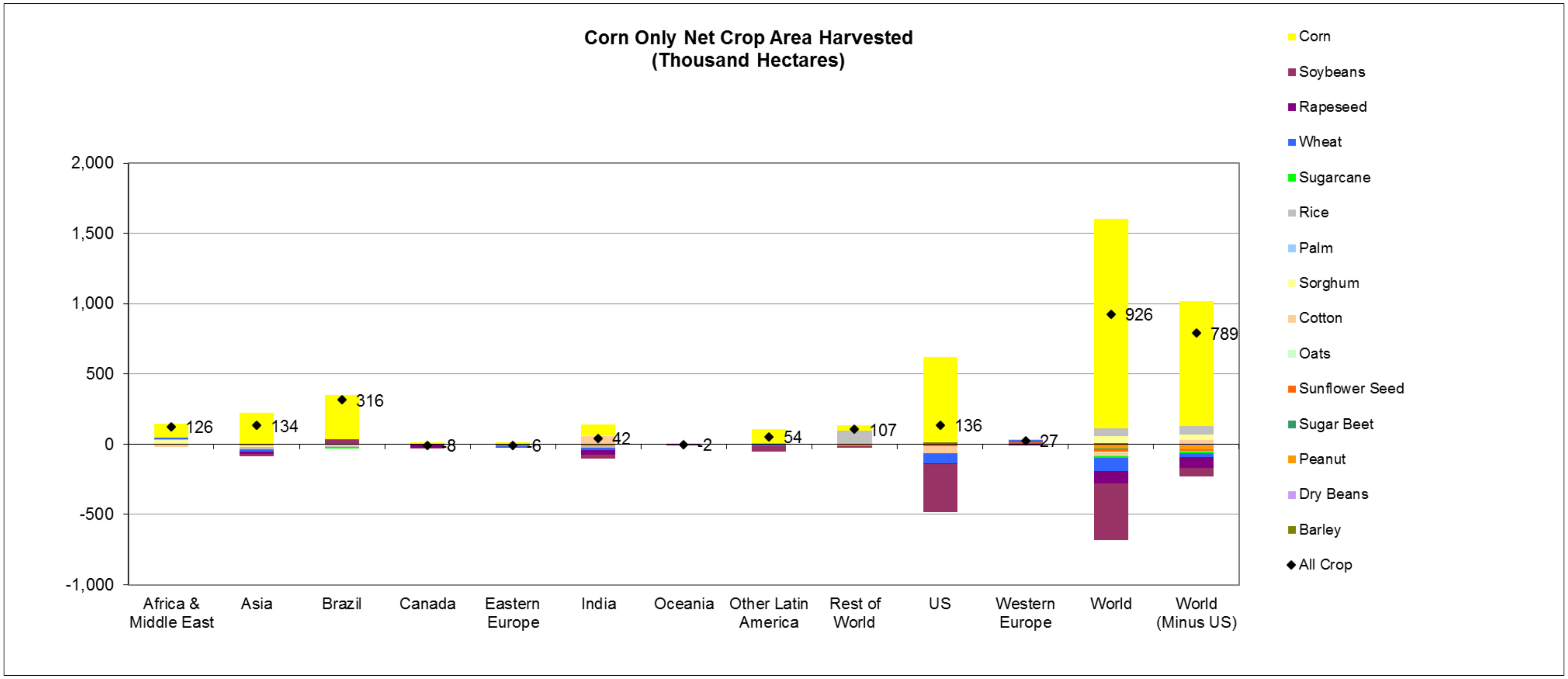

Figure 2-7: Corn Only Scenario Compared to Control Scenario: Changes in Harvested Hectares (000 ha) by 2022 (EPA, 2010a)

To calculate the international land-use change impact, the FAPRI-CARD results were subsequently multiplied by the country-specific emission factors developed by Winrock using satellite data to analyze recent land-use changes around the world. The satellite data were combined with various estimates of carbon stocks associated with different types of land at the state level in order to determine the land-use change by country (EPA, 2010b).

2.5.2. Comparison of Predicted Results to Actual Land-Use Trends

Literature published since the release of the RFS2 RIA indicates that drivers exist that were not considered during the RIA development. These drivers include how land is allocated to biofuels, and regional policies and trends in Brazil.

Figure 2-8 shows a comparison of the annual forest area lost in the Brazilian amazon compared to U.S. corn ethanol production. Despite the increase in corn ethanol production (from 3.4 billion gallons in 2004 to 14.8 billion gallons in 2015), deforested land in Brazil decreased over the same period.

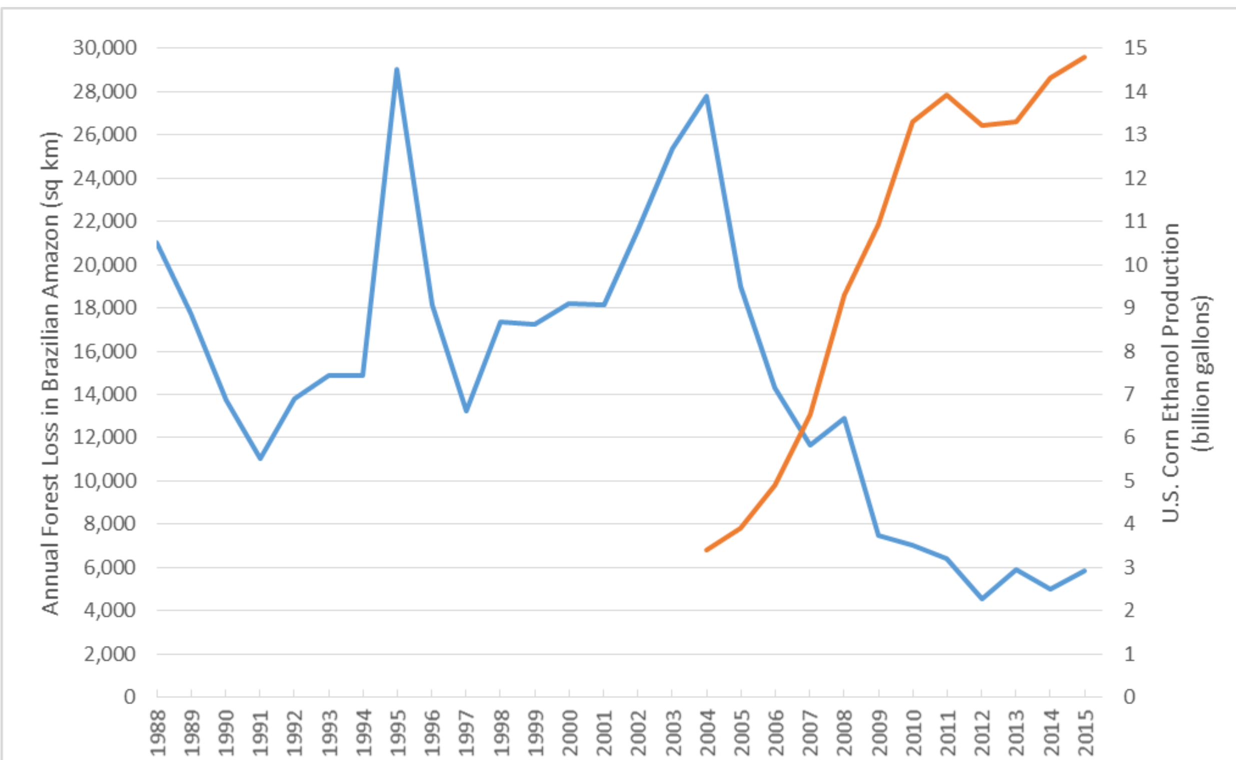

Figure 2-8: Comparison of Brazilian Deforestation (sq. km) and U.S. Corn Ethanol Production (billion gallons) by Year (Sources: Deforestation from the Brazilian National Institute of Space Research (INPE, 2014); U.S. corn ethanol production from the U.S. Energy Information Administration (EIA, 2015))

A report by Boland and Unnasch (2014) entitled “Carbon Intensity of Marginal Petroleum and Corn Ethanol Fuels” presents a broad range of international land-use change emission estimates for corn ethanol ranging from Searchinger’s 104 g CO_2e/MJ to Argonne National Laboratory’s analysis of 9.0 g

CO_2e/MJ. The latter estimate used GTAP model results and applied more accurate carbon stock factors than those used by Tyner et al. (2010). These results were incorporated into Argonne National Laboratory's GREET 1 2013 update. Boland and Unnasch (2014) comment that although multiple analyses use the Global Trade Analysis Project (GTAP) modeling framework (including CARB's Low Carbon Fuel Standard; Tyner et al., 2010; and GREET1_2013), different parameter estimates, model assumptions, and treatment of data will cause disparities in the results. Study results are ordered by year published in Figure 2-9.

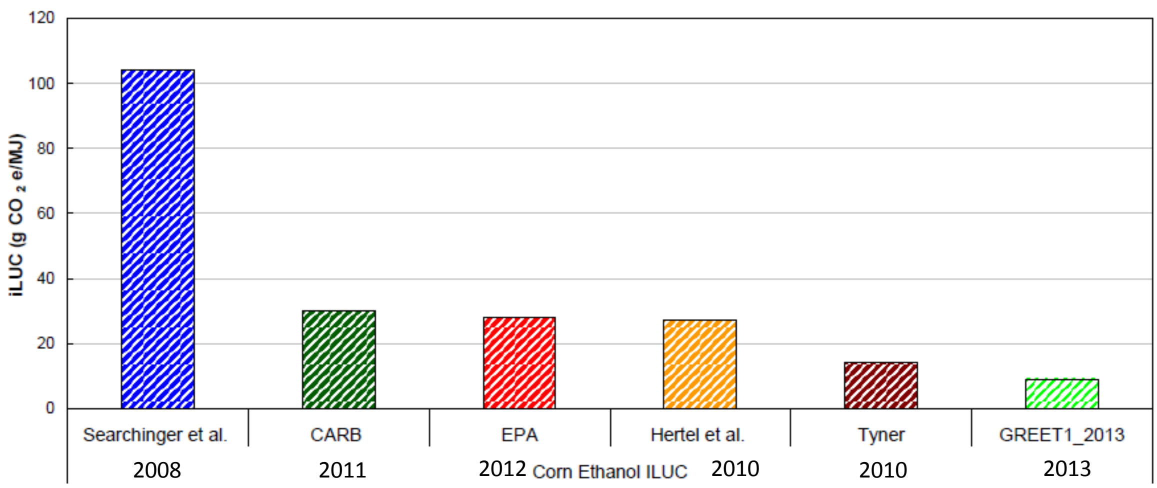

Figure 2-9: Comparison of International Land-use Change from Various Sources (Boland and Unnasch, 2014)

Kim et al. (2012) note the allocation methods for land use between fuel, animal feed, and human feed. The publication states that international LUC GHG emissions should be allocated between ethanol and human dietary preferences via a human nutrition-based method (Kim et al., 2012). By applying their proposed approach, they lowered the estimate of GHG emissions by up to 73 percent when compared to the GTAP model output (Kim et al., 2012). This study elicits the notion that allocation of land goes beyond the decisions made by ethanol producers and is subject to the consumer's preference. The paper suggests that price competition of vegetable-based and animal-based proteins should be included in these economic models (Kim et al., 2012).

The Institute for International Trade Negotiations (ICONE) produced a 2013 report, "Comparing the trends and strength of determinants to deforestation in the Brazilian Amazon in consideration of biofuel policies in Brazil and the United States," that outlines possible drivers of deforestation in Brazil that are not considered within economic modelling. Rural settlements, which are not considered in economic modeling, are responsible for 15 percent of the total area deforested in the Amazon. The report notes that land reform and the establishment of rural settlements has increased significantly between 1995 and 2009. The rate of deforestation has also increased during this time period, however the increase has not been linear (Nassar et al., 2013). The report also observes that Brazilian states with higher pasture area also have higher rates of secondary vegetation. This trend indicates that areas previously occupied by pasture or annual crops are now in recovery for natural vegetation (Nassar et al., 2013). This reversion to natural land is an important consideration for long-term, land-use trend analyses. Lastly, recent Brazilian policies have targeted deforestation and would not be present in the current economic modelling. These policies include the Climate Change National Policy launched in 2010 which targets deforestation reduction until 2020 and efficient public policies in the Legal Amazon which lead to enforcement and compliance with the established laws and implementation of interim measures (Nassar et al., 2013).

Other literature evaluates whether the increased demand for crops would cause land expansion or more efficient use of the land. Bruce Babcock and Zabid Iqbal's publication "Using Recent Land Use Changes to Validate Land Use Change Models" concludes increases in harvested land may be due to the more intensive use of land already in production rather than being new land into production. Based on data from the Statistics Division of FAO (FAOSTAT), the largest changes in harvested land were found in India, China, Africa, Indonesia, and Brazil (Babcock and Iqbal, 2014). Figure 2-10 looks at the change in harvested land between an average of 2010–2012 and an average of 2004–2006 FAOSTAT data. The paper notes that while an increase in harvested land may suggest an increase in land conversion, the increase in harvested land is likely the result of double and tripled cropped land and not the result of an increase in planted land.

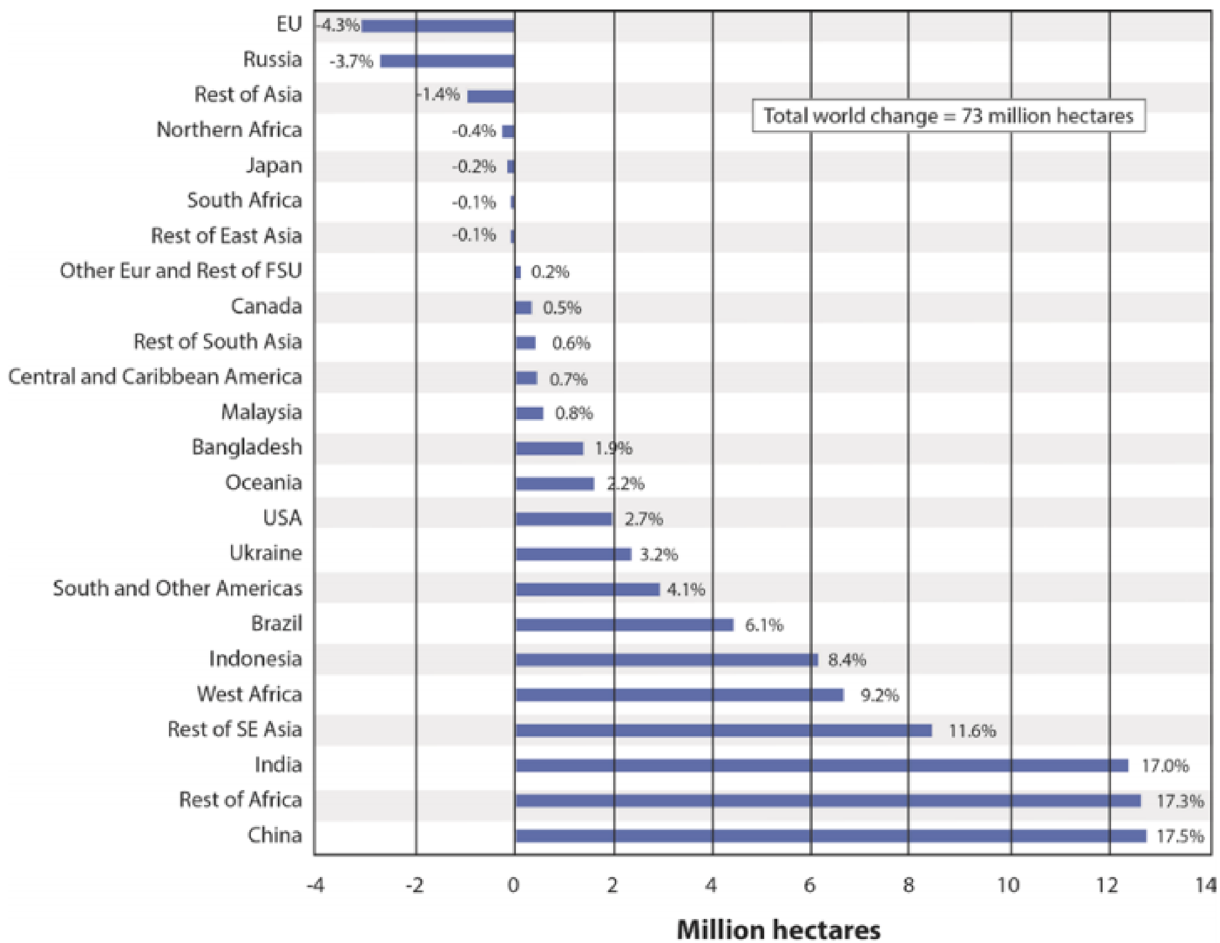

Figure 2-10: Change in Harvested Land 2010–2012 Average Minus 2004–2006 Average (Note: Percentage indicates country's share of total world change) (Source: Babcock and Iqbal, 2014)

Babcock and Iqbal's analysis finds that, for different countries, a connection exists between harvested land area and double cropped land area. If the change in the second cropland area over time is positive, the perspective is that the FAO data on total harvested land over-estimates the land-use change by that amount. Table 2-32 indicates harvested land data for Brazil and India where the difference in harvested land implies that land change is driven by land-use intensification as opposed to land expansion, as implied in the RFS2 RIA FAPRI-CARD results (Babcock and Iqbal, 2014).

Table 2-32: Changes in Harvested Land and Changes in Double Cropping (Babcock and Iqbal, 2014)

Country	Change in Harvested Land (million ha)	Change in Double Cropping (ha)	Percentage of Land Area that can be Attributed to Intensification of Land Use
Brazil	5.4	4.1	76%
India	12.4	−0.147	0%

The intensification of land use in India shown in Table 2-32 is attributed to a 6 million hectare increase in irrigated land. More irrigation allowed for a greater proportion of planted acres to be harvested. India also increased its support prices and input subsidies in the mid-2000s, which increased the value of the established cropland. The increased change in harvested land in sub-Saharan Africa is likely a better measurement of the change in planted land given the proportion of African crop production that occurs on small farms. Increased food production in the region matches the increase in the amount of land planted. Lack of technology and capital signifies that double-cropping is not common. World-wide, the extensive change (land expansion) was a net increase of 24 million hectares from 2004–2006 to 2010–2012, while the aggregate intensive land-use change was 49.1 million hectares (Babcock and Iqbal, 2014). This difference led Babcock and Iqbal to conclude that the reliability of current models would be increased if intensification of land use was considered.

2.5.2.1. Actual Land-Use Trends by Region

The FAPRI-CARD and GTAP models are the most widely used international models to predict land-use changes associated with increased biofuel production. Both models allow crop yields to respond to an increase in pricing, however they do not allow for adjustments in land-use intensity. Given the observed trends presented above in Table 2-32, Babcock and Iqbal conclude that specific countries (e.g., Brazil) and regions included within the EPA's *Renewable Fuel Standard Program Regulatory Impact Analysis* (RFS2 RIA) analysis have not followed the predicted trends from the FAPRI-CARD analysis (Babcock and Iqbal, 2014).

Babcock and Iqbal looked at the intensive and extensive margin for each country/region in order to determine how much of the change in land was attributable to land expansion or double cropping. Intensive margin changes are those due to double cropping and a decrease in land that is planted but not harvested. Extensive margin changes are those that show an increase in harvested land. Figure 2-11 below shows their analysis of FAOSTAT data between 2004–2006 to 2010–2012 for each country/region indicating whether the change in harvested land area was intensive or extensive (Babcock and Iqbal, 2014).

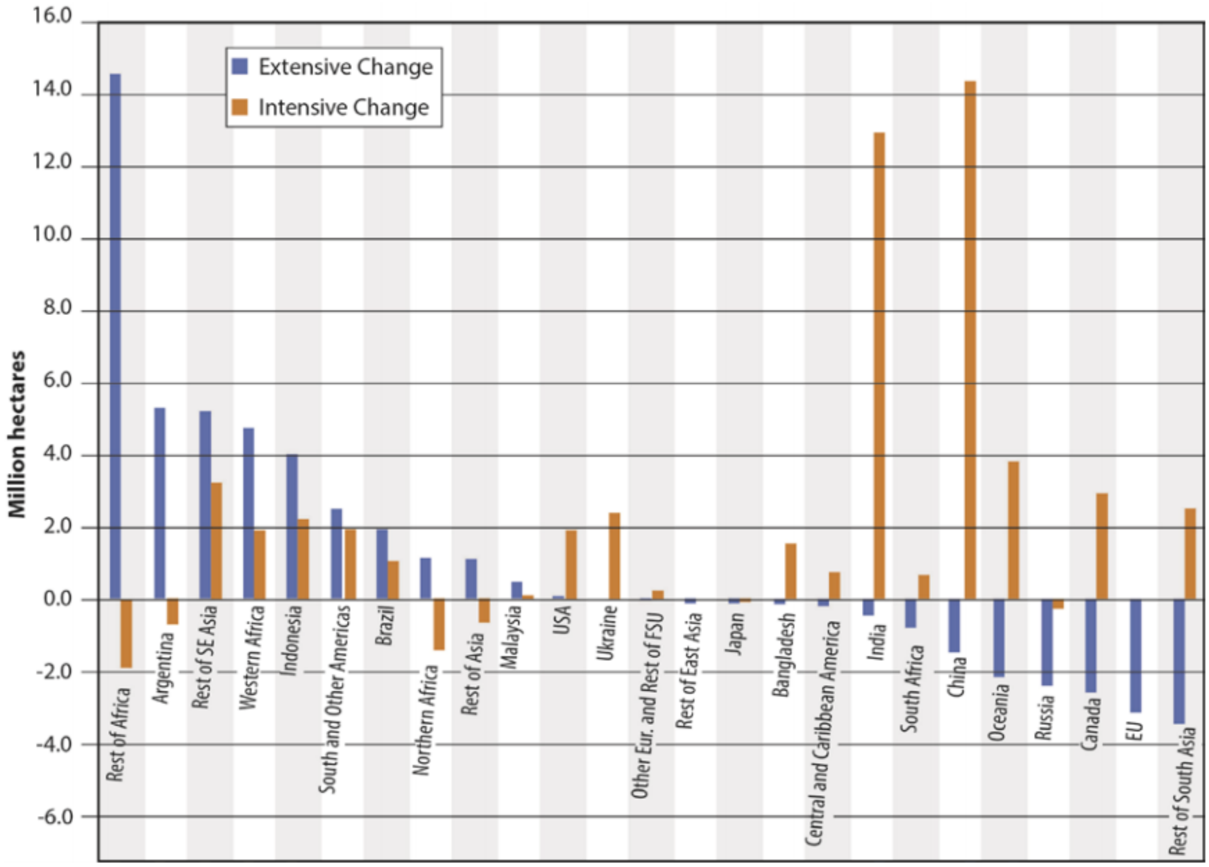

Figure 2-11: Extensive and Intensive Land-use Changes: 2004–2006 to 2010–2012 from FAOSTAT (Source: Babcock and Iqbal, 2014)

The publication highlights two regions where the FAPRI-CARD land-use predictions did not come to realization: South America and sub-Saharan Africa (Babcock and Iqbal, 2014).

2.5.2.2. Brazil and Argentina

The FAPRI-CARD analysis for the RFS2 RIA showed a high concentration of the land-use change occurring in Brazil which Babcock and Iqbal (2014) believe was over-estimated. The paper compares the FAPRI-CARD prediction to the extensive land-use change that actually occurred. They conclude that the predicted land-use change within Brazil due to higher prices is far too high relative to the surrounding countries. The FAPRI-CARD results predicted almost no land-use change in Argentina due to high prices (Babcock and Iqbal, 2014). However, as shown in Figure 2-12, Argentina increased land use at the extensive margin almost four times the rate of Brazil (Babcock and Iqbal, 2014).

2.5.2.3. Africa

FAPRI-CARD includes a limited number of crops for a limited number of Africa countries and therefore implicitly assumes that commodities produced in Africa will not reach world markets. The paper comments that the large land-use changes shown in Figure 2-12 would have occurred regardless of high commodity prices (Babcock and Iqbal, 2014). Based on this trend, the FAPRI-CARD results for the RFS2 RIA underestimated Africa's connection to the world commodity market, and the impact that the connectedness would have on extensive land-use change (Babcock and Iqbal, 2014).

2.5.3. Alternative to FAPRI-CARD Modelling

Given that the attributes and assumptions of the FAPRI-CARD analysis may not reflect actual land use change trends, other models provide an alternative analysis to develop international land-use estimates.

FAPRI-CARD, as noted in Section 2.5.1, is a partial-equilibrium model that is multi-market and non-spatial. Because the model is non-spatial, it does not distinguish between the sources and destinations of trade between regions and countries (FAPRI, 2008). FAPRI did not develop an updated 2011 baseline due to budget constraints, causing this data output to be antiquated.

GTAP is a computable equilibrium model with perfect competition and links production and consumption by region. The GTAP-BIO model is specifically tailored to estimate the land use impact of an exogenous policy shock. The GTAP-BIO database has been updated based on trends in land-use patterns and updated data are available. In the EPA RIA analysis, geospatial data was used to distinguish which types of land were converted and reverted while GTAP's output includes this modeled data.

GTAP allows three land types to be used for biofuel production: forest, grassland, and cropland-pasture land. Crop-pasture land is agricultural land that has been converted to agriculture dominated by the production of biofuel feedstocks. GTAP results are available for two pertinent biofuel production scenarios. Both scenarios reflect a shock of 11.59 billion gallons of increased demand for corn as a feedstock commodity. Scenario Case A was modeled in 2011 and Case H was modelled in 2013 (Argonne National Laboratory, 2014). The production scenarios are shown below in Table 2-33 and were taken from Argonne National Laboratory's Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) model.

Table 2-33: GTAP Modeling Scenarios (Argonne National Laboratory, 2014)

Case[18]	Case Description	Gallons	Source
A	An increase in corn ethanol production from its 2004 level (3.41 billion gallons [BG]) to 15 BG	11.59	Taheripour et al., 2011
H	An increase in corn ethanol production from its 2004 level (3.41 BG) to 15 BG with GTAP recalibrated land transformation parameters	11.59	Taheripour and Tyner, 2013

Although Case A and H model the same production volume, there were key aspects within the GTAP model run that cause different results.

[18] Note: Case lettering is referred to within the cited publications.

- Land Transformation: Land transformation elasticity reflects the ease of land transition from one state to another. A low value indicates limited land transitions. In 2011, GTAP included only one land transformation elasticity for the world. Taheripour and Tyner (2013) updated the land transformation data to develop region-specific elasticities using two United Nations Food and Agriculture Organization land-cover datasets. The updates allowed for determination of changes in agricultural land area and the characterization of changes in harvested area for crop types. Based on this change, Taheripour and Tyner (2013) found that that the United States moved a sizeable amount of agricultural land to produce corn and oilseed crops without significant expansion in overall agricultural land (Argonne National Laboratory, 2014).
- Treatment of Conversion Costs: In 2011, converting pasture and forest to cropland cost the same amount. In 2013, GTAP was adjusted to reflect the greater cost of converting of forest to cropland compared to converting pasture to cropland. In the updated dataset, it is more costly to convert forest to cropland than in the prior model version.

Taheripour and Tyner (2013) used observed land-use trends as a guide for the most recent update of GTAP. This methodology was used to reconcile the differences between modeled predictions and the observed trends. They specifically address how land-use changes responded to changes in global commodity pricing.

The raw GTAP data is grouped by land-use type (forest, grassland, cropland pasture, and cropland). Each country/region contains the hectares converted for each of the 18 Agro-ecological Zones (AEZ). A summary table of the GTAP total hectares by region for Scenario A is shown below in Table 2-34 and Scenario H is shown in Table 2-35 (Argonne National Laboratory, 2014).

The GTAP 2011 data (Scenario A) shows an increase in international (excluding U.S.) Forest and Cropland acres while there is a decrease in Grassland and Cropland-Grassland acres. The international change in hectares for GTAP 2013 output shows similar trends for Cropland, Grassland, and Cropland-Grassland hectares although the change for each category is consistently smaller. For the change in Forest hectares, the GTAP 2013 output shows a decrease in area change—a difference of 123,249 hectares.

Table 2-34: Scenario Case A—GTAP Output Taken from Argonne National Laboratory's CCLUB Model. Results Generated from Taheripour and Tyner (2011) and Taken from Argonne National Laboratory's CCLUB Model (Argonne National Laboratory, 2014)

Description	United States	European Union 27	Brazil	Canada	Japan	China and Hong Kong	India	Central and Caribbean Americas	South and Other Americas	East Asia	Malaysia and Indonesia
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	−331,465	−79,923	41,670	−116,440	−3,069	23,469	−2,137	32,240	81,988	3,992	5,567
Grasslands	−639,484	−46,108	−123,236	−57,213	−455	−74,127	−3,086	−52,806	−143,149	−4,818	−3,735
Cropland-Grassland	−1,168,943	0	−238,170	0	0	0	0	0	0	0	0
Cropland	970,916	126,034	81,625	173,636	3,526	50,663	5,230	20,560	61,167	822	−1,844

Description	Rest of South East Asia	Rest of South Asia	Russia	Other East Europe and Rest of Former Soviet Union	Rest of European Countries	Middle Eastern and North Africa	Sub Saharan Africa	Oceania Countries	Totals	International Total (w/o USA)
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	2,609	−1,824	185,508	−21,230	−24	−101	−45,781	−859	−225,811	**105,654**
Grasslands	−5,256	−22,341	−194,098	−84,787	−1,548	−84,989	−225,457	−85,234	−1,851,927	**−1,212,443**
Cropland-Grassland	0	0	0	0	0	0	0	0	−1,407,113	**−238,170**
Cropland	2,659	24,161	8,640	105,999	1,571	85,144	271,213	86,102	2,077,826	**1,106,910**

Table 2-35: Scenario Case H—GTAP Output Taken from Argonne National Laboratory's CCLUB Model. Results Generated from Taheripour and Tyner (2013) and Taken from Argonne National Laboratory's CCLUB Model (Argonne National Laboratory, 2014)

Description	United States	European Union 27	Brazil	Canada	Japan	China and Hong Kong	India	Central and Caribbean Americas	South and Other Americas	East Asia	Malaysia and Indonesia
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	−64,772	−14,718	62,449	−25,352	−5,041	−1,692	−7,005	4,456	68,910	2,245	892
Grasslands	−92,616	−18,836	−219,140	−14,759	−144	−86,841	−3,539	−9,855	−183,326	−3,762	−2,973
Cropland-Grassland	−1,788,463	0	−213,931	0	0	0	0	0	0	0	0
Cropland	157,426	33,524	156,666	40,129	5,187	88,554	10,546	5,395	114,364	1,506	2,070

Description	Rest of South East Asia	Rest of South Asia	Russia	Other East Europe and Rest of Former Soviet Union	Rest of European Countries	Middle Eastern and North Africa	Sub Saharan Africa	Oceania Countries	Totals	International Total (w/o USA)
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	−11,849	−3,098	87,330	−7,356	−240	167	−167148	−545	−82369	**−17,595**
Grasslands	−2,527	−21,561	−145,276	−21,477	−188	−21975	−294,787	−17,308	−1,160,891	**−1,068,274**
Cropland-Grassland	0	0	0	0	0	0	0	0	−2,002,393	**−213,931**
Cropland	14,360	24,657	58,007	28,820	429	21779	461,846	17,891	1,243,153	**1,085,730**

2.5.4. References: International Land-Use Change

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2.6. International Farm Inputs and Fertilizer N_2O

Two country-specific data sets exist for evaluating trends in international farm inputs, especially nitrogen consumption:

- International Fertilizer Industry Association, IFA Statistics[19]
- Food and Agriculture Organization of the United Nations, FAOSTAT

Both of these sources have data on consumption by country. Table 2-36 presents nitrogen consumption by region and Table 2-37 presents data for a sample country, Brazil. As indicated in the tables, N consumption increased from 2010 to 2013 in most countries. Table 2-38 presents data as provided by the Food and Agriculture Organization of the United Nations (FAO) for Brazil. 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, 2015, p. ix). FAO indicates that nitrogen inputs will increase at an annual growth rate of 1.4 percent.

Table 2-36: 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

[19] The RFS2 RIA was based on use of data provided in a report by the International Fertilizer Industry Association.

Country	Product	2010	2011	2012	2013
	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
	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

Country	Product	2010	2011	2012	2013
	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
	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 2-37: Consumption by Country (Brazil in this Case) by Calendar Year as Provided by International Fertilizer Industry Association (metric ton of N)

Country	Product	2010	2011	2012	2013
Brazil	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 2-38: Nitrogen Fertilizers Consumed (N Total Nutrients) in Brazil as Provided by Food and Agriculture Organization of the United Nations (metric ton of N)

Country	Product	Year	N total nutrients
Brazil	Nitrogen Fertilizers	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).

2.6.1. References: International Farm Inputs and Fertilizer N_2O

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2.7. International Rice Methane

A review of the recent literature shows that global rice production and corresponding methane emissions increased between 1990 and 2012 with some fluctuation between years. Harvested acres increased from approximately 363 to 400 million acres and emissions increased from 465,000 to 522,000 MMTCO$_2$e during this period (USDA ERS, 2015; FAO, 2016a). The RFS2 RIA FAPRI data underestimates global harvested rice acreage, but has higher projections for future harvested acres in 2023 than the FAO projections for 2030 and 2050 (FAO, 2016a). For example, both the RFS2 RIA FAPRI Control Case and the Reference Case have lower predicted harvested acres of rice in 2012 (384.32 million acres for the Reference Case and 384.10 million acres for the Control Case) than were actually harvested (390.92 to 401.1 million acres depending on the source) (USDA ERS, 2015; FAO, 2016a). Emission factors used to develop the RFS2 RIA are based on the Tier 1 defaults from the 2006 IPCC Guidelines. A review of the recent Second National Communications (SNC) from the top five rice-producing countries (China, India, Indonesia, Bangladesh, and Vietnam) indicates that all of the countries except for Bangladesh have created their own Tier 2 or Tier 3 emission factors for rice methane emissions. The RFS2 RIA emission factors cannot be directly compared to those in the SNCs as they are expressed in different units according to the Tier 2 or Tier 3 estimation equations. The total projected 2012 global rice methane emissions from the RFS2 RIA are approximately 3 percent of those from the FAO. The RFS2 RIA estimated 2012 emissions are 17,800 Gg CO_2e for the Control Case and 18,410 Gg CO_2e for the Reference Case compared to 521,991 Gg CO_2e from the FAO (FAO, 2016a).

2.7.1. Background on Methane from Different Rice Production Systems and Global Rice Production

As described for Domestic Rice Methane, the amount of methane produced by rice cultivation is influenced by multiple factors, including water management (EPA, 2015; Garthorne-Hardy, 2013; Hussain et al., 2015). While all rice produced in the United States is grown under continuously flooded, shallow water conditions, additional production methods or cropping regimes are used in other countries. The IPCC (2006) has developed emission factors for four categories of rice cropping regimes:

- Irrigated
- Rainfed lowland
- Upland
- Deepwater

More than 90 percent of global rice is grown under irrigated or rainfed lowland rice fields (GRiSP, 2013).

2.7.2. Global Rice Production Area

According to the most recently published reports, between 1990 and 2014 the global estimated acreage of harvested rice generally increased with some fluctuations (USDA ERS, 2015; FAO, 2016a). In 1990, 363 million acres of rice were harvested and in 2012 between 390 and 401 million acres were harvested, depending on the data source. Table 2-39 shows global harvested acres and projected harvested acres from multiple sources.

Table 2-39: Global Harvested Rice Area (Millions of Acres)

Year	USDA Rice Yearbook[a]	FAO[b]	RFS2 RIA FAPRI-CARD (Control Case)[c]	RFS2 RIA FAPRI-CARD (Reference Case)[c]
1990	363.17	363.15	-	-
1991	364.45	362.56	-	-
1992	361.97	364.18	-	-
1993	359.13	361.99	-	-
1994	364.10	363.96	-	-
1995	366.59	369.66	-	-
1996	370.87	371.40	-	-
1997	374.89	373.43	-	-
1998	378.36	374.86	-	-
1999	385.15	387.48	-	-
2000	376.70	380.70	-	-
2001	374.00	375.47	-	-

Year	USDA Rice Yearbook[a]	FAO[b]	RFS2 RIA FAPRI-CARD (Control Case)[c]	RFS2 RIA FAPRI-CARD (Reference Case)[c]
2002	362.99	364.80	-	-
2003	368.97	366.98	-	-
2004	375.21	372.03	-	-
2005	380.56	382.99	378.26	378.26
2006	382.02	384.46	380.21	380.21
2007	382.27	383.12	381.39	381.39
2008	390.67	395.36	385.10	385.10
2009	384.89	390.76	385.70	385.71
2010	390.89	398.31	385.46	385.51
2011	396.05	402.29	385.12	385.25
2012	390.92	401.10	384.10	384.32
2013	397.55	-	383.88	383.56
2014	394.48	-	384.26	383.96
2015	-	-	384.59	384.32
2016	-	-	384.73	384.47
2017	-	-	384.46	384.19
2018	-	-	384.34	384.25
2019	-	-	384.30	384.36
2020	-	-	385.06	385.09
2021	-	-	386.11	386.08
2022	-	-	385.56	385.48
2023	-	-	385.74	385.65

[a] USDA ERS (2015).
[b] FAO (2016a).
[c] EPA (2010).

Global rice harvest estimates from both the USDA Rice Yearbook and the FAO data show an overall increase in acreage from 1990 through 2014 with slight differences between them (USDA ERS, 2015; FAO, 2016a). For example, the USDA Rice Yearbook estimated more harvested acres than the FAO seven out of the 15 years between 1990 and 2004, and the FAO estimated higher acreage the remaining eight years. However, between 2005 through 2012 the FAO consistently estimates more acreage than the USDA Rice Yearbook and the difference between the estimates increases to 5 to 10 million acres.

Between 2005 and 2014 (the only years for which we have overlapping data) the RFS2 RIA FAPRI-CARD data for both the Control Case and the Reference Case both underestimate the number of acres harvested for global rice production compared to the USDA Rice Yearbook and the FAO data, except for 2009, where the RFS2 RIA acreage for both Cases is higher than the USDA Rice Yearbook. The difference between the RFS2 RIA FAPRI-CARD and the USDA and FAO acreage is greatest between 2010 and 2014 where the RFS2 RIA FAPRI-CARD estimates are between 5 million and 15 million acres lower than the USDA and FAO data. Given that the RFS2 RIA consistently underestimates acres of harvested rice (especially between 2010 and 2014) the RFS2 RIA most likely underestimates global methane emissions from rice production for both cases (depending on the emission factors used).

While rice is produced in all regions around the world, the majority of rice is produced and consumed in Asia (GRiSP, 2013). The top five rice producing countries (in order of production) are:

1. China
2. India
3. Indonesia
4. Bangladesh
5. Vietnam

Combined these countries comprise approximately 65 percent of harvested rice acreage globally. Table 2-40 below shows the comparison between FAO data for harvested acres for the top five rice producing countries from 1990 through 2012 and the RFS2 RIA FAPRI-CARD Control estimated harvested acres for the same countries between 2005 and 2023.

Table 2-40: Top Five Rice Producing Countries (Millions of Acres Harvested)

Year	China, Mainland		India		Indonesia		Bangladesh		Vietnam	
	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]
1990	81.71	-	105.48	-	25.95	-	25.79	-	14.93	-
1991	80.53	-	105.39	-	25.41	-	25.32	-	15.57	-
1992	79.30	-	103.23	-	27.44	-	25.15	-	16.00	-
1993	75.01	-	105.12	-	27.21	-	24.48	-	16.21	-
1994	74.56	-	105.80	-	26.52	-	24.51	-	16.31	-
1995	75.97	-	105.76	-	28.27	-	24.59	-	16.72	-
1996	77.61	-	107.25	-	28.59	-	25.21	-	17.31	-
1997	78.49	-	107.42	-	27.53	-	25.36	-	17.54	-
1998	77.13	-	110.71	-	28.99	-	25.01	-	18.19	-
1999	77.31	-	111.59	-	29.56	-	26.47	-	18.91	-
2000	74.04	-	110.49	-	29.14	-	26.69	-	18.94	-
2001	71.20	-	110.95	-	28.42	-	26.34	-	18.52	-
2002	69.69	-	101.75	-	28.47	-	26.62	-	18.54	-
2003	65.50	-	105.25	-	28.36	-	26.50	-	18.42	-
2004	70.13	-	103.56	-	29.46	-	25.32	-	18.40	-
2005	71.28	71.28	107.89	107.25	29.26	29.16	26.01	27.43	18.11	18.07
2006	72.39	71.51	108.26	108.73	29.13	29.41	26.14	27.68	18.10	17.80
2007	71.46	71.46	108.51	108.73	30.02	29.41	26.13	27.18	17.81	18.32
2008	72.26	72.16	112.53	109.96	30.42	29.41	27.87	28.12	18.29	18.01
2009	73.21	72.73	103.58	110.63	31.84	29.84	28.06	28.33	18.38	18.42
2010	73.82	70.78	105.92	111.22	32.75	29.70	28.49	28.21	18.51	18.62
2011	74.27	70.87	108.65	111.51	32.62	29.80	28.49	28.07	18.92	18.82
2012	74.47	69.15	104.80	111.81	33.23	29.85	28.23	28.07	19.16	18.93
2013	-	68.44	-	112.18	-	29.85	-	28.11	-	19.06
2014	-	68.58	-	112.14	-	30.00	-	28.27	-	19.12
2015	-	67.82	-	112.65	-	30.07	-	28.44	-	19.14
2016	-	67.48	-	113.04	-	30.11	-	28.76	-	19.17

Year	China, Mainland		India		Indonesia		Bangladesh		Vietnam	
	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]	FAO[a]	RFS2 RIA (Control Case)[b]
2017	-	67.29	-	113.17	-	30.23	-	29.01	-	19.19
2018	-	67.01	-	113.65	-	30.17	-	29.22	-	19.22
2019	-	66.84	-	113.90	-	30.23	-	29.51	-	19.25
2020	-	66.56	-	114.09	-	30.25	-	29.79	-	19.28
2021	-	66.22	-	114.33	-	30.33	-	30.14	-	19.32
2022	-	65.80	-	114.59	-	30.30	-	30.42	-	19.37
2023	-	65.53	-	114.92	-	30.33	-	30.76	-	19.45

[a] FAO (2016a).
[b] EPA (2010).

The data show that the RFS2 RIA harvested acres projections are relatively close to the FAO estimates for the top five rice producing countries for the eight years with overlapping data (2005–2012). Specifically, the RFS2 RIA FAPRI-CARD underestimates harvested acres compared to FAO data between 2008 and 2012 in China, in 2005 and 2008 in India, in 2005, and between 2007 and 2012 in Indonesia, between 2010 and 2012 in Bangladesh and in 2005, 2006, 2008, 2011, and 2012 in Vietnam. The other years for each country are either overestimates, or are the same values as the FAO data. The RFS2 RIA FAPRI-CARD data shows the largest difference with FAO data for India between 2009 and 2012 where the RFS2 RIA estimates are between 3 and 7 million acres higher than those of the FAO.

2.7.3. Global Methane Emission Factors for Rice Production

Global methane emissions from rice were estimated using similar assumptions to those used to calculate domestic rice emissions (see Domestic Rice Methane above). Based on the IPCC 2006 methodology (see Equation 5.1 below), the total area of rice harvested in a given country was sub-divided into IPCC cropping regimes, multiplied by the appropriate GHG emission factor, and the planting to harvest season length. Specifically, the FAPRI-CARD model was used to predict the area of rice harvested internationally, which was 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). The rice cultivation season length data were based on data from the International Rice Research Institute (IRRI) (IRRI, 2008). Using this formula (see Equation 5.1 below), effective emission factors were developed for each country.

EQUATION 5.1
CH_4 EMISSIONS FROM RICE CULTIVATION

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

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

A review of current literature shows that all of the top five rice producing countries have submitted Second National Communications (SNCs) to the UNFCCC since 2010 (UNFCCC, 2016). A review of the SNCs shows that all of the countries (except Bangladesh) have developed country-specific rice methane emission factors. Table 2-41 below shows the country, SNC date, type of method used to estimate rice methane emissions, and reporting year 2000 methane emissions from rice in both methane and CO_2e.

Table 2-41: Methods Used to Estimate Rice Methane Emissions from Second National Communications of Top Five Rice Producing Countries

Country	Data Source	Methane Estimation Method	RY 2000 Methane Emissions (Gg CH_4)	RY 2000 Methane Emissions (Gg CO_2e)
China	Second National Communication (2012)[a]	Estimated by dividing all harvested acres into four rice production systems and multiplying those acres by CH4MOD[20] modeled emission factors (three categories) and using an empirically produced emission factor for the fourth category	7,930.00	198,250.00
India	Second National Communication (2012)[b]	Estimated by dividing harvested acres in each state into rice production systems and multiplying by state level empirically developed seasonal emission factors	3,540.98	88,524.25
Indonesia	Second National Communication (2012)[c]	Estimated using data on rice field area and planting intensity. Domestic scaling factors for soil types and water regimes were developed from empirical data.	1,660.00	41,500.00

[20] CH4MOD is a biogeophysical model for simulating methane emissions from wetlands.

Country	Data Source	Methane Estimation Method	RY 2000 Methane Emissions (Gg CH_4)	RY 2000 Methane Emissions (Gg CO_2e)
Bangladesh	Second National Communication (2012)[d]	Estimated by dividing all harvested acres into different rice production systems and multiplying by a scaling factor (IPCC, 2006), correction factor, and seasonally integrated emission factor (used mean value from continuously flooded rice in India).	380.75	9,446.65
Vietnam	Second National Communication (2010)[e]	Estimated using harvested area divided into different production systems and multiplying by country-specific methane emission factors.	1,782.37	43,209.25

[a] People's Republic of China (2012). Note that the acreage and emission factors used to develop national rice methane emissions were not included in this National Communication.
[b] Government of India (2012).
[c] Republic of Indonesia (2012). Note that the acreage and emission factors used to develop national rice methane emissions were not included in this National Communication.
[d] Bangladesh (2012).
[e] Socialist Republic of Viet Nam 2010. Note that the emission factors used to develop national rice methane emissions were not included in this National Communication.

Of the five top rice producing countries, only India and Bangladesh include their national emission factors and or scaling factors in their SNCs (UNFCCC, 2016). Table 2-42 below shows the IPCC 2006 scaling factors, emission factors used in the Indian and Bangladesh Second National Communications and the emission factors used in the RFS2 RIA. Note that the factors cannot be directly compared as they are expressed in different units.

Table 2-42: Global Rice Methane Emission Factors

Rice Conditions		IPCC 2006 (Disaggregated Case Scaling Factor)[a]	India NC 2000 (kg CH_4/ha/season)[b]	Bangladesh NC 2000 (kg CH_4/ha/yr)[c]	RFS2 RIA Emission Factors (kg CH_4/ha/day)[d]
Irrigated	**Continuously flooded**	1.00	162.00	52.44	1.24
	Single aeration	0.60	66.00		
	Multiple aeration	0.52	18.00		
Rain-fed	**Regular**	0.28	-	28.00	0.44
	Drought-prone	0.25	66.00	25.00	-
	Flood-prone	-	190.00	11.46	-
Deep Water	**Regular**	0.31	190.00	-	0.49
Upland	**Regular**	-	-	0.00	0.00

[a] IPCC (2006). Table 5.12 Default CH_4 emission scaling factors for water regimes during the cultivation period relative to continuously flooded fields.
[b] Government of India (2012).
[c] Bangladesh (2012).
[d] EPA (2009a).

2.7.4. Annual Methane Emissions from Global Rice Production

According to the most recently published reports annual global methane emissions from rice production increased from 1990 through 2013 with some fluctuations. Global emissions were 465,640.31 Gg CO_2e in 1990 and 521,991.07 Gg CO_2e in 2012 (FAO, 2016a). The only RFS2 RIA methane emissions data for the Control Case and the Reference Case available were for 2012 (EPA, 2009b). Table 2-43 shows FAO global methane emissions from 1990–2012 and FAO estimates for global methane emissions from rice in 2030 and 2050, and the RFS2 RIA FAPRI-CARD data for 2012.

Table 2-43: Global Emissions from Rice Production (Gg CO_2e)

Year	Emissions from Rice Cultivation (FAO)[a]	RFS2 RIA Methane Emissions Control Case[b]	RFS2 RIA Methane Emissions Reference Case[b]
1990	465,640.31	-	-
1991	464,265.84	-	-
1992	467,291.86	-	-
1993	463,266.76	-	-
1994	467,416.84	-	-
1995	476,108.88	-	-
1996	481,444.47	-	-
1997	483,732.16	-	-
1998	481,696.28	-	-
1999	500,543.32	-	-
2000	490,302.96	-	-
2001	483,417.15	-	-
2002	472,564.07	-	-
2003	471,980.61	-	-
2004	481,405.88	-	-
2005	492,539.39	-	-
2006	495,469.85	-	-
2007	495,065.75	-	-
2008	509,146.22	-	-
2009	508,672.98	-	-
2010	517,627.84	-	-
2011	520,008.28	-	-
2012	521,991.07	17,800.00	18,410.00
2013	-	-	-

[a] FAO (2016a).
[b] EPA (2009b).

The data show that similar to global harvested rice acreage, the FAO emissions[21] increase from 465,640.31 Gg CO_2e in 1990 to 521,991.07 Gg CO_2e in 2012 (FAO, 2016a). The RFS2 RIA values for 2012 are approximately 3 percent of the FAO values.

2.7.5. Conclusions

A review of the current literature shows that global rice production and corresponding methane emissions have increased between 1990 and 2012, with some fluctuation between years. The RFS2 RIA FASOM data underestimates global harvested rice acreage. Emission factors used to develop the RFS2 RIA are based on Tier 1 IPCC 2006 guidelines. A review of the recent Second National Communications (SNC) from the top 5 rice producing countries shows that most of the countries have now created their own Tier 2 or Tier 3 country or region specific methane emission factors for rice. The RFS2 RIA emission factors cannot be directly compared to the SNCs as they are expressed in different units. The total projected 2012 global rice methane emissions from the RFS2 RIA are approximately three percent of those from the FAO.

2.7.6. References: International Rice Methane

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Socialist Republic of Viet Nam, 2010. Viet Nam's second national communication to the United Nations Framework Convention on Climate Change. http://unfccc.int/resource/docs/natc/vnmnc02.pdf

2.8. Fuel and Feedstock Transport

EPA's RFS2 RIA estimated that fuel and feedstock transportation accounted for less than 5 percent of total life-cycle GHG emissions from corn ethanol (about 3.5 g CO_2e/MJ). This estimation used GREET emission factors for rail, barge and truck. In 2015, GREET researchers substantially expanded the capabilities of the model's truck transportation LCA. This expansion included five varieties of diesel and gasoline freight vehicles. Beyond traditional fossil fuel vehicles, the update includes alternative fuel vehicles for hybrid and hydraulic technologies: 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 used 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 methodology determined these emission factors by analyzing industry inputs and outputs from over 400 economic sectors. The study also assessed transportation through fossil fuel pipelines. While there is little pipeline infrastructure for transportation of biofuels, recent research projected that existing fossil fuel pipelines could be retrofitted to transport biofuels. Depending on the electricity mix used for pumping, the researchers found that significant GHG emissions savings exist for transporting biofuels through pipelines (Strogen et al. 2013). This potential of pipeline transportation could be taken into account in future corn ethanol LCAs.

2.8.1. References: Fuel and Feedstock Transport

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2.9. Fuel Production

Recent LCA literature has shown that corn ethanol production accounts for over 40 percent of life-cycle GHG emissions (Wang et al., 2012). Technological advancements in production, introduction of new co-products, and refinement of LCA methodologies project significant savings from the GHG intensity previously determined by EPA (2010).

Table 2-44 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). Applicable Subparts are likely to include Subpart C (stationary combustion), Subpart HH (municipal solid waste landfills), and Subpart II (wastewater treatment).Emissions are primarily from fuel combustion on-site from both fossil and biogenic fuel sources. The GHGRP and EIA data show that the total national GHG intensity has declined by 4 percent between 2010 and 2014.

Table 2-44: GHG Intensity for Corn Ethanol Production Facilities

Datum	Year				
	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 gallon)	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 2-12 shows that as the corn ethanol production has grown, the industry has become more efficient, using fewer bushels of corn to produce a gallon of ethanol. Several factors contributed 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 also enabled the development of better enzymes and yeast strains for improved output per bushel of corn.[22]

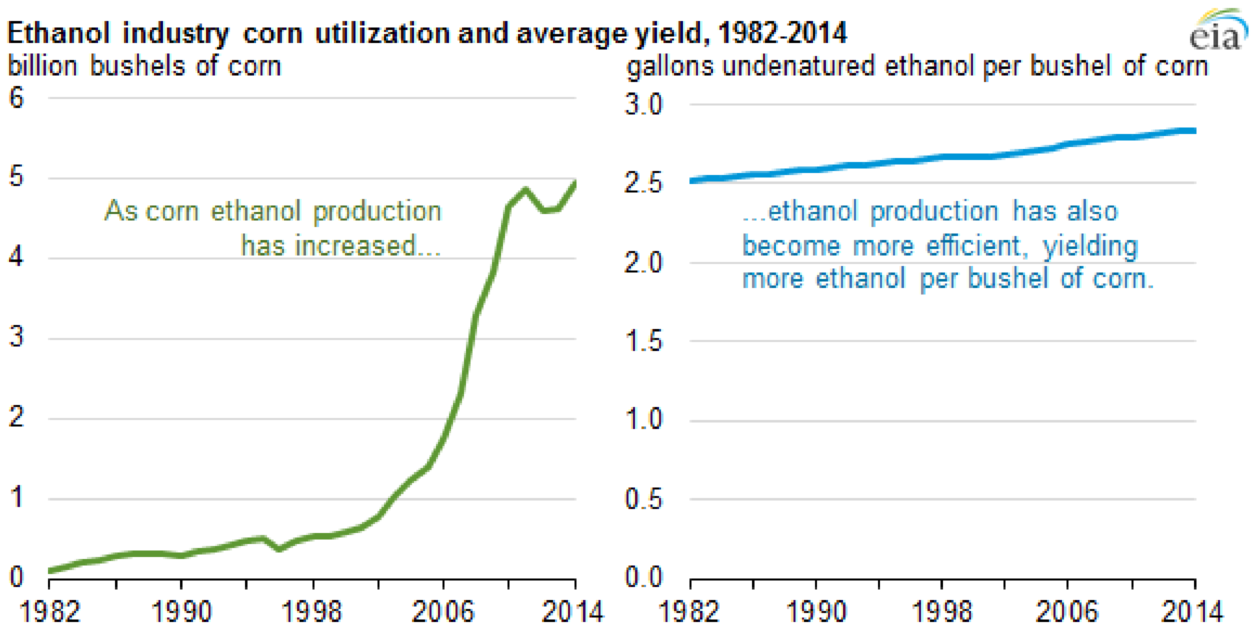

Figure 2-12: Ethanol Industry Corn Utilization and Average Yield, 1982–2014

The GREET model used primarily in the EPA's assessment has subsequently been updated to include new co-products, production pathways, and co-product allocation methods. Argonne researchers estimated current corn ethanol production using natural gas contributed 30 g CO_2e/MJ to the fuel's

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

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 Argonne 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, 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 EPA report, 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 based on the specific method.

Boland and Unnasch (2014) projected significant reductions in life-cycle corn ethanol GHG intensity, using the EPA (2010) 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 EPA report. The study projected these GHG intensities to decline by 8–20 percent from 2012–2022 due to efficiency improvements.

2.9.1. References: Fuel Production

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2.10. Tailpipe

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.[23]

The EPA (2010) report used the EPA's motor vehicle emission simulator (MOVES) 2009 model to estimate CH_4 and N_2O emissions from gasoline and diesel vehicles. The MOVES model derived emission factors from federal GHG emission testing. The EPA has updated MOVES twice since the 2009 model in 2010 and 2014. The 2010 update included multiple improvements for gasoline and diesel GHG emission rates for the following criteria (EPA, 2014):

- 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
- 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 present opportunities for improvements in accuracy for future LCA models, it should be noted that tailpipe emissions only represent about 1 percent of total life-cycle GHG emissions from corn ethanol (EPA, 2010a).

2.10.1. References: Tailpipe

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[23] 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.

3. Current GHG Emission Values for Each Emissions Source Category

This chapter presents an assessment of the GHG footprint of corn-based ethanol today. For each emission source category, we include a summary of the methods, data sources, and emissions projection developed in the EPA RIA, describe the methods used here to quantify the contribution to corn ethanol's current GHG profile attributable to that category, and quantify that contribution.

The chapter is organized by emission category,specifically:

- Domestic farm inputs and fertilizer N_2O
- Domestic land-use change
- Domestic rice methane
- Domestic livestock
- International livestock
- International land-use change
- International farm inputs and fertilizer N_2O
- International rice methane
- Fuel and feedstock transport
- Fuel production
- Tailpipe
- Result of combining the current GHG emission category values

3.1. Domestic Farm Inputs and Fertilizer N_2O

The domestic farm inputs evaluated in the EPA 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. EPA also quantified N_2O emissions due to application of synthetic fertilizers.

3.1.1. EPA RIA Methodology and Data Sources

The EPA RIA used the domestic agricultural inputs for fertilizer, pesticides, and energy use from the Forestry and Agriculture Sector Optimization Model (FASOM) output (Adams et al., 2005). [24] 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

[24] The Forestry and Agriculture Sector Optimization Model 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. It has collaborators at Oregon State, Research Triangle Institute, Electric Power Research Institute, EPA, USDA, and USDA-Forest Service.

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. The energy use in FASOM represented the fuels used for grain drying. 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. The 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 the Greenhouse Gas, Regulated Emissions, and Energy use in Transportation (GREET) spreadsheet analysis tool developed by Argonne National Laboratories. GREET version 1.8c was primarily used. The electricity emission factors represent average U.S. grid electricity production and were also based on GREET (EPA, 2009).

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.[25] The 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 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. These crop residues 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.

[25] 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.

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, also emits N_2O and CH_4, which are considered a net source of GHG emissions.

3.1.2. EPA RIA Results

National-level input data for domestic farm inputs based on the FASOM output are shown in Table 3-1. The RIA provides the domestic inputs in units per MMBtu as they are attributed to the corn ethanol production.

Table 3-1: Summary of Domestic Agricultural Inputs for Corn Ethanol, 2022 (Source: Table 2.4-5 from EPA RIA)

Input	Units per MMBtu	Fuel-Specific Scenario	Control Scenario	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: 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. The GHG emission factors for the domestic farm inputs can be found in Table 3-3. 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 3-2. In the calculation spreadsheets, the analysis in some cases was only performed for the volume difference between the corn-ethanol scenario and the control case scenario. The negative values below represent negative emissions.

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

Emission Category	Units	2012			2017	2022
		Fuel-Specific	Control Case	Difference	Difference	Difference
N Fertilizer Application Practices under Managed Soil	000 Tons CO_2e	N/P	N/P	363.5	574.8	442
Emissions from N Fixing Crops	000 Tons CO_2e	N/P	N/P	−823.5	−1,330	−1,157
Emissions from Crop Residue Retention	000 Tons CO_2e	N/P	N/P	−152.8	−180.1	−218
Domestic Fertilizer Use	000 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 3-1 was then multiplied by the emission factors shown in Table 3-3 to calculate the total emissions for domestic farm inputs.

Table 3-3: Emission Factors for Domestic Farm Inputs and Fertilizer N_2O
(Units: Emissions—grams per ton of nutrient; Energy Use—MMBtu per ton of nutrient)

	Average Nitrogen Fertilizer	Phosphate (P_2O_5) Fertilizer	Potash (K_2O) Fertilizer	Lime ($CaCO_3$) Fertilizer	Herbicide	Pesticide
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
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, this category of emissions is projected to be 10,313 g CO_2e/MMBtu for domestic agricultural inputs by 2022 (the emission intensity was not reported for 2014).

Table 3-4: Domestic Agricultural Input Emissions including Ethanol Co-Product Credit

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	10,313

3.1.3. ICF Methodology and Data Sources

ICF analyzed the GHG emissions impact of RFS2-related corn ethanol production on domestic agricultural inputs—specifically, nitrogen (N) fertilizer, phosphorus (P) fertilizer, potassium (K) fertilizer, herbicides, insecticides, and fungicides—and fuel consumption. Upstream emissions factors are included for all chemical applications 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 Agricultural Resource Management Survey (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 rates for all regions except for the Corn Belt region, due to the lack of data for these regions. We assumed that the diesel fuel use is 7.74 gallons per corn-acre under conventional tillage, based on 2015 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).[26] Table 3-5 present the results of this analysis. ARMS data did not report corn acres in the Delta and Pacific regions, hence they these regions are excluded from Table 3-5 (USDA ERS 2016).

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

Table 3-5: Effective Chemical Application Rates (Pounds per Acre) Using 2010 ARMS Data

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

ICF used the RIA's projected number of additional bushels of corn in the control scenario (i.e., compliance with the RFS2 regulation), compared to the reference scenario (i.e., no RFS2 is enacted) (773,956,000 bushels in 2017, which we assume is also the marginal increase for 2014) to determine the additional number of corn acres that can be attributed to the RFS2 rule. 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 3-6, were then allocated by region based on the ARMS corn acreage data by region (USDA ERS, 2016). The total projected change in acreage under ICF's analysis is 4.9 million acres in 2017 and 3.4 million acres in 2022. For comparison, the RIA projected an additional 4.9 million acres in 2017 and 3.6 million acres in 2022. These acreage increases are less than 6 percent of the total acreage.

Table 3-6: Calculated Changes in Corn Production in the ICF: 2014 Current Conditions Control Scenario (Acres)

Year	Appalachia	Corn Belt	Lake States	Mountain	Northeast	Northern Plains	Southeast	Southern Plains	Total Acres
2014	138,120	2,359,057	855,620	81,279	146,676	1,255,923	18,338	140,572	4,995,585
2017	135,879	2,320,783	841,738	79,960	144,296	1,235,546	18,040	138,291	4,914,536
2022	95,090	1,624,126	589,064	55,957	100,981	864,657	12,625	96,778	3,439,282

ICF multiplied the acreages in Table 3-6 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 Argonne National Laboratory's GREET 2015 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 after the farm "gate" from 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.

Table 3-7: 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	389.26	2.31	0.83	10,815
Fertilizer and Pesticides	301.67	1.79	0.64	8,382
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

3.1.4. 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 lifecycle analysis (LCA) standard approach for handling these animal feed co-products (see Argonne's GREET model, the California Air Resources Board, and EPA) is to credit the co-product via the displacement methodology. For the displacement methodology, all of the energy and emissions for farming, fertilizer, feedstock transport, and ethanol production are allocated to the primary product from ethanol production (i.e., the ethanol), and the ethanol pathway is credited for co-product displacing animal feed.

ICF utilized the GREET 2015 assumptions for the breakdown of the animal feed components, including corn, soybean meal, urea, and soybean oil, that are being displaced. Table 3-8 indicates that feed displacement values vary by ethanol refining process and displaced animal feed.

Table 3-8: Ethanol Production Market Breakdown and Animal Feed Displacement by Ethanol Plant Type

Ethanol Plant Type	Ethanol Market Share	Total Displaced Animal Feed (Pounds per Gallon of Ethanol)			
		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	70.9%	4.210	1.656	0.122	-

Ethanol Plant Type	Ethanol Market Share	Total Displaced Animal Feed (Pounds per Gallon of Ethanol)			
Extraction					
Wet Mill	11.4%	7.149	-	0.109	0.980

ICF modified the GREET default values for corn farming farm 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 3-9 shows the resulting DGS credit per gallon of ethanol and per MMBtu.

Table 3-9: 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**

3.1.5. ICF Results

The combined domestic agricultural inputs emissions related to the RFS2 rule in 2014 (i.e., under current conditions) is approximately 9,065 g CO_2e/MMBtu. This estimate is the sum of the ethanol co-product credit in Table 3-9 (−12,749 g CO_2e/MMBtu) and the domestic inputs emissions impact in Table 3-7 (+21,814 g CO_2e/MMBtu). The difference in emissions from the EPA RIA is small and is attributed primarily to the lower GWP value for N_2O in AR4 and the slightly higher chemical application rates used in our analysis.

Table 3-10: Domestic Agricultural Input Emissions including Ethanol Co-Product Credit

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2014 Current Conditions	9,065

3.1.6. 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 equally.

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, this analysis did not include the emissions 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 developed in Chapter 4.

3.1.7. References: Domestic Farm Inputs and Fertilizer N_2O

Adams, D., Alig, R., McCarl, B. A., & Murray, B. C. (2005). *FASOMGHG Conceptual Structure and Specification: Documentation.* Retrieved from http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf

EPA. (2009, October 30). GREET. *RFS2 FRM modified version of GREET1.8c Upstream Emissions Spreadsheet*.

IPCC. (2006). *2006 IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme, Eggleston H.S., Buendia L., Miwa K., Ngara T. and.* Japan: IGES.

3.2. Domestic Land-Use Change

To model the land-use change within the United States, EPA used the FASOM model to project the land conversions (Adams et al., 2005). In particular, EPA used the model to project land-use change from the increase in corn ethanol production and the change in GHG emissions from the changes in land use.

3.2.1. EPA RIA Methodology and Data Sources

The FASOM model includes the land-use categories cropland, cropland pasture, forestland, forest pasture, rangeland, developed land, and acres enrolled in the Conservation Reserve Program (CRP). 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.

Since the publication of the EPA RIA, FASOM has been updated to allow analysis across the forest and agricultural sector combined as opposed to separate runs of the forest and agricultural sector components. These model updates are not reflected in the RIA results. FASOM did not explicitly account for the corn oil extracted from distillers grain. Since the RIA, the model has been modified to add this pathway as part of the dry milling process. The original analysis is based on the assumption that by 2022, 70 percent of dry mill ethanol plants will withdraw corn oil via extraction, 20 percent will withdraw corn oil via fractionation, and 10 percent will do neither (EPA, 2010a).

Since the RIA, FASOM was also updated with distillers grain and soluble replacement rates for corn and soybean meal in animal feed. These replacement rates are based on research published by Argonne National Laboratory (Arora et al., 2008).

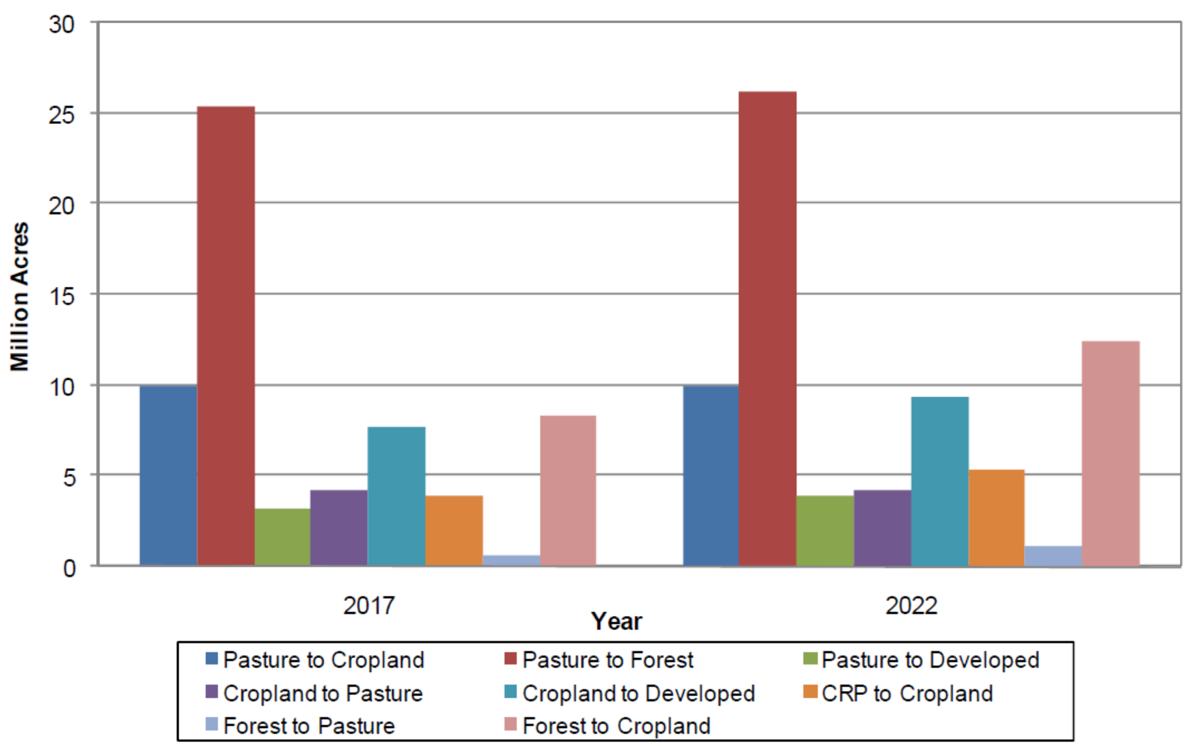
For the corn ethanol scenario, the relative demand for crop and livestock production had a direct and indirect effect on land use. These assumptions are presented in Table 3-11.

Table 3-11: Changes in Cropland Based on FASOM

Cropland Categories	Change in Cropland Used for Production and Idled
Total Cropland	+0.9 million acres
Total Cropland Pastures	−0.9 million acres
Total Forest Pasture	+0.2 million acres
Forestland	−0.03 million acres

Source: FASOM output; "EPA_2010_RFS2_regulatory_impact_assessment.pdf".

The land-use allocation over time is shown in Figure 3-1 for the Fuel-Specific Scenario.



Source: RTI International, 2010.

Figure 3-1: Changes in Land Allocation Over Time (2017 and 2022) for the Fuel-Specific Scenario

The land-use change is modelled across three phenomena:

1. **Developed Land**: FASOM assumed that developed land is of higher value than all other land categories, the amount of developed land increased at a steady rate over time and the rate of urbanization is assumed to be exogenous 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 excludes carbon stored in annually cultivated crops. Changes in sequestration for land moved from the forestry and agricultural sectors into developed land is tracked within FASOM.

3. **Agricultural Land-Use Change GHG Emission Factors**: FASOM agricultural land GHG emission factors were updated with the DAYCENT/CENTURY model runs to reflect scientific updates at the time of the model runs (RTI International, 2010).

To calculate the annualized timing of cumulative GHG emissions due to land-use change, all emissions associated with agricultural land (CO_2 and N_2O from cropland, pastureland, and CRP land) and forestland between 2000 and 2022 (CO_2 from biomass, soil, and forest products) are summed as the emissions from these categories accumulate over time. EPA's RIA states, "The GHG emissions associated with converting land into crop production would accumulate over time with the largest release occurring in the first few years due to clearing with fire or biomass decay. After the land is converted, moderate amounts of soil carbon would continue to be released for approximately 20 years. Furthermore, there would be foregone sequestration associated with the fact that the forest would have continued to sequester carbon had it not been cleared for approximately 80 years."

3.2.2. EPA RIA Results

The aggregate GHG emissions from domestic land-use changes are a result of the difference in land-use change and management practices in 2022 and dependent on changes in the land-use patterns that occurred prior to 2022. FASOM generates GHG emissions estimates with land-use change for every five-year period within the identified timeframe (Adams et al., 2005). Using these data, the EPA RIA calculated the GHG emissions changes for corn ethanol and annualized the cumulative change (EPA, 2010a). The change in emissions is shown in Figure 3-2.

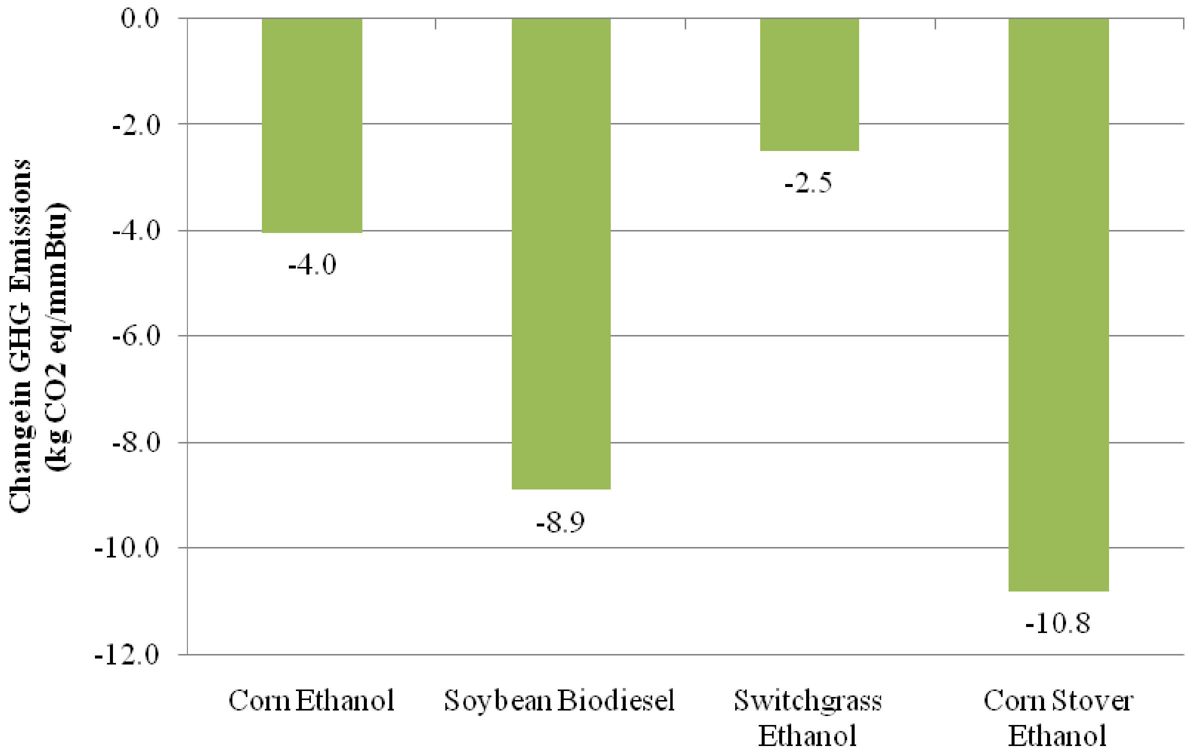


Figure 3-2: Change in GHG Emissions Due to Domestic Land-use Change by Scenario, 2022, Annualized Over 30 years for the Different Fuels within RFS2 (Source: Figure 2.4-19 in EPA RIA) (Units: kg CO_2e/MMBtu)

Table 3-12 below shows the same EPA RIA result in g CO_2e/MMBtu.

Table 3-12: Domestic Land Use Change Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	-4,000

3.2.3. ICF Methodology and Data Sources

ICF estimated the domestic land-use change GHG emissions from expanding cropland to produce corn for ethanol production using the most recent related datasets, analyses, and available LUC models. The RIA relied on projections and estimates from the Forest and Agricultural Sector Optimization Model (FASOM), which are discussed above. Actual U.S. corn acreage through 2014 has exceeded the RIA acreage projections. The domestic LUC assessment combines new domestic acreage change estimates with improved carbon flux emission factors.

The RIA domestic LUC analysis used FASOM acreage change projections and emission factors. In the ICF analysis, we used emission factors from FASOM that had been updated with DAYCENT/CENTURY modeling efforts. These emission factors better reflect irrigation effects and N_2O emissions from cropland and pastureland. The RIA assessed CO_2 and N_2O emissions from cropland, pastureland, and Conservation Reserve Program (CRP) acreage conversions, as well as CO_2 emissions from projected conversions of forest to cropland. For the RIA, the total emissions were summed for all the conversions to generate cumulative GHG emissions over the time horizon (2000–2022).

ICF's domestic LUC analysis closely followed the 2015 GREET model's Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) (Dunn et al. 2015). ICF's specific method used U.S. acreage conversions to corn ethanol from the previously described GTAP model available within CCLUB. GTAP quantifies acreage change for 18 Agro-ecological Zones (AEZs), but only AEZs 7–16 are relevant (i.e., non-zero) for the United States.[27] The types of acreage included are forests, grassland, cropland-pasture, and young forest shrub (YF shrub). YF shrub acreage change and conversion emissions were quantified by applying the relevant forest correction factor to the forest conversion values and emission factors for the GTAP model only. Table 3-13 shows the GTAP data for the AEZs, land types, and GTAP dataset year (2011, 2013). The improvements made in the GTAP model between 2011 and 2013 resulted in the significant decreases in acres converted. ICF performed our analysis on the 2013 model results. Negative values denote reductions of each land type (e.g. forest, grassland, crop-pasture) that are converted to feedstock (corn). A positive value would denote an increase in land of that type.

Table 3-13: GTAP Data for U.S. Acreage Changes by Year, AEZ, and Land Type

AEZ Number	Forest to Corn (ha)		Grassland to Corn (ha)		Cropland-Pasture to Corn (ha)		Young Forest Shrub to Corn (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**

[27] The Domestic and International Land-Use Change sections of the Literature Review discuss in detail AEZs (Agro-Ecological Zones).

ICF varied the acreage conversion GHG emissions for the three available models in CCLUB for domestic LUC: Century/COLE, Woods Hole, and Winrock. Century/COLE included regional variations (AEZs) for all available GTAP acreage changes, along with non-soil and annual growth emissions. Winrock included three emission factor options (forest, grassland, cropland-pasture), and Woods Hole two (forest, grassland). The Century/COLE emission factors also provided variations for tillage and soil depth, which were included as scenarios in the final results. For each LUC variation, the total cumulative emissions were annualized for the CCLUB default input of 30 years. We converted the results to the final g CO_2e/MMBtu based on the CCLUB values for annual ethanol production increases from the 2004 base year (11.59 billion gallons to reach the 15 billion gallons mandate) and lower heating value (76,330 Btu/gal). Sections 2.2.2 and 2.2.3 of the literature review detail the Winrock and Woods Hole conversion emission factors, respectively. Table 3-14 and Table 3-15 show the Century/COLE emission factor variations for the conventional and reduced till scenarios assessed in Chapter 3. Emission factors varied by AEZ, soil depth (100 cm, 30 cm), and land conversion type. Positive emission factors denote carbon emissions from the soil and negative values denote sequestration of carbon within the soil.

Table 3-14: Soil Carbon Emission Factors for Reduced Till in Century/COLE

AEZ Number	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)	
	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

Table 3-15: Soil Carbon Emission Factors for Conventional Till in Century/COLE

AEZ Number	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)	
	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 Number	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 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

3.2.4. ICF Results

Table 3-16 shows the final results for all the scenarios run using the CCLUB methodology. Conservatively, ICF recommends utilizing the Century/Cole 100 cm conventional till scenario of −2,038 g CO_2e/MMBtu.

Table 3-16: Final Scenario Results for 2013 GTAP Acreage Change Data

	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	−1,965
Century/COLE—100cm—Reduced Till	−62,656,429	−2,088,548	−180.2	−2,359
Century/COLE—30cm—Conventional Till	−45,625,214	−1,520,840.5	−131.2	−1,718
Century/COLE—100cm—Conventional Till	−54,120,694	−1,804,023.1	−155.7	−2,038
Woods Hole	48,163,909	1,605,464	138.5	1,813.7
Winrock	280,879,558	9,362,652	807.8	10,577.1

Table 3-17 shows the ICF current conditions value, which utilizes the CCLUB model with 2013 GTAP acreage change data.

Table 3-17: Domestic Land Use Change Emissions

	Emissions Impacts ($g\ CO_2e/MMBtu$)
ICF: 2014 Current Conditions	−2,038

3.2.5. Limitations, Uncertainty, and Knowledge Gaps

The major variations in domestic LUC results between GTAP modeling years highlights the need for more study to determine if a stable trend or value emerges regarding emissions from LUC. Future research should continue to closely track annual corn acreage for ethanol production and the associated acreage conversions to generate a more certain assessment of the linkages between corn ethanol production and domestic LUC. Until these datasets, trends, and quantitative uncertainty assessments can be established, LUC will continue to be the most difficult life-cycle element to accurately analyze.

3.2.6. References: Domestic Land-Use Change

Adams, D., Alig, R., McCarl, B. A., & Murray, B. C. (2005). *FASOMGHG Conceptual Structure and Specification: Documentation.* Retrieved from http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf

Arora, Salil, May Wu, and Michael Wang. (2008, September). *Update of Distillers Grains Displacement Ratios for Corn Ethanol Life-Cycle Analysis*. Retrieved from Argonne National Laboratory: http://www.transportation.anl.gov/pdfs/AF/527.pdf

Dunn JB, Mueller S, Qin Z, Wang MQ (2014) Carbon Calculator for Land Use Change from Biofuels Production (CCLUB 2015). Argonne National Laboratory (ANL).

RTI International. (2010, March). *Forest and Agricultural Sector Optimization Model (FASOM) Technical Report for Renewable Fuel Standard (RFS2) - U.S. Agricultural and Forestry Impacts of the Energy Independence and Security Act: Forest and Agricultural Sector Optimization Model (FASOM) R.* Retrieved from EPA-HQ-OAR-2005-0161-3178: http://www.regulations.gov/#!documentDetail;D=EPA-HQ-OAR-2005-0161-3178

3.3. Domestic Rice Methane

The methane emissions associated with domestic rice production were included in the EPA RIA analysis. When rice fields are flooded, the organic material decomposes causing a lack of oxygen in the soil. These anaerobic conditions cause the production of methane, a portion of which is diffusively transported from the soil to the atmosphere. Methane can escape from the soil and bubble through the flood waters.

3.3.1. EPA RIA Methodology and Data Sources

FASOM was used to model the methane emissions from rice produced in the United States that is grown in flooded fields (Adams et al., 2005). The model assumed that a reduction of rice acreage corresponded in a reduction in rice cultivation methane emissions. The model did not consider any additional changes in rice cultivation practices (e.g., nutrient management, ratooning) that could also affect emissions. Therefore, the changes in emissions from rice cultivation were the direct result of changes in the planted acreage within the model.

Methane emissions per acre were calculated based on the regional emission factors by acre for each region based on the EPA's U.S. GHG inventory for 1990–2003 (EPA, 2005). FASOM assumed that rice methane emissions would decrease for all fuel pathways, including corn ethanol production due to decreased domestic rice acreage.

3.3.2. EPA RIA Results

Table 3-18 shows the emission factors used in FASOM.

Table 3-18: Average Methane Emission Factors from Irrigated Rice Cultivation by Region (Source: Table 2.4-9 from EPA RIA) (Units: 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: FASOM output; "EPA_2010_RFS2_regulatory_impact_assessment.pdf".
N/A = Not Applicable.

Table 3-19 shows the relative emissions change based on the change in acreage from rice production to corn production.

Table 3-19: Relative Change in Domestic Methane from Rice Production

Emission Category	Units	2012			2017			2022		
		Fuel-Specific	Control Case	Difference	Fuel-Specific	Control Case	Difference	Fuel-Specific	Control Case	Difference
Methane from Rice Cultivation	000 Tons CO_2e	18,410	17,800	−359.8	N/P	N/P	−227.5	N/P	N/P	−352

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

EPA's analysis resulted in a reduction of 42,000 tons CO_2e (see Table 2.4-10 from EPA RIA).

The RIA estimated the overall contribution of domestic rice methane to the corn ethanol life-cycle GHG emissions to be less than −500 g CO_2e/MMBtu. The RIA value is shown in Table 3-20 below.

Table 3-20: Domestic Rice Methane Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	−500

3.3.3. ICF Methodology and Data Sources

Chapter 2 identified several areas where recent trends in domestic rice production, and the associated methane emissions differ from the production and emissions projected in the RIA. Most notably, at least through 2014, the RIA overestimated total rice acreage (and thus the associated methane emissions). Countering these overestimates, however, the RIA used the IPCC AR2 CH_4 GWP of 21. The IPCC revised this GWP to 25 in AR4, which implies a downward bias in the projected CH_4 emissions associated with domestic rice production in the RIA. In this analysis, ICF used a methodology similar to that used in the RIA but incorporates new rice production data and uses the AR4 CH_4 GWP.

ICF determined the GHG emission impact of RFS2-related corn ethanol production on domestic rice methane emissions using the following methodology. Step 1 identified the difference in harvested rice acreage and associated emissions between the control case (i.e., where corn ethanol production has expanded under the RFS2) and the reference case (i.e., no RFS2). EPA projections for harvested rice acreage (based on FASOM simulations) for 2012 and 2017 for three scenarios are shown in Table 3-21 where increased corn production for ethanol results in reduced domestic rice acres. Values for 2014 are interpolated from the 2012 and 2017 values. The "Corn Only Case" shows FASOM model results that exclude any effects of other RFS2 biofuels on the control case (i.e., the control case reflects full multi-fuel compliance with the RFS2).

Table 3-21: EPA RIA Domestic Rice Acreage for Corn Only, Control, and Reference Scenarios

Year	Million Acres			Acre Ratios	
	Corn Only Case	Control Case	Reference Case	Reference Case / Control Case	Corn Only Case / Control Case
2012	3.50	3.36	3.82		
2014	3.63	3.50	3.90	1.12	1.04
2017	3.84	3.72	4.03		

To calculate the total rice methane emissions, ICF used the same regional assessment method as the RIA. As discussed and detailed in the literature review (see Section 2.3.3), the regional acreage and associated emission factors have been updated in recent EPA reports. Our assessment used these data (EPA 2016) to calculate new results for methane emissions in both reference and control cases. The acreage data in the recent reports were used as the control case, and ICF determined reference and corn only case acreage by applying the average ratio of reference acreage to control acreage and corn only to control acreage from the available projections (see Table 3-21). Table 3-22 indicates the ICF scenario acreages and associated emissions for the regions assessed.

Table 3-22: ICF Regional Acreage and GHG Emissions for Domestic Rice Methane

Region	Harvested Acreage (million acres)			GHG Emissions (MMT CO_2e)	
	2014 Actual Acres (Control Case)	Reference Case	Corn Only Case	Corn Only Case	Reference Case
Arkansas	1.98	2.12	2.05	7.65	8.23
California	0.68	0.73	0.70	1.51	1.62
Florida	0	0	0	0.00	0.00
Illinois	0	0	0	0.00	0.00
Louisiana	0.78	0.83	0.81	3.01	3.24
Minnesota	0.002	0	0.003	0.01	0.01
Mississippi	0.13	0.14	0.14	0.51	0.55
Missouri	0.26	0.28	0.27	0.82	0.88
New York	0	0	0	0.00	0.00
South Carolina	0	0	0	0.00	0.00
Total	**3.82**	**4.10**	**3.97**	**13.50**	**14.52**

To estimate a final life-cycle emission factor, ICF calculated the difference in total GHG emissions (all regions included) between the “reference case” and “corn only case” scenarios to quantify the incremental GHG emissions from the reference to the corn only case. These incremental emissions were then divided by the incremental corn ethanol production from the RIA’s reference and corn only case (3.03 billion gallons in 2014). We then converted this GHG emissions per volume of ethanol value to an emission factor (g CO_2e/MMBtu) using the heating value of ethanol to convert the volume in gallons to energy in Btus.

3.3.4. ICF Results

Relative to the RIA, ICF found an increased reduction in corn ethanol emissions associated with changes in domestic rice production related to RFS2 compliance. The ICF value is shown in Table 3-23 below.

Table 3-23: Domestic Rice Methane Emissions

	Emissions Impacts (g CO_2e/MMBtu)

ICF: 2014 Current Conditions	−4,034

3.3.5. Limitations, Uncertainties, and Knowledge Gaps

ICF's domestic rice methane assessment continued to rely on the relationships (i.e., scenario acre ratios) derived from the FASOM-modeled RFS2 RIA projections for rice acreage for the control and reference cases (see Table 2-21). Future work should reevaluate (i.e., remodel) these acreage numbers to better assess the difference, if any, between these two cases. While our assessment used updated emission factors to generate an assessment to compare to the RFS2 RIA, the lack of data in the reference and control cases for acreage limit the reliability 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.

3.3.6. References: Domestic Rice Methane

Adams, D., Alig, R., McCarl, B. A., & Murray, B. C. (2005). *FASOMGHG Conceptual Structure and Specification: Documentation.* Retrieved from http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf

Dunn JB, Mueller S, Qin Z, Wang MQ (2014) Carbon Calculator for Land Use Change from Biofuels Production (CCLUB 2015). Argonne National Laboratory (ANL).

EPA. (2005). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2003. EPA 430-R-05-003.* Retrieved from http://www3.epa.gov/climatechange/Downloads/ghgemissions/05CR.pdf

EPA. (2016). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2014. U.S. Environmental Protection Agency. EPA 430-R-16-002*. https://www3.epa.gov/climatechange/Downloads/ghgemissions/US-GHG-Inventory-2016-Main-Text.pdf

3.4. Domestic Livestock

Domestic livestock production and management contribute non-combustion GHG emissions through enteric fermentation and manure management. Enteric fermentation produces methane emissions during the animals' digestive processes. Ruminant animals (i.e., cattle, buffalo, sheep, and goats) are the largest emitters of methane from enteric fermentation. Manure management also emits methane, with the largest contributors being large hog and dairy farms. The animals evaluated in EPA's analysis include dairy and beef cattle, swine, and poultry.

3.4.1. EPA RIA Methodology and Data Sources

FASOM was used to model the changes in methane emissions associated with livestock enteric fermentation and manure management based on changes in the number of livestock. FASOM models the change in livestock production as costs for feed changes due to corn ethanol production. The enteric fermentation emissions were determined based on the number of livestock by type, and the average emissions per animal. Within FASOM, emissions mitigation options are available, however in EPA's analysis they were not used. Enteric fermentation emissions were estimated based on the number of animals within each livestock category (Adams et al., 2005).

3.4.2. EPA RIA Results

The emission factors per animal are based on EPA's U.S. GHG inventory report for 1990–2003 and are presented in Table 3-24 (EPA, 2005).

Table 3-24: Domestic Livestock Emission Factors

Emission Source	Dairy	Cattle	Swine	Poultry
Enteric Fermentation (kg CH_4/head-year)	121	53	1.5	N/A
Manure Management (kg CH_4/head-year)	78	2	23.5	0.02

Source: EPA's U.S. GHG inventory report for 1990–2003; "Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx," "Input_Ag" tab.
N/A = Not Applicable.

Table 3-25 show the differences in livestock populations reported in the EPA RIA.

Table 3-25: Differences in Livestock Populations from the RIA

Livestock Type	Change in Population (Head)
Dairy (mature cows)	−20,000
Beef	+90,000
Poultry	−58,840,000
Swine	−220,000

In the RIA, corn ethanol was projected to result in a change in domestic livestock emissions of −3,746 g CO_2e/MMBtu.

Table 3-26: Domestic Livestock Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	−3,746[a]

[a] Includes a decrease in CH_4 (−3,381 gCO_2e/MMBtu ethanol) from DGS.

3.4.3. ICF Methodology and Data Sources

In the RIA, EPA estimated the impact of the RFS2 on future livestock populations by modeling the change in livestock with and without the RFS2. ICF utilized the RIA change in livestock population data for dairy cows (mature only), beef cattle, swine, and poultry in conjunction with revised emission factors for these livestock types for enteric fermentation and manure management from the *Inventory of U.S. Greenhouse Gases Emissions and Sinks: 1990–2014* (EPA 2016). For poultry populations, ICF assumed that the change in population shown in the RIA represented a change in poultry slaughtered, rather than the change in annual average poultry populations. In order to apply the annual emission factor developed in the *Inventory of U.S. Greenhouse Gases Emissions and Sinks: 1990–2014* (EPA 2016), ICF first had to use a scaling factor to adjust poultry populations. For dairy, beef, and swine populations, ICF used the RIA estimated changes in population directly.

To estimate the livestock emissions impacts from the implementation of the RFS2, ICF utilized the difference between the RIA's control and reference cases, as shown in Table 3-27. Given that the RIA did not report a change in head for intermediate years, and given our methodology, ICF was not able to estimate associated emission estimates for intermediate years (i.e., 2014). As a result, we have used the same domestic livestock result of our analysis for 2022 as the domestic livestock contribution in our estimation of the LCA value for 2014.

Table 3-27: Differences in Livestock Populations from the RIA

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.

Table 3-28 shows the combined emission factors per head when taking into account the GWPs from the RIA (AR2 values) and the AR4 values that were used in this analysis. Table 3-28 also shows what the current emission factor would be if the AR2 GWP values were used.

Table 3-28: Livestock GHG Emissions Per Head (g CO_2e/head)

Livestock Type	Enteric Methane (g CO_2e/head)			Manure Management (g CO_2e/head)		
	RIA (AR2)	ICF (AR4)	ICF (AR2)	RIA (AR2)	ICF (AR4)	ICF (AR2)
Dairy	2,541	3,625	3,045	1,021	2,065	1,799
Beef	1,113	1,850	1,554	107	143	140
Poultry	N/A	N/A	N/A	4.57	3.21	2.83
Swine	31.5	37.5	31.5	296	378	323

As a result of the changes in livestock populations shown in Table 3-25 and the revised emission factors shown in Table 3-28, the associated changes in emissions related to enteric fermentation and manure management for 2022 are shown in Table 3-29.

Table 3-29: Livestock GHG Emissions

Livestock Type	Enteric Methane Emissions (g CO_2e/MMBtu)	Manure Management Emissions (g CO_2e/MMBtu)
Dairy	−351	−200
Beef	+807	+62
Poultry	N/A	−195
Swine	−40	−403

Table 3-30 shows the combined changes in emissions from both sources.

Table 3-30: Total Combined Enteric and Manure Management GHG Emissions

Livestock Type	Combined Enteric Methane and Manure Management Emissions (g CO_2e/MMBtu)
Dairy	−551
Beef	869
Poultry	−195
Swine	−443
Total	**−320**

3.4.4. Reduced Methane from DGS as Animal Feed: Domestic Livestock

The use of DGS as an animal feed for beef cattle replacing conventional animal feed reduces the methane emissions from beef livestock. ICF utilized the GREET 2015 reduction factors of 0.084 kg CO_2e/dry lb of dry DGS (DDGS) and 0.059 kg CO_2e/dry lb of wet DGS (WDGS) for every dry pound of DGS consumed by beef cattle. Based on Renewable Fuels Association data,[28] 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 fuel production inputs in Section 3.10 and market share by production type. Table 3-31 shows the factors and results for reduced emissions per gallon and per MMBtu.[29]

Table 3-31: 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

3.4.5. ICF Results

In our analysis, the combined emissions are −2,463 g CO_2e/MMBtu. The differences between the results of this analysis and the RIA's analysis can largely be attributed to the revised assumptions used in GREET to calculate the reduced methane emissions from DGS fed to livestock.

Table 3-32: Domestic Livestock Emissions

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2014 Current Conditions[a]	−2,463

[a] Result is based on 2022 change in livestock data.

3.4.6. Limitations, Uncertainty, and Knowledge Gaps: Domestic Livestock

Because ICF did not have access to the RIA's original control and reference scenario data, there is uncertainty surrounding the populations utilized to create the original changes in livestock. Additionally, as the original RIA only provided a single output for the year 2022, data was not available to develop changes in livestock emissions for intermediate years, therefore the emission changes for 2022 are used as a proxy. Finally, we do not believe the RIA accounted for increases in livestock production over time,

[28] http://www.ethanolrfa.org/resources/industry/co-products/#1456865649440-ae77f947-734a
[29] Calculations take into account GREET defaults of 12% moisture content for DDGS and 65% moisture content for WDGS

e.g., dairy milk production and beef weight increases when accounting for the population changes in future years. Therefore, the population changes also do not consider these production changes.

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. This analysis, like the RIA, only takes into account the change in livestock populations between the reference and control cases.

3.4.7. References: Domestic Livestock

Adams, D., Alig, R., McCarl, B. A., & Murray, B. C. (2005). *FASOMGHG Conceptual Structure and Specification: Documentation.* Retrieved from http://agecon2.tamu.edu/people/faculty/mccarl-bruce/papers/1212FASOMGHG_doc.pdf

EPA, 2005. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2003. EPA 430-R-05-003. Retrieved from http://www3.epa.gov/climatechange/Downloads/ghgemissions/05CR.pdf

EPA, 2010a. Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. EPA-420-r-10-006. February 2010.

EPA, 2016. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2014. U.S. Environmental Protection Agency. EPA 430-R-16-002. https://www3.epa.gov/climatechange/Downloads/ghgemissions/US-GHG-Inventory-2016-Main-Text.pdf

USDA, 2016b. USDA Agricultural Projections to 2025. USDA Agricultural Projections No. (OCE-2016-1) 99 pp, February 2016. http://www.ers.usda.gov/publications/oce-usda-agricultural-projections/oce-2016-1.aspx

3.5. International Livestock

In order to be congruous with the domestic livestock emissions, enteric fermentation and manure management were evaluated for international livestock. The GHG impacts associated with changes in livestock across seven regions were calculated. The number of livestock was determined for: Canada, Western Europe, Eastern Europe, Oceania, Latin America, Africa, the Middle East, and India using the FAPRI-CARD model (FAPRI, 2004). The animals evaluated include dairy and beef cattle, swine, sheep, and poultry.

3.5.1. EPA RIA Methodology and Data Sources

Based on a similar methodology to the domestic livestock impacts, the FAPRI-CARD model determined the change in livestock production based on feed prices, and these changes were multiplied by the GHG emission factors for both enteric fermentation and manure management. The enteric fermentation emissions were determined based on the number of livestock by type, and the average emissions per animal. The manure management emissions similarly were determined by applying regional default methane and nitrous oxide emission factors by livestock type to the regional livestock production (FAPRI, 2004). The default 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).

3.5.2. EPA RIA Results

Changes in livestock numbers attributed to the RFS2 are shown in Table 3-33. The differences shown are the difference (in thousand livestock head) between the Fuel-Specific Scenario and the Control Scenario.

Table 3-33: International Livestock Changes Due to Corn Ethanol Production

Region/Animal Type	Units	2012	2017	2022
Canada				
Dairy	000 Head	−0.9	−3.0	−3.0
Beef	000 Head	−7.8	10.5	61.2
Swine	000 Head	−190.8	−457.2	−307.8
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	390.8	857.3	700.7
Western Europe				
Dairy	000 Head	0.2	−1.4	−1.1
Beef	000 Head	−3.3	−21.9	−28.7
Swine	000 Head	10.7	5.7	−9.9
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	147.1	538.4	733.8
Eastern Europe				
Dairy	000 Head	0.0	0.0	0.1
Beef	000 Head	5.5	19.4	18.3
Swine	000 Head	−58.7	−143.7	−51.6
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	1,209.1	3,566.5	3,528.7
Oceania				
Dairy	000 Head	0.1	1.8	3.6
Beef	000 Head	11.6	104.4	196.0
Swine	000 Head	21.2	3.9	−4.3
Sheep	000 Head	−11.3	1.9	35.4

Region/Animal Type	Units	2012	2017	2022
Poultry	000 Head	−205.9	733.5	1,342.1
Latin America				
Dairy	000 Head	−42.2	−112.1	−105.0
Beef	000 Head	−73.6	−342.3	−377.4
Swine	000 Head	−15.5	−43.1	36.0
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	−1,806.5	328.3	2,072.8
Asia				
Dairy	000 Head	−20.4	−55.6	−46.6
Beef	000 Head	901.8	788.3	964.3
Swine	000 Head	6.3	−254.8	−72.6
Sheep	000 Head	−534.2	−1,132.0	−702.2
Poultry	000 Head	−1,578.2	−682.2	1,477.3
Africa and Middle East				
Dairy	000 Head	−65.6	−195.4	−214.8
Beef	000 Head	−9.0	−32.3	−37.3
Swine	000 Head	0.0	0.0	0.0
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	−502.2	−660.1	−312.1
India				
Dairy	000 Head	0.0	−0.1	−0.1
Beef	000 Head	−4.2	−55.7	−31.2
Swine	000 Head	0.0	0.0	0.0
Sheep	000 Head	0.0	0.0	0.0
Poultry	000 Head	−745.5	−622.6	26.2

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

The emission factors from the IPCC are shown below in Table 3-34 (IPCC, 2006). The enteric fermentation and manure management emission factors were multiplied by the activity data in Table 3-33 to estimate the emissions from each livestock practice.

Table 3-34: International Livestock Emission Factors

Emission Source/Region	Dairy	Cattle	Swine	Sheep	Poultry
Enteric Fermentation (kg CH_4/head-year)					
Western Europe	121	53	1.5	8	N/A
Eastern Europe	109	57	1.5	8	N/A
Oceania	89	58	1	5	N/A
Latin America	81	60	1	5	N/A
Asia	63	56	1	5	N/A
Africa and Middle East	61	47	1	5	N/A
Indian Subcontinent	40	31	1	5	N/A
Manure Management (kg CH_4/head-year)					
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: IPCC Guidelines; “Renewable Fuel Lifecycle Greenhouse Gas Calculations (1).xlsx,” “Input_Ag” tab.
N/A = Not Applicable.

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

Table 3-35. International Livestock Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	3,458

3.5.3. ICF Methodology and Data Sources

There is very limited data related to international livestock populations for determining the current population of livestock. ICF utilized the RIA international livestock population changes for the corn ethanol case modeled by FAPRI-CARD for 2022 (EPA 2010). The population changes for diary, beef, swine, sheep, and poultry are shown in Table 3-36.

Table 3-36: International Livestock Changes Due to Corn Ethanol Production by Region in 2022 (head/billion Btu)

Region	Dairy	Beef	Swine	Sheep	Poultry
Canada	0.00	0.05	−0.17	0.00	1.37
Western Europe	0.00	−0.07	0.12	0.02	1.58
Eastern Europe	0.00	−0.83	0.01	0.00	17.72
Oceania	−0.02	0.11	0.01	0.07	3.53
Latin America	−0.15	3.44	0.48	0.00	0.05
Asia	-0.09	0.17	-0.04	−1.19	−1.53
Africa and Middle East	−0.03	−0.45	0.32	0.00	−3.01
India	0.00	0.12	0.02	0.00	−3.66

For international livestock emission factors, ICF analyzed updated factors as available for enteric methane and methane and N_2O emissions from manure management. The only available updated factors for international livestock were for Canadian cattle. The other international livestock data in the RIA were distributed by global region, so we were unable to update effective emission factors.

3.5.4. ICF Results

The primary changes to the emissions impacts from international livestock as a result of the corn ethanol portion of the RFS2 rule are due to the updated GWPs (and updated emission factors for Canada). Additionally, we have projected population changes only for 2022. The emissions impact is 3,894 g CO_2e/MMBtu.

Table 3-37: International Livestock Emissions

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2014 Current Conditions	3,894

3.5.5. References: International Livestock

EPA, 2010a. Renewable Fuel Standard Program (RFS2) Regulatory Impact Analysis. EPA-420-r-10-006. February 2010.

EPA, 2016. Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2014. U.S. Environmental Protection Agency. EPA 430-R-16-002. https://www3.epa.gov/climatechange/Downloads/ghgemissions/US-GHG-Inventory-2016-Main-Text.pdf

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3.6. International Land-Use Change

To model the change in cropland land internationally in response to increased corn ethanol production in the United States, the RFS2 RIA used the integrated Food and Agricultural Policy and Research Institute International model, maintained by the Center for Agricultural and Rural Development at Iowa State University (FAPRI-CARD) (FAPRI, 2004).[30] The Center for Agricultural and Rural Development at Iowa State University ran the FAPRI-CARD model on behalf of EPA.

3.6.1. EPA RIA Methodology and Data Sources

FAPRI-CARD projected the total changes in land area used for commodity production (crops and livestock) cropland by region. The land-cover types (forests, grassland, etc.) affected and the location of the land conversions were determined using MODIS satellite data provided by Winrock International who produces the land-use conversions internationally from 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

[30] The Farm and Agricultural Policy Research Institute's FAPRI CARD model examines and projects the production, use, stocks, prices, and trade for ethanol for several countries and regions of the world.

- Natural Ecosystems to/from Pasture

Natural ecosystems include forests, grasslands, savannas, shrublands, wetlands, and barren land.

The assessment assumes that the social, political, and economic forces that drove land-use change during this period of time will remain the same through 2022.

The international land-use change emission impacts are based on:

- **Land Conversion Categories**: The different types of land conversions were analyzed with satellite data to show their location and the land-cover types affected in order to estimate the international land-use change.
- **Forest Carbon Stock Estimates**: EPA's emission factors 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).
- **Land Clearing with Fire**: Fire for land clearing is assumed to occur in all countries included in the analysis except China and Argentina. These estimates are 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**: The changes in soil carbon stocks on land converted to cropland were calculated 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).
- **Foregone Forest Sequestration**: 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).
- **Land Reversion Carbon Uptake Factors**: All reversion factors (except reversion to forest) were estimated as the reverse of emission factors, and all increases in biomass stocks occurred in Year 1. Forest reversion factors are based on the assumption that biomass accumulates every year over the entire 30-year time period.
- **Change in Pasture Land Conversion**: The analysis accounted for changes in pasture area resulting from livestock fluctuations in order to create a link between the livestock and land used for grazing. The regional pasture stocking rates determine the amount of land needed for pasture. Any unneeded pasture areas are available for cropland or to be returned to their natural state. In countries where the livestock rates increased, the land used for pasture can be added to the abandoned cropland, unused grassland, or result in deforestation. The average stocking rates for each of the 54 FAPRI-CARD regions were determined based on data on livestock populations from the United Nations Food and Agricultural Organization (FAO) (see Table 2.4-31 from EPA RIA) (EPA,

2010a). Outliers such as countries within the "CIS, Other" FAPRI-CARD region, Kazakhstan and Turkmenistan, were removed. Countries with unusually low regional stocking rates were adjusted.

- **Agricultural Land-Use Change GHG Emission Factors**: Winrock International produced emission factors based on IPCC guidelines to calculate the GHG emissions associated with the projected land conversions. The international land-use change GHG impacts were annualized over 30 years with a 0 percent discount rate.

Accounting for pasture areas was essential as internationally more land is used for livestock production than crop production. As a result, the representation of Brazil within FAPRI-CARD explicitly accounts for changes in pasture area.

3.6.2. EPA RIA Results

Figure 3-3 presents the harvest area changes by crop and region. These results are for the corn ethanol scenario for 2022. The total change in international crop area harvested for 2022 corn ethanol was 789,000 hectares, which results in 3.94 hectares/billion Btus (see Table 2.4-29 from EPA RIA) (EPA, 2010a). The change in international pasture area decreased by 446,000 hectares, which resulted in a decrease of 2.23 hectares/billion Btus (see Table 2.4-32 from EPA RIA) (EPA, 2010a).

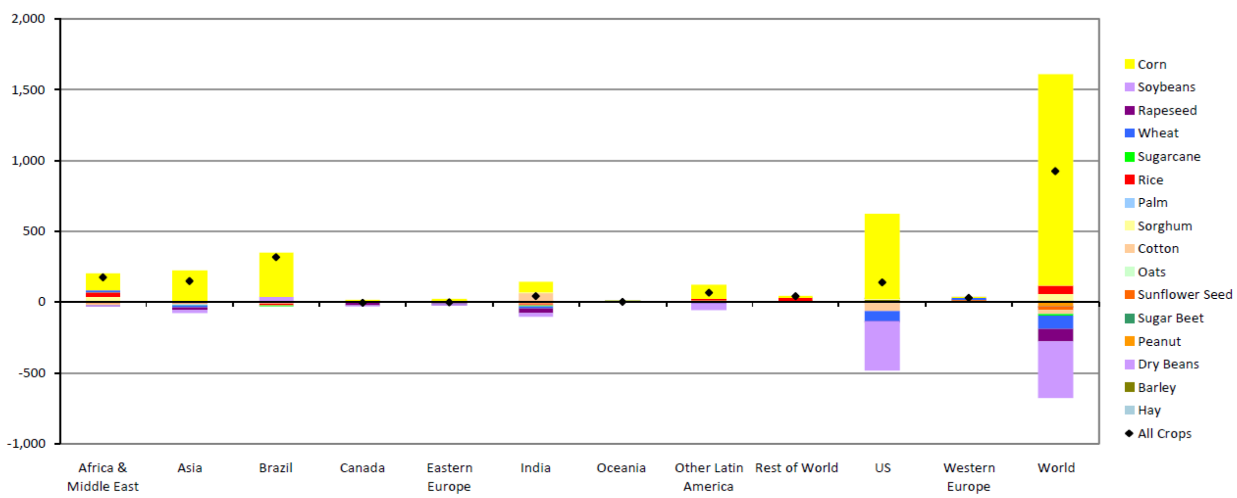

Figure 3-3: Harvest Crop Area Changes by Crop and Region for Corn Ethanol, 2022 (Source: Figure 2.4-21 from EPA RIA) (Units: 000s ha)

The emission impacts for each region are shown in Table 3-38. These emission factors reflect the amount of carbon dioxide associated with each MMBtu of corn ethanol by region associated with the increased demand for corn ethanol and annualized over 30 years. Positive values indicated increases in emissions associated with the change in land use.

Table 3-38: International Land-Use Change GHG Emission Impacts by Region, 2022 (Source: Table 2.4-47 from EPA RIA) (Units: 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”.

The RIA reported emissions due to U.S. corn ethanol production from changes in international land use as 31.79 kg CO_2e/MMBtu or 31,790 g CO_2e/MMBtu in 2022 (see Table 3-39).

Table 3-39: International Land-Use Change Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	31,790

3.6.3. ICF Methodology and Data Sources

To evaluate the impact of U.S. production of corn ethanol on international land-use change, ICF utilized a variety of land-use change modeling results that have been published since 2010, as well as recent data and analysis on international land-use change that were not available when the RIA was conducted. We also considered alternative emission factors for land converted. A review of published literature finds that much of the international land-use change impacts projected in the RIA have not materialized. As a result, the emissions path associated with land-use change in the RIA is much higher than those that have been estimated based on current conditions, and estimated for future years.

3.6.3.1. Changes in Acreage Data

The international land-use change from U.S production of corn ethanol in the RIA was modeled using the output from the FAPRI-CARD model. This model uses a number of factors including population and GDP growth; production and consumption trends; existing trade patterns; and both international and domestic prices to determine the change in acres across 20 crops and 54 countries. The model, however, cannot distinguish what types of land will be affected by a given shock to the global agricultural system.

Since 2010, Tahierpour and Tyner (2013) published a GTAP modelling scenario that reflects an increase in corn ethanol production from its 2004 level (3.41 billion gallons) to 15 billion gallons with GTAP recalibrated land-transformation parameters. This modelling scenario includes updated land-transformation data to develop region-specific elasticities using two United Nations Food and Agriculture Organization (FAO) land-cover datasets. It also reflects evidence from recent studies that the costs of converting forest to cropland are higher than had been assumed in prior land-use change studies. The complete set of GTAP region land-use change simulation results from Taheripour and Tyner (2013) are available in Argonne National Laboratory's CCLUB model (Dunn et al, 2014). These results are also shown in Table 3-40.

Table 3-40: GTAP Land-Use Change Output Generated by Taheripour and Tyner (2013) and Taken from Argonne National Laboratory's CCLUB Model

Description	United States	European Union 27	Brazil	Canada	Japan	China and Hong Kong	India	Central and Caribbean Americas	South and Other Americas	East Asia	Malaysia and Indonesia
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	−64,772	−14,718	62,449	−25,352	−5,041	−1,692	−7,005	4,456	68,910	2,245	892
Grasslands	−92,617	−18,835	−219,140	−14,759	−146	−86,841	−3,539	−9,854	−18,3325	−3,763	−2,974
Cropland-Grassland	−1,788,462	0	−213,930	0	0	0	0	0	0	0	0

Description	Rest of South East Asia	Rest of South Asia	Russia	Other East Europe and Rest of Former Soviet Union	Rest of European Countries	Middle Eastern and North Africa	Sub-Saharan Africa	Oceania Countries	Totals	Internationa l Total (w/o USA)
	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)	(ha)
Forests	−11,849	−3,099	87,329	−7,354	−240	168	−167,148	−543	−82,369	**−17,589**
Grasslands	−2,528	−21,562	−145,276	−21,478	−188	−21,975	−294,788	−17,307	−1,160,890	**−1,068,278**
Cropland-Grassland	0	0	0	0	0	0	0	0	−2,002,393	**−213,930**

Source: Dunn et al. 2014

Since 2010, a number of studies have evaluated the land-use change outcomes projected in the RIA (see Chapter 2). These studies generally conclude that there is not a strong link between corn ethanol production in the United States and deforestation in other countries, particularly in Brazil where much of the RIA's emissions related to indirect land use change were projected to occur. Additionally, among the broad range of emission estimates associated with indirect land-use change, across studies these estimates have decreased over time. For the land-use change that has been observed, Bruce Babcock and Zabid Iqbal's publication "Using Recent Land Use Changes to Validate Land Use Change Models" confirmed that the primary response from farmers across the world during the period 2004–2012 was to use available land resources more efficiently rather than to expand the amount of land in production. Farmers in Brazil, India, and China have increased double cropping, reduced unharvested planted area, reduced fallow land, and reduced temporary pasture which explains why the land-use changes projected in the RIA for Brazil and elsewhere have not materialized (Babcock and Iqbal, 2014).

To develop an updated picture of regional land-use changes that have occurred since 2010 as a result of increases in corn ethanol production in the United States, ICF incorporated qualitative data from Babcock and Iqbal (2014) along with recent GTAP simulation results from Dunn et al. 2014. The acres adjustments relied on one source in order to be consistent across regions.

ICF identified five regions for adjustments based on observed land practices and FAO data analysis.

- **Brazil:** Babcock and Iqbal (2014) show that 76 percent of Brazil's change in acres was due to double cropped land. This analysis assumes that the 76 percent change can be applied the acreage within the GTAP output that was attributed to U.S. corn demand.
- **India**: Babcock and Iqbal (2014) note that 100 percent of India's change in acres should be attributed to double cropping leading ICF to adjust GTAP 2013 change in acres to zero.
- **China**: Between 2010 and 2012, Babcock and Iqbal (2014) state that 29 percent of China's change in harvested acres should be attributed to double cropping. ICF adjusted the GTAP 2013 output to attribute 71 percent of the country's change in acres to U.S. corn demand.
- **Sub-Saharan Africa**: According to Babcock and Iqbal (2014), much of region's crop production was conducted by small-scale producers without modern farming equipment leading to the idea that double cropping is not widely adopted. The authors note that given domestic food demand from growing populations in the region, the extensive land-use increase equaled 20.7 million hectares or 1.35 percent (Babcock and Iqbal 2014). ICF adjusted the GTAP Sub-Saharan Africa region to allocate 1.35 percent of the GTAP 2013 change in acres to corn ethanol.
- **Indonesia:** Babcock and Iqbal (2014) cite multiple studies that state that the land-use change in Indonesia attributed to corn production is most likely inflated due to the prevalence of double cropping and the significant expansion of palm oil production. They commented that a significant portion of the corn production increase is due to double cropping (Babcock and Iqbal 2014). ICF attributed 50 percent of the GTAP 2013 acres to those due to corn ethanol demands.

Based on the adjustments stated above and the GTAP 2013 modelling scenario, ICF created a second data set for international changes in acres. Table 3-41 below shows the changes in acres for the five regions.

Table 3-41: Comparison of GTAP 2013 Change in Acres 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
	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. 2014; Babcock and Iqbal 2014

The updated acreage changes are compared to those presented for corn ethanol in the RIA in Table 3-42.

Table 3-42: Comparison of International Crop Area Change between RIA and Proposed Data

	International Crop Area Change (000s ha)
RIA Corn Ethanol	789
GTAP 2013	214
GTAP 2013 Adjusted with Babcock and Iqbal (2014) Data	51.4

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

3.6.3.2. Updated Emission Factors

ICF considered two sets of emission factors, one from Winrock International and the other from the California ARB's Low Carbon Fuel Standard Agro-ecological zones (AEZ) model. The Winrock emission factors were used in the RIA. They were developed based on historical land-use trends using MODIS satellite imagery from 2001 and 2004 and include emission factors for each land conversion and reversion type for each of the 19 regions in GTAP (ICF International 2009).

The use of the ARB AEZ emission factors is consistent with the 19 regions and 18 zones reported by GTAP (CARB 2015) and maintains the 342 region-zone land conversion combinations while the use of the Winrock emission factors requires aggregation of AEZs within each region. Both data sets are displayed in ICF's literature review. ICF generated emissions factors by conversion and reversion type for each of the 19 GTAP regions by weighting each country's individual factors by the percent contribution to total arable land in each region.

For ICF's literature review, the AEZ factors were averaged by GTAP region for the purpose of comparison. A comparison of these emission factors can be seen in Table 2-10, Table 2-11*,* and Table 2-12. Overall, there is not one methodology that consistently overestimates or underestimates emission factors when compared to the other alternatives. Deviations are specific to each country/region. As mentioned in the literature review, Winrock does have consistently lower emission factors associated with the Grassland to Annuals conversion while AEZ has lower emission factors for Cropland-Pasture to Annuals conversion.

3.6.4. ICF Results

Based on the updated data for changes in acres as well as emission factors, ICF generated a range of estimates for the international land-use change caused by increased U.S. corn demand based on the available acre change and emission factor data sets. An average value for the international land-use change emission category was calculated taking these estimates and recently published (i.e., 2015 and 2016) values from the literature.

The estimates assumed an increase of 11.59 billion gallons of ethanol and the emissions are amortized over the 30 year period (EPA 2010). The 11.59 billion gallons of reflects the total additional amount of corn ethanol required by the RFS2 compared to the production volume in place prior to the RFS1 in 2004. The emissions below would be released annually due to this increased demand. These estimates are presented below in Table 3-43.

Table 3-43: International Land-Use Change Results by Acre Change Data Set and Emission Factor Data Set

Acre Change Data Set	Emission Factor Data Set	Emissions (g CO_2e/MMBtu)
EPA's RIA Analysis (2022)		
FAPRI-CARD	Winrock	31,790
ICF's Analysis		
GTAP 2013	ARB LCFS AEZ Model	17,802
GTAP 2013	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

Source: ICF analysis; EPA 2010

All emission calculations presented above are lower that EPA's RIA estimate of the impacts from international land-use change.

In regards to acreage data, the GTAP 2013 modelling scenario is more conservative than the GTAP 2013 adjusted with Babcock and Iqbal (2014) data. Although the quantitative analysis conducted by Babcock and Iqbal (2014) attempts to better represent the actual acreage change for the five regions due to corn ethanol production, the evidence is not strong enough to solely recommend the qualitative adjustments that were made. The GTAP 2013 adjusted with Babcock and Iqbal (2014) data with Winrock emission factors scenario provides the lower bound for this estimate and illustrates that increased corn ethanol demand could have only a small impact on international land-use change.

The ARB LCFS AEZ does have higher emissions impact estimates than the Winrock data. This analysis is in line with what was observed during the literature review, where it was determined (see Section 2.2) that ARB LCFS AEZ would provide the highest emission estimates. These values provide the upper bound for this analysis.

To reflect the full range of recently published literature relating to the contribution of international land-use change to the current GHG profile of corn ethanol, ICF adopted a composite approach that averaged the results of three recently published studies (CARB, 2015; Dunn et al., 2015; and GTAP, 2013) and four scenarios developed from their results that allow for alternative sets of emissions factors and the increased use of double cropping (Babcock and Iqbal, 2014). These seven results are shown in Figure 3-4. Dunn et al. (2015) quantify two emissions related to international land-use change distinguished by the use of the Winrock and the Woods Hole emissions factors (EFs). ICF developed four scenarios from the results of the most recently published GTAP study (GTAP 2013) to account for the use of ARB EFs and Winrock EFs as well as increased double cropping (denoted "Adjusted" in Figure 3-4). Across these seven results, the average emissions impact is 8.61 g CO_2e/MJ. This value converts to 9,082 g CO_2e/MMBtu, which is the value ICF used as the contribution of international land-use change to corn ethanol's current GHG profile (see Table 3-44).

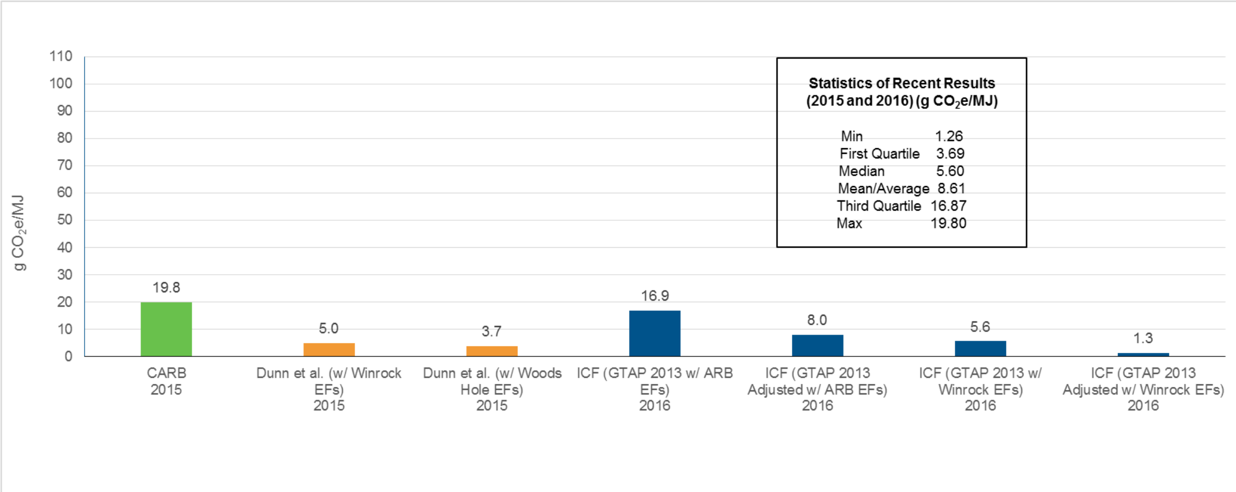

Figure 3-4: Literature and ICF Values for International Land-Use Change Due to U.S. Corn Ethanol Demand

Table 3-44: International Land-Use Change Emissions

	Emissions Impacts ($g\ CO_2e/MMBtu$)
ICF: 2014 Current Conditions	9,082

3.6.5. Limitations, Uncertainty, and Knowledge Gaps

This analysis does not account for any additional yield changes over time in excess of those embedded in GTAP simulations. Increases in yield could have a large impact on the overall results. This GTAP analysis assumes that each country has a specific yield of bushels of corn per hectare. These direct assumptions are not publically available, however Keeney and Hertel (2009) does evaluate the percent change in yield following ethanol mandates for the United States and Rest of World (Keeney and Hertel, 2009). These results are not in enough granularity to support a robust analysis. When projecting the land-use emissions, a change in yield could be considered given the historical increases in yield that have been seen domestically.

3.6.6. References: International Land-Use Change

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3.7. International Farm Inputs and Fertilizer N_2O

The international farm inputs included in the RFS2 analysis include fertilizers, herbicides, pesticides, energy use, and direct and indirect fertilizer N_2O emissions.

3.7.1. EPA RIA Methodology and Data Sources

The activity data for international farm inputs are based on the following methods and sources:

- **Fertilizer Application Rates**: The changes in crop area and production by crop type and country output from the FAPRI-CARD model was used to determine the applied amount of fertilizer. Regional fertilizer application rates (kg/ha) were taken from the International Fertilizer Industry

Association (IFA) report, "Assessment of Fertilizer Use by Crop at the Global Level, 2006/07–2007/08." The report covers 23 countries and 11 crops groups. The RFS2 RIA averaged the results from two reporting periods (2006/2007 and 2007/2008) (Heffer, 2009) to account for seasonal applications. The application rates were then divided by the total consumption 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 was provided by FAO's FAOStat data set for pesticide consumption. The data did not include China. Herbicide and pesticide activity data was provided by the U.S. Department of Agriculture's (USDA) Economic Research Service (ERS) (FAO, 2009; USDA, 2009).
- **N_2O Emission Impacts**: The international N_2O emissions from synthetic fertilizer application were also considered. The amount of direct and indirect N_2O emissions were calculated in the same manner as the domestic emissions.
- **Agricultural Energy Use**: The International Energy Agency's (IEA) data on total CO_2 emissions from agricultural electricity and fuel use by country was 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 proportionally scaled to represent the entire fuel life cycle based on the ratio of combustion to life-cycle GHG emissions from U.S. electricity and fuel use provided by IEA (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-level crop acreage changes from FAPRI-CARD to determine the fuel-related emission for corn ethanol.

3.7.2. EPA RIA Results

Activity data for the international farm inputs analysis are shown in Table 3-45. The emission factors used for each source are provided in Table 3-3 and were based on GREET (EPA, 2009).

Table 3-45: Changes in International Agricultural Inputs

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

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

Table 3-46: Relative Change in International Fertillizer N_2O Emissions

Emission Category	Units	2012			2017			2022		
		Fuel-Specific	Control Case	Difference	Fuel-Specific	Control Case	Difference	Fuel-Specific	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 Table 2.4-18 from EPA RIA).

The RIA estimates are: 672 g CO_2e/MMBtu for agricultural inputs, 3,380 g CO_2e/MMBtu for direct and indirect N_2O emission, and 1,700 g CO_2e/MMBtu for energy emissions, which result in a reported total of: 5,720 g CO_2e/MMBtu (5,752 g CO_2e/MMBtu actual total).

Table 3-47: International Farm Inputs and Fertilizer N_2O Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	5,720

3.7.3. ICF Methodology and Data Sources

ICF calculated the emissions impacts of changes in international agricultural input use related to higher levels of corn ethanol production under the RFS2 based on changes in international cropland acres attributable to increased U.S. production of corn ethanol. To assess this acreage change, ICF used the output of the GTAP model from 2013 (Dunn et al., 2014), which reflects an increase of 11.59 billion gallons of corn ethanol.[31] ICF used the GTAP 2013 changes in acres for the international inputs acres instead of the GTAP 2013 adjusted acres based on Babcock and Iqbal (2014) data. The GTAP 2013 acres are a more accurate representation as they are based on the most recent data available. For more information on the change in acres due to an increased demand in U.S corn ethanol, see the International Land-Use Change section.

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 Food and Agriculture Organization (FAO) of the United Nations and the International Energy Agency (IEA) and compiled in FAO's FertiStat

[31] The 11.59 billion gallons of reflects the total additional amount of corn ethanol required by the RFS2 compared to the production volume in place prior to the RFS1 in 2004.

Database (EPA 2010b). ICF updated the herbicide and pesticide use data using the most 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 take from FAO.

Life-cycle emission factors for nitrogen, phosphate, potassium, calcium carbonate, and insecticide were based on Argonne National Laboratory's GREET 2015 model (Argonne National Laboratory 2015). Emission factors for herbicides and insecticides 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).

The direct and indirect N_2O emission calculations are based on IPCC (2006) guidance. The guidance uses the nitrogen fertilizer application 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 volatization 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 emissions factor for each country (EPA 2010). The emission factors developed for the RIA were not updated because IEA no longer publically 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 3-48 shows the emissions contributions from each of the international agricultural inputs.

Table 3-48: 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**

3.7.4. ICF Results

These values are significantly lower than the RIA's estimates. The main driver of this difference is that GTAP 2013 modelling predicts a 73 percent reduction in hectares changed due to corn ethanol demands.

Table 3-49: International Farm Inputs and Fertilizer N_2O Emissions

	Emissions Impacts ($g\ CO_2e/MMBtu$)
ICF: 2014 Current Conditions	2,217

3.7.5. Limitations, Uncertainty, and Knowledge Gaps

One limitation of note is since EPA's development of the RIA, IEA no longer publically 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.

3.7.6. References: International Farm Inputs and Fertilizer N_2O

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3.8. International Rice Methane

Assumptions and boundaries similar to domestic rice methane were made to calculate the emissions associated with international rice methane.

3.8.1. EPA RIA Methodology and Data Sources

Based on the IPCC methodology used in the EPA RIA, the area of rice harvested, a GHG emission factor, and the planting to harvest season length are required. The FAPRI-CARD model was used to predict the impact of increased biofuels demand in the United States on international rice production and the area of rice harvested. The IPCC default emission factors for irrigated, rainfed lowland, upland, and deepwater by country were used (IPCC, 2006). The rice cultivation season length was based on data from the International Rice Research Institute (IRRI) (IRRI, 2008).

3.8.2. EPA RIA Results

The area of rice harvested internationally was calculated on an annual basis. The FAPRI-CARD results for 2022–2023 are shown in Table 3-50.

Table 3-50: International Rice Production

	Thousand Acres Harvested in 2022–2023
Harvested Area	155,970

Source: FAPRI-CARD output; “EPA-HQ-OAR-2005-0161-3167 (1).xlsx,” “Rice2009” tab.

Table 3-51 shows the emissions as a result of land-use change from increased demand from biofuels and converting land from rice acres to corn acres.

Table 3-51: Relative Change in International Methane from Rice Production

Emission Category	Units	2012			2017			2022		
		Fuel-Specific	Control Case	Difference	Fuel-Specific	Control Case	Difference	Fuel-Specific	Control Case	Difference
Methane from Rice Cultivation	000 Tons CO_2e	18,410	17,800	−359.8	N/P	N/P	−227.5	N/P	N/P	−352

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

The RIA reported emissions due to U.S. corn ethanol production from changes in international rice methane as 3,000 g CO_2e/MMBtu in 2022 (see Table 3-52).

Table 3-52: International Rice Methane Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	3,000

3.8.3. ICF Methodology

The literature review found data available after 2010 that indicated both the trend in international rice acres and the associated CH_4 emissions are different from the projections in the RIA (see Table 2-39 and Table 2-43). ICF used these acre and CH_4 emission data to determine new contributions of international rice methane to corn ethanol's life-cycle GHG emissions. However, similar to the domestic rice methane assessment, this analysis was again limited by a lack of data to construct scenarios distinguishing international rice acres for the corn only, control, and reference cases. Region specific methane emission factors were also unavailable.

The methodology for assessing international rice methane emissions is similar to that used to assess emissions related to domestic rice methane emissions. That is, harvested acreage projections for the reference, control, and corn only cases are used to determine the country-specific changes in rice acres associated with the increase in U.S. corn ethanol production. The corn-only EPA 2017 FAPRI acreage projections isolate the RFS2 effects of corn ethanol. Country-specific annual rice methane emission factors were taken from the EPA's *Foreign Agricultural Impact Calculations for Biofuel Lifecycle Analysis* (EPA 2010). Table 3-53 shows the international acreage change (i.e., difference between control and reference cases acreage), emission factors, and total GHG emissions. Methane was converted to GHG emissions using the AR4 GWP coefficient.

Table 3-53: 2017 International Rice Acreage, Emission Factors, and Associated GHG Emissions with Corn Ethanol Expansion

Country	1,000 Acres			kg CH_4/acre/yr	2017 Mg CO_2e
	2017 Corn Only Control Case	2017 Reference Case	Difference		
Bangladesh	28,354	28,347	6	56.77	8,660
Brazil	7,431	7,443	-12	37.04	-10,567
China	67,847	67,930	-83	72.49	-144,248
Egypt	1,669	1,669	0	76.60	0
EU	996	996	0.1	91.82	258
India	112,354	112,254	101	119.55	288,864
Indonesia	29,048	29,042	6	137.02	18,107

Country	1,000 Acres			kg CH_4/acre/yr	2017 Mg CO_2e
	2017 Corn Only Control Case	2017 Reference Case	Difference		
Iran	1,672	1,671	1	47.35	687
Iraq	391	390	1	63.13	1,756
Ivory Coast	1,790	1,787	2	11.41	599
Japan	3,373	3,372	1	107.13	2,380
Myanmar	17,814	17,814	0	98.60	0
Nigeria	5,792	5,791	1	32.67	396
Pakistan	6,662	6,659	4	107.13	10,109
Philippines	11,136	11,131	5	119.44	15,541
ROW	31,366	31,356	10	82.53	20,030
South Korea	2,161	2,160	1	76.60	1,561
Thailand	26,159	26,128	30	93.80	68,506
Turkey	235	235	0.1	55.24	106
Uruguay	511	511	1	90.61	1,151
Vietnam	17,657	17,655	3	124.61	7,575
TOTAL	**377,415**	**377,338**	**78**	**N/A**	**291,471**

3.8.4. ICF Results

The final life-cycle emissions for changes in international rice acres were determined using the same method that was used to determine the emissions associated with changes in domestic rice methane production. The total GHG emissions associated with the acreage difference between the control and reference cases (see Table 3-54) was divided by the annual RFS2 incremental corn ethanol production (3.03 billion gallons in 2014). Using the (lower) heating value of 76,330 (Btu/gallon), the emissions are 1,480 g CO_2e/MMBtu.

Table 3-54: International Rice Methane Emissions

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2014 Current Conditions	1,480

3.8.5. Limitations, Uncertainty, and Knowledge Gaps

The international rice methane analysis had similar constraints to the domestic rice assessment: while updated datasets existed from the previous RFS2 RIA assessment, these data were limited for both acreage and emission factors. As noted in the literature review, regional updates to emission factors have only just recently been developed for a small set of rice-producing countries. Future research should utilize these new emission factors as more become available. Acreage projection data available for this assessment was limited to only a few data points, and future efforts should develop country-specific control and reference acreage data that consistently reflects historical trends.

3.8.6. References: International Rice Methane

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3.9. Fuel and Feedstock Transport

The RIA includes the GHG impacts of transporting biofuel feedstock from the field to the biofuel facility and the impacts of transporting the finished fuel (e.g., corn ethanol) and co-products (e.g., distillers grains with solubles).

3.9.1. EPA Methodology and Data Sources

Argonne National Laboratory's GREET model was used as the basis for the corn transportation between the farm and bioethanol facility. The model assumes a default truck transportation of 10 miles from farm to stacks and 40 miles from stacks to plant. For the distillers grains with solubles (DGS), the percentage shipped by mode assumptions are shown in Table 3-55 and were based on data provided by USDA as well as Association of American Railroads, Army Corps of Engineers, Commodity Freight Statistics, and industry estimates. The distances for DGS were based on GREET default distances for other commodities shipped by those transportation modes.

Table 3-55: Transportation Distance and Mode Assumptions for 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 3-56 (Oak Ridge National Laboratory, 2009).

Table 3-56: Transportation Distance and Mode Assumptions for 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.

For each mode of transportation the GREET default assumptions and emission factors were used. These emission factors are shown in Table 3-57.

3.9.2. EPA RIA Results

The emission factors shown in Table 3-57 represent the distances outlined in Table 3-55 and Table 3-56 for both the corn product per bushel and the DGS per ton.

Table 3-57: Emission Factors Used for Fuel and Feedstock Transport
(Units: Emissions—grams/bushel or ton; Energy—Btu per bushel or ton)

Fuel/ Feedstock	CO	NO_x	PM10	PM2.5	SO_x	CH_4	N_2O	CO_2	CO_2e	Coal Energy	Natural Gas Energy	Petroleum Energy
Corn per Bushel	0.150	0.464	0.049	0.024	0.115	0.000	0.529	0.013	469	485	163.232	313.600
DGS per Ton	4.044	12.028	1.555	0.709	3.873	0.000	17.856	0.409	15,866.8	16,369.2	5,204.6	10,021.1

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

The RIA reported emissions due to U.S. corn ethanol production from fuel and feedstock transport as 4,265 g CO_2e/MMBtu in 2022 (see Table 3-58).

Table 3-58: Fuel and Feedstock Transport Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	4,265

3.9.3. ICF Methodology

Fuel and feedstock transportation represents a minimal portion of total corn ethanol life-cycle GHG emissions, contributing less than 5 percent (EPA, 2010a). However, transportation systems are dynamic and since 2010 have continually evolved to become more fuel and GHG efficient. Key developments that may have affected the GHG LCA profile of corn ethanol include:

- Improved transportation technologies, such as improved fuel economies for medium and heavy duty (MDHD) diesel trucks (Cai et al., 2015).
- Infrastructure retrofits, such as utilizing existing liquid fuel pipelines for ethanol transport (Strogen et al., 2013).
- Decreasing GHG intensity of the average fuel mix used in transportation (Cai et al., 2015).

Given these potential sources of GHG reductions, our assessment applied the latest data and emission factors using a similar methodology to the EPA's report.

Figure 3-5 illustrates the stages involved in fuel and feedstock transportation based on the most recent GREET model.

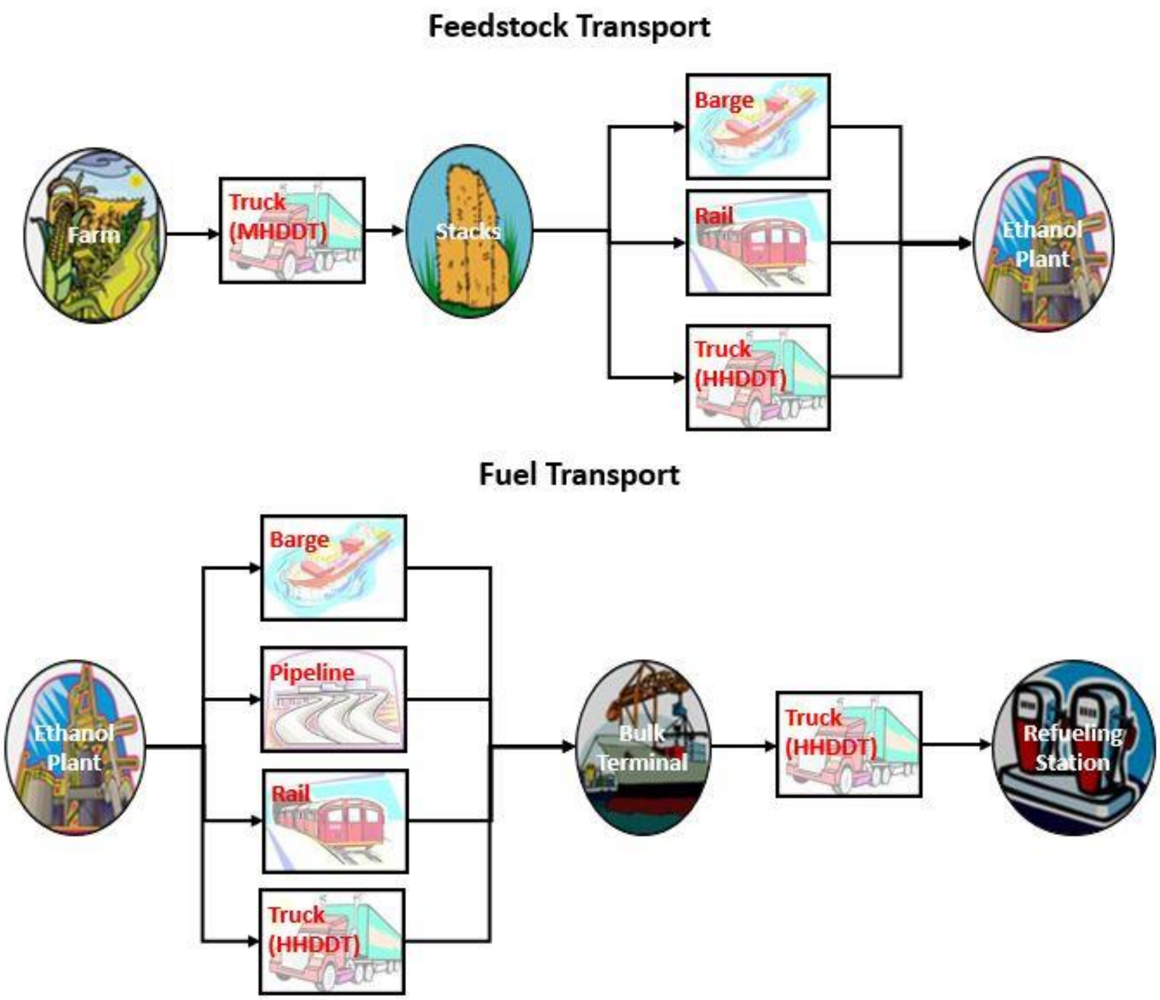

Figure 3-5: GREET Process Maps for Fuel and Feedstock Transportation (HHDDT denotes heavy heavy-duty diesel trucks and MHDDT denotes medium heavy-duty diesel trucks.)

EPA used a combination of sources to determine fuel and feedstock transportation emissions. The GREET 2009 model was utilized by EPA to calculate final GHG emissions (Argonne, 2009) for the modes and distances. For feedstock transportation, the study used the standard GREET inputs of mode and distance for farm to stacks (truck, 40 miles), and stack to plant (truck, 30 miles). EPA used an Oak Ridge National Laboratory (ORNL) study to estimate the projected (2022) fuel transportation modes and distances from the ethanol plant to the bulk terminal (Oak Ridge National Laboratory, 2009). These modes and distances were applied to GREET to determine GHG emissions. For co-products, the EPA study used USDA mode and distance estimates for DGS transportation, and did not include any transportation requirements for corn oil.

Our methodology used the more recent 2015 GREET model, which includes the recent expansion in freight vehicle LCA emission factors (Cai et al., 2015) as detailed in Section 2.8 of the literature review. Our analysis also uses the current GREET standard inputs for fuel and feedstock modes, distances, and emissions 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 3-59 show the assumptions in mode and distance for transportation used in our analysis. Both the EPA and our study assumed no ethanol is currently being transported through pipelines.

Table 3-59: Mode and Distance Assumptions

Mode	Farm to Stacks		Stacks to Plant		Plant to Terminal		Terminal to Refueling Station		DGS	
	% 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

3.9.4. ICF Results

Figure 3-6 shows the results for fuel and feedstock transportation, separated by transportation phase and co-product. The RIA total is also included for comparison. The final DGS transportation result is a weighted average of dry and wet DGS based on the expected yields shown in Table 3-64 for the industry average modeled in fuel production.

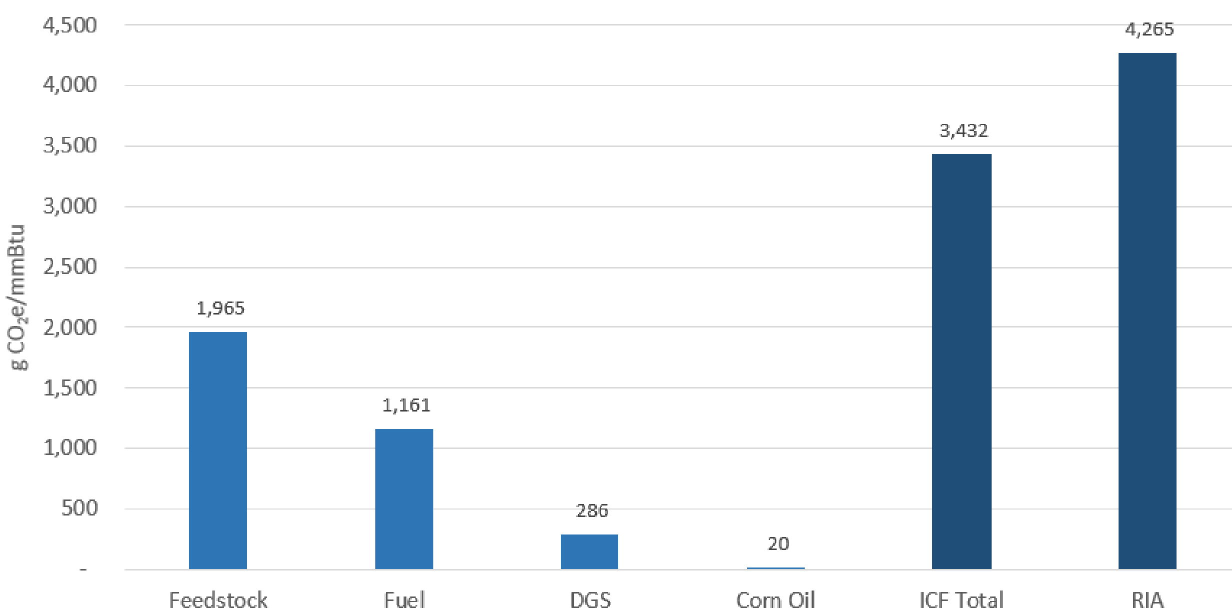

Figure 3-6: Fuel and Feedstock Transportation Emissions

Table 3-60: Fuel and Feedstock Transport Emissions

	Emissions Impacts ($g\ CO_2e/MMBtu$)
ICF: 2014 Current Conditions	3,432

3.9.5. Limitations, Uncertainty, and Knowledge Gaps

Figure 3-6 shows similar results between the EPA RIA and our analysis. This similarity is due to the use of similar emission factors in GREET, as there has not been substantial implementation of the potential transportation decarbonization efforts that are outlined at the beginning of this section. 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 fully determine 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 life-cycle emissions result, since as stated previously, fuel and feedstock transportation contributes relatively little to the total cor ethanol life-cycle GHG emissions.

3.9.6. References: Fuel and Feedstock Transport

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3.10. Fuel Production

There are two methods for producing ethanol from corn: dry milling and wet milling. The dry milling process included grinding the entire corn kernel and fermenting it to produce ethanol. The rest of the corn components are left wet or dried for animal feed—i.e., dried distillers grains with solubles (DDGS). Wet milling includes separating the starch from the kernel by soaking the corn kernel, and then using the starch to make the ethanol. This process is more expensive than dry milling. Dry mill plants comprises the majority of ethanol plants in the United States.

3.10.1. EPA RIA Methodology and Data Sources

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 and FAPRI-CARD (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). The energy use for dry mill plants was based on the ASPEN models from USDA. Future plant energy consumption was projected based on what would be built to meet increased ethanol production.

The fuel upstream emission factors were based on the GREET model (EPA, 2009).

3.10.2. EPA RIA Results

The amount of fuel by plant type and technology is shown in Table 3-61.

Table 3-61: 2022 Energy Use at Ethanol Plants with CHP (Source: Table 2.4-55 from EPA RIA) (Units: 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
	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

Plant Type	Technology	Natural Gas Use	Coal Use	Biomass Use	Purchased Electricity
	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.

The upstream emission factors used for natural gas, coal, biomass, diesel, and electricity were taken from GREET, and are shown in Table 3-62.

Table 3-62: 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
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
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.

The RIA reported emissions due to U.S. corn ethanol production from fuel production as 30,000 g CO_2e/MMBtu in 2022 (see Table 3-63).

The RIA emissions from fuel production results apply to a projected composite average corn ethanol refinery in 2022 (i.e., 63 percent dry mill, 37 percent wet mill). The RIA emissions for this refinery are 30,000 g CO_2e/MMBtu (100 percent natural gas), 50,000 g CO_2e/MMBtu (100 percent coal), and 15,000 g CO_2e/MMBtu (100 percent biomass). The RIA analysis included only single thermal energy sources, and the natural gas result is shown in Table 3-63.

Table 3-63: Fuel Production Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	30,000

3.10.3. ICF Methodology

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 distillers grains and solubles (DGS), corn oil is now recovered as a co-product, and 80 percent of dry grind mills are now capable of corn oil recovery (Argonne 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 corn ethanol production GHG emissions.

The RIA used process-level data for energy use at corn ethanol production facilities. The data accounted for both dry and wet mill processes, where EPA modeled variations of primary energy (i.e., coal, natural gas, biomass) and electricity demands. The wet mill model did not include any electricity use. For the dry mill model, five process variations were modeled for both dry and wet DGS outputs (i.e., 10 total):

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

The study restricted wet milling variations to only three primary energy use variations (100 percent natural gas, 100 percent coal, 100 percent biomass). The final average plant results were based on a combination of dry milling with fractionation (63 percent) and wet milling (37 percent), where both processes used natural gas as the primary energy source.

Our analysis uses more recent corn ethanol production data and emission factors available to estimate the current GHG intensity of production processes. The modeling utilizes the more recent GREET corn ethanol pathway updates (Argonne 2014), which use process-level data from Mueller and Kwik (2012).

We maximize the available variations in GREET to mimic the scenarios modeled by EPA as closely as possible. These variations included (with primary energy source details):

- 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 3-64 shows the assumptions and inputs for each of these scenarios. The industry average and wet milling processes are the only production pathways that include corn oil recovery. It should be noted that dry milling includes electricity consumption with the primary energy demands.

Table 3-64: 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

ICF customized the allocation of co-products based on the methods available in GREET—using the displacement method for DGS and the marginal method for corn oil. The displacement method allocates all energy for DGS drying to the ethanol production process, and the benefits are assumed to displace animal feed (see the *Domestic Farm Inputs and Fertilizer N_2O* section). The marginal method does not allocate the energy required for corn oil extraction to the ethanol process, but there are no benefits (i.e., displacement of other commodities reducing the ethanol carbon intensity, such as production of biodiesel) of corn oil production included in the assessment from any potential downstream use.

3.10.4. ICF Results

Table 3-65 shows the results of the modeling for each of the scenarios described.

Table 3-65: 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

The RIA emissions from fuel production results apply to a projected composite average corn ethanol refinery in 2022 (i.e., 63 percent dry mill, 37 percent wet mill). Our analysis also reflects a composite industry average refinery (18 percent dry milling without corn oil extraction, 71 percent dry milling with corn oil extraction, and 11 percent wet milling). Our resulting weighted industry average is 34,518 g CO_2e/MMBtu. The higher level of emissions obtained in this analysis is mainly due to the use of current plant configurations that utilize a variety of thermal energy sources. The RIA analysis included only single thermal energy sources, and the natural gas result is shown in Table 3-63. Also, as the electricity grid mix continues to become cleaner with increased renewable resources, the production emissions will continue to decrease.

Table 3-66: Fuel Production Emissions

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2014 Current Conditions	34,518

Figure 3-7 shows our complete results for the industry average modeling.

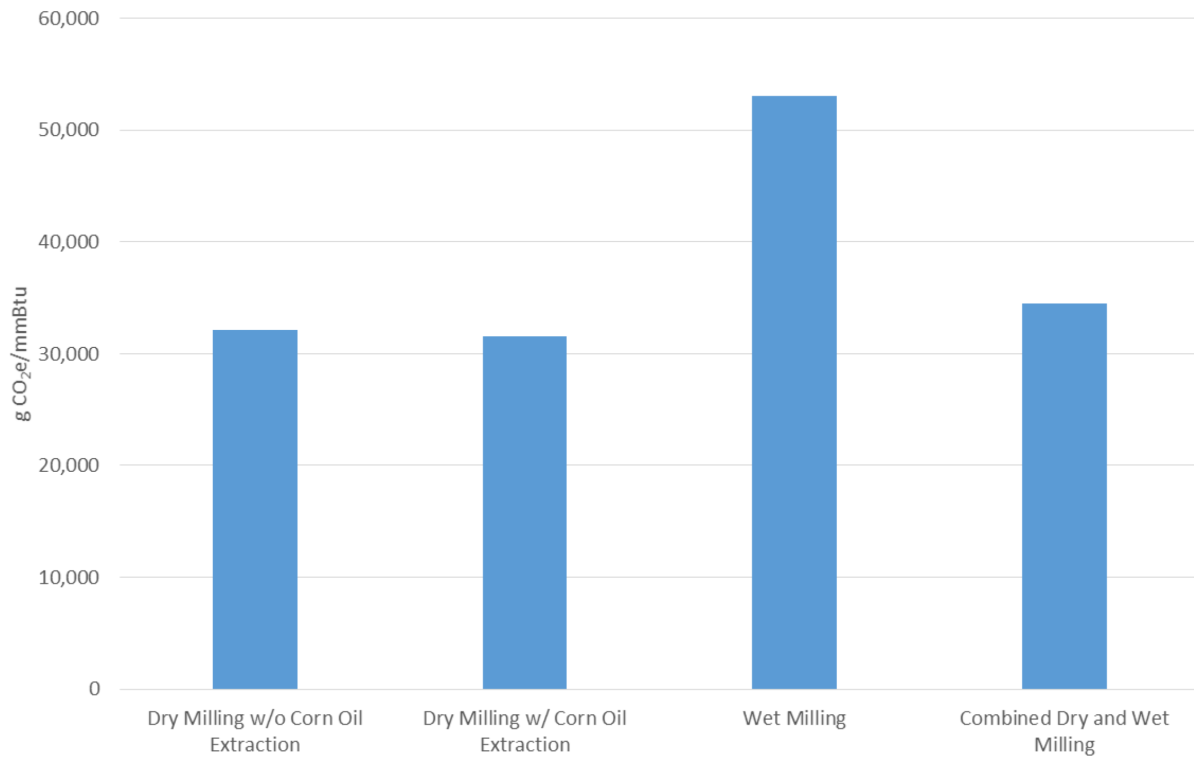

Figure 3-7: Industry Average Fuel Production Emissions for Varied Milling Processes

3.10.5. Limitations, Uncertainty, and Knowledge Gaps

Our assessment relies heavily 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.

3.10.6. References: Fuel Production

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Mueller, S., Kwik, J., 2012. 2012 Corn Ethanol: Emerging Plant Energy and Environmental Technologies. http://ethanolrfa.3cdn.net/fe5f4b7a4bdbc12101_2gm6bejk4.pdf

3.11. Tailpipe

Tailpipe emissions for ethanol were based on the carbon content of the fuel.

3.11.1. EPA RIA Methodology and Data Sources

The carbon dioxide emissions from corn ethanol are assumed to not increase the atmospheric CO_2 emissions as the biogenic carbon emitted is offset by the carbon uptake of new growth biomass. Life-cycle CO_2 emissions from biofuel tailpipe combustion are not included in the analysis. The biofuel tailpipe combustion CH_4 and N_2O emissions are included however. These emission factors are based on EPA's MOVES model results (EPA, 2015b; EPA, 2010g).[32]

3.11.2. EPA RIA Results

The tailpipe emission factor is shown in Table 3-67.

Table 3-67: Emission Factors for Tailpipe Combustion (Source: Table 2.4-71 from EPA RIA)

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

Source: MOVES model output; "epa_2010_RFS2_regulatory_impact_assessment.pdf" Table 2.4-71.

The RIA reported tailpipe emissions due to U.S. corn ethanol production as 880 g CO_2e/MMBtu in 2022 (see Table 3-68).

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

Table 3-68: Tailpipe Emissions

	Emissions Impacts (g CO_2e/MMBtu)
EPA RIA: 2022	880

3.11.3. ICF Methodology

The RIA found tailpipe emissions to have an insignificant impact on total GHG emissions (less than 1 percent in all scenarios). All CO_2 emitted from corn ethanol combustion is considered biogenic and not accounted for in the carbon emissions.

EPA used the 2009 MOVES model to estimate the GHG emissions from vehicle ethanol combustion. Since CO_2 emission from combustion are assumed to be biogenic, the assessment included only CH_4 and N_2O emissions in the final value. Our assessment used the most recent and relevant values for E85 and ethanol tailpipe CH_4 and N_2O emissions from the available literature. We selected E85 as the most relevant fuel available in the version of GREET used for comparison purposes with the EPA RIA study.

3.11.4. ICF Results

Table 3-69 shows the literature results, as well as EPA emission factors. For the emission factors from the Washington Department of Ecology (2016), CH_4 and N_2O were not separated from total GHG emissions in the available results. To determine the non-CO_2 emissions, we subtracted the GREET 2015 CO_2 E85 tailpipe emissions from these values. The EPA RIA and Washington Department of Ecology (2016) results reflect pure ethanol combustion, and the GREET and CA-GREET are results for E85 blends.

Table 3-69: Ethanol Tailpipe Emissions

Source	g CH_4/MMBtu	g N_2O/MMBtu	g CO_2e/MMBtu
GREET 2015 (used by ICF: 2014 Current Conditions)	2.01	1.77	578
CA-GREET 2.0	2.45	1.85	613
Washington Department of Ecology (2016)	-	-	187
EPA RIA: 2022	8.97	2.31	880

There are large variations in the results, with the most recent results showing a declining trend in estimated emissions. Again, these results represent a minimal portion of the total overall life-cycle GHG emissions of corn ethanol. ICF uses the GREET 2015 emission values for our analysis.

3.11.5. Limitations, Uncertainty, and Knowledge Gaps

The EPA 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, this study instead 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 a minimal effect on the overall accuracy of the corn ethanol LCA, as tailpipe emissions are comparatively less significant.

3.11.6. References: Tailpipe

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3.12. Result of Combining the Current GHG Emission Category Values

This section presents a current GHG LCA for corn ethanol production. The data used to develop this LCA span the 2010–2014 timeframe and, consequently, the ICF: 2014 Current Conditions analysis is appropriately viewed as the current GHG profile of corn ethanol. The EPA RIA LCA was a projection, done in 2010, of GHG emissions from a new natural gas powered ethanol refinery in 2022. The RIA and ICF LCAs are directly comparable because the large majority of existing refineries use natural gas (i.e., the industry has already shifted away from coal-fired plants) and industry ethanol production, that is 13.5–14.5 billion gallons a year, is very close to the 15 billion gallon cap in the RFS2.

Figure 3-8 shows the results of combining the 11 emission categories from the EPA RIA: 2022 and ICF: 2014 Current Conditions analyses.

The EPA RIA: 2022 LCA value for corn ethanol is 79,180 g CO_2e/MMBtu compared to 98,000 g CO_2e/MMBtu for the 2005 gasoline baseline which is used as the fossil fuel carbon intensity reference in the RFS2.

Our ICF: 2014 Current Conditions value is 55,731 g CO_2e/MMBtu.

The ICF analysis shows a 30 percent emissions reduction compared to the RIA total carbon intensity and a 43 percent emissions reduction compared to the 2005 gasoline baseline.

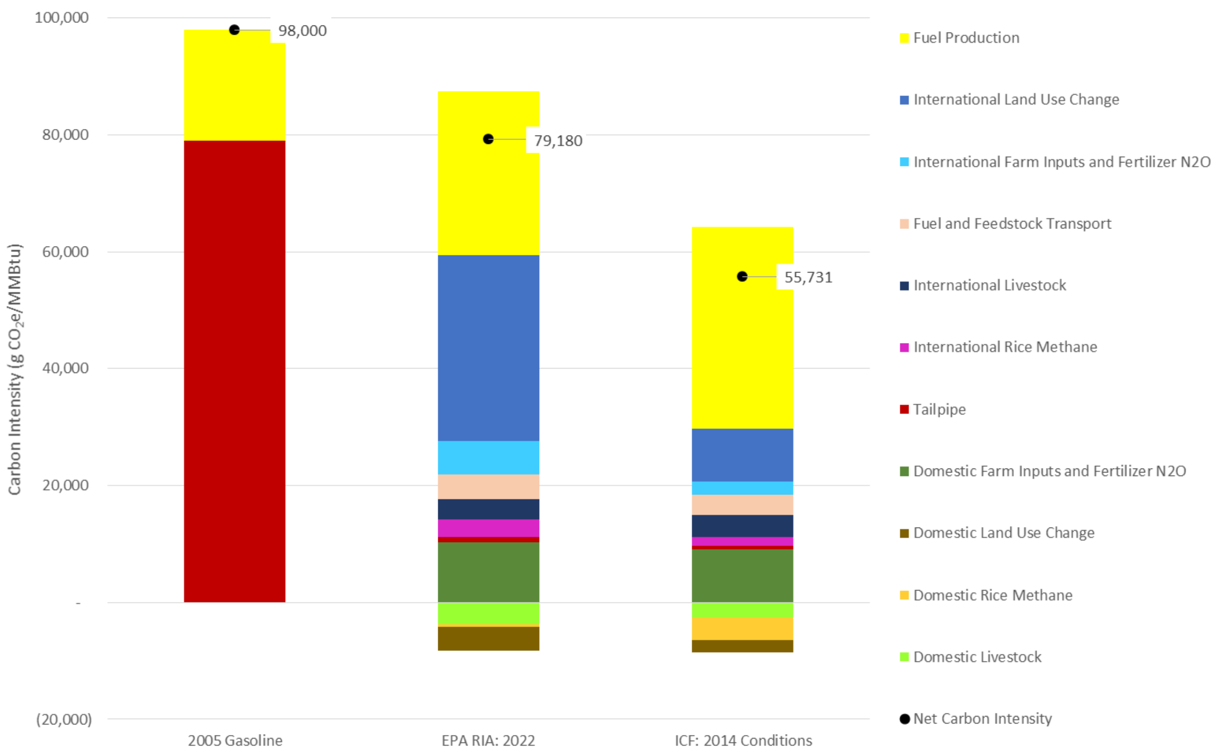

Figure 3-8: Comparison of EPA-RIA and ICF Carbon Intensities

4. Projected GHG LCA Emissions Values for a Business-As-Usual Scenario and a Building-Blocks Scenario for Corn Ethanol in 2022

Based on the current GHG emissions profile of corn ethanol developed in Chapter 3, 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. The second projection, labeled the USDA Building-Blocks 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), switch to biomass as a process fuel, and locating confined livestock operations in close proximity to refineries.

The remainder of the chapter is organized as follows:

- Key Parameters and BAU and Building-Blocks Scenarios
-
- Domestic Farm Inputs and Fertilizer N_2O
- Domestic Land-Use Change
- Fuel Production
- Fuel and Feedstock Transportation
- Summary of the ICF: 2022 BAU and ICF: 2022 Building-Blocks Scenarios Results

4.1. Key Parameters and BAU and Building-Blocks Scenarios

Table 4-1 summarizes the key variables ethanol producers can adjust under each scenario.

Table 4-1: Key Parameters and Scenarios Considered

Source Category	Key Parameter	ICF: 2022 BAU Scenario	ICF: 2022 Build-Blocks 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

Source Category	Key Parameter	ICF: 2022 BAU Scenario	ICF: 2022 Build-Blocks Scenario
Domestic Land-Use Change	• Tillage practices: – Conventional tillage – Reduced tillage	Conventional tillage	Reduced tillage
Fuel Production	• Increased corn to corn ethanol yield (based on the literature) • 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

4.2. Domestic Farm Inputs and Fertilizer N_2O

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

Within the framework of the USDA Building Blocks for Climate Smart Agriculture and Forestry,[33] improved nitrogen fertilizer management and use of cover crops align with the Nitrogen Management Building Block. In the Building-Blocks projection, the GHG benefits from adopting these practice are consistent with USDA's COMET-Planner Report.

4.2.1. Methodology: ICF: 2022 BAU Scenario

The BAU scenario for the Domestic Farm Inputs and Fertilizer N_2O emission category assumes that corn yields (bushels per acre) will increase between 2016 and 2022 as shown in Table 4-2. This assumption is calculated

[33] http://www.usda.gov/wps/portal/usda/usdahome?contentidonly=true&contentid=climate-smart.html

based on USDA's long-term projections of U.S. corn production (million bushels) and corn acres harvested (USDA ERS, 2015).

Table 4-2: 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	5,150.00	13,940.00	90.00	82.40	37%	169.2	92%
2017	5,100.00	14,105.00	90.00	82.40	36%	171.2	92%
2018	5,075.00	14,270.00	90.00	82.40	36%	173.2	92%
2019	5,075.00	14,355.00	89.50	81.90	35%	175.3	92%
2020	5,075.00	14,520.00	89.50	81.90	35%	177.3	92%
2021	5,100.00	14,595.00	89.00	81.40	35%	179.3	91%
2022	5,125.00	14,760.00	89.00	81.40	35%	181.3	91%

Source: USDA ERS, 2015.

USDA estimates that total U.S. harvested area will remain below RFS2 RIA assumed values until 2017 and will exceed the RIA 2022 corn harvested area by over 0.5 million acres. Based on these acreage projections, crop yields will increase from 169.2 bushels/acre in 2016 to 181.3 bushels/acre in 2022 (USDA ERS, 2016).

4.2.2. Methodology: ICF: 2022 Building-Blocks Scenario

The Building-Blocks 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. The specific CPSs 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.

4.2.2.1. 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.

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 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 remained the same as in conventional tillage systems (University of Tennessee, 2015). This resulted 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 volatization 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 represents a 74.4 percent reduction in volatization N_2O emissions (here measured in kg N_2O/acre per kilogram of nitrogen applied).

4.2.2.2. 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 application management 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 Building-Blocks 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 publically 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).

4.2.2.3. CPS 340—Cover Crops

Cover crops are planted in addition to seasonal crops to increase the 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 nitrogen (e.g., N_2O). The 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 represents a 76.8 percent reduction in leaching N_2O emissions (here measured in kg N_2O/acre per kilogram of nitrogen applied). ICF identified the moisture levels based on the Climate Categories from COMET-Planner (Swan et al., n.d.).

4.2.3. 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 4-1 shows the range of emissions from the ICF: 2014 Current Conditions on the far left to the ICF: 2022 Building-Blocks Scenario on the far right. The current conditions LCA represents current emissions, which are estimated at 21,814 g CO_2e/MMBtu of ethanol. The 2022 BAU Scenario incorporates projected changes in corn yields between 2016 and 2022 from the 2016 USDA Baseline. These are estimated at 20,259 g CO_2e/MMBtu. The ICF: 2022 Build-Blocks Scenario, estimated at 16,734 g CO_2e/MMBtu, further accounts for the adoption by corn farmers of all three CPSs in 2022. The central three bars represent the three CPSs isolated from each other.

The values presented in Figure 4-1 do not include the ethanol co-product credit from DGS displacing corn, soybean meal, and urea. To be consistent with the analysis in Chapter 3, 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) to develop the unique co-product credit for each scenario. Both the BAU and the Building-Blocks scenarios were modified to incorporate corn farming farm inputs and fertilizer N_2O. In the Building-Blocks 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 4-3 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 4-3: 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
ICF: 2014 Current Conditions	21,814	−12,749	9,065
ICF: 2022 BAU Scenario	20,259	−12,069	8,190
ICF: 2022 Building-Blocks Scenario	15,883	−11,393	4,490

Figure 4-1: Range of Emissions for the Domestic Farm Inputs and Fertilizer N_2O Emission Category Based on Adoption of USDA Conservation Practice Standards

4.2.3.1. Limitations, Uncertainty, and Knowledge Gaps

The largest area of uncertainty are the upstream production emissions associated with the nitrification inhibitor Nitrapyrin. A compound was used as a proxy 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.

4.2.4. References: Domestic Farm Inputs and Fertilizer N_2O

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4.3. Domestic Land-Use Change

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

- Continuation of conventional till practices by farms for producing corn for ethanol; versus
- Adoption of reduced till practices by farms producing corn for ethanol.

4.3.1. Methodology

The methodology and results for determining total acreage change and emission factors can be found in the Chapter 3 (see Section 3.1.7). This assessment used the same emission factors and anticipated acreage changes as the ICF current conditions LCA. Acreage changes are based on the 2013 corn ethanol production scenario in the GREET model's Carbon Calculator for Land Use Change from Biofuels Production (CCLUB) (Dunn et al., 2015). 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 Build-Blocks scenario is the continued adoption of conventional till in the BAU scenario and the adoption of reduced till in the Building-Blocks scenario.

4.3.2. Domestic Land-Use Change Results

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

Table 4-4: 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— ICF: 2022 BAU Scenario	−1,803,611	−155.6	−1.9	−2,038
Reduced Till— ICF: 2022 Build-Blocks Scenario	−62,656,429	−2,088,548	−180.2	−2,359

4.3.3. 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 all corn farming for ethanol production will use reduced till. Total domestic land-use change benefits might vary based on the actual reduction of conventional tilling. Additionally, acreage conversions through 2022 could also vary, perhaps significantly, from the CCLUB.

4.3.4. References: Domestic Land-Use Change

Dunn JB, Mueller S, Qin Z, Wang MQ (2014) Carbon Calculator for Land Use Change from Biofuels Production (CCLUB 2015). Argonne National Laboratory (ANL).

4.4. Fuel Production

For the BAU scenario and Building-Blocks scenario, ICF re-estimated the corn ethanol Fuel Production emissions in the ICF current conditions LCA to reflect two type of reductions in carbon intensity for fuels used in refinery processes. Relative to the current conditions LCA, the BAU scenario includes the substitution of natural gas to replace coal as a process fuel in dry milling ethanol production. The Building-Blocks scenario includes biomass as the process fuel combined with an increase ethanol yield (in gallons) per bushel of corn.

4.4.1. Methodology

This assessment followed the Chapter 3 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 Building-Blocks scenario, production yields were increased from 2.80 gallons/bushel (2010, Chapter 3 assumption) to 2.93 gallons/bushel based on Energy Information Administration (EIA) data (EIA, 2015) and GREET's projected dry milling with corn oil extraction's yield of 2.95 gallons/bushel, up from 2.82 gallons/bushel in 2010.

This analysis focused only on dry milling, as recent industry trends have revealed 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 (Boland and Unnasch, 2014).

4.4.2. Fuel Production Results

Table 4-5 and Table 4-6 show the results of our analysis for the two emission reduction scenarios. Table 4-6 also details other scenarios based on variations in production yield, fuel mix, and process type (with or without corn oil extraction). Figure 4-2 depicts these same results. For both the BAU and the Building-Blocks scenarios, ICF assumed Dry Mill with corn extraction based on the expectation that by 2022 all Dry Mill ethanol plants will have corn oil extraction. For the BAU scenario, the more conservative natural gas fuel case was selected and for the Building-Blocks scenario, the more optimistic biomass fuel case with increase ethanol yield was selected.

Table 4-5: ICF Analysis Results for Fuel Production Emission Reduction Scenarios

Model Scenario	Production Yield (gallon/bushel)	Fuel Mix Share			Production Carbon Intensity	
		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%	32,373.62	30.7
Dry Mill w/ Extraction – Default	2.82	92%	8%	0%	31,843.69	30.2
Dry Mill w/o Extraction – Biomass	2.80	0%	0%	100%	9,693.82	9.2
Dry Mill w/ Extraction – Biomass	2.82	0%	0%	100%	9,594.08	9.1
Dry Mill w/o Extraction - NG	2.80	100%	0%	0%	31,519.94	29.9
ICF: 2022 BAU Scenario: Dry Mill w/ Extraction - NG	**2.82**	**100%**	**0%**	**0%**	**31,006.19**	**29.4**
Dry Mill w/o Extraction – Default	2.93	92%	8%	0%	32,473.28	30.8
Dry Mill w/ Extraction – Default	2.95	92%	8%	0%	31,944.41	30.3
Dry Mill w/o Extraction – Biomass	2.93	0%	0%	100%	9,793.47	9.3

Model Scenario	Production Yield (gallon/bushel)	Fuel Mix Share			Production Carbon Intensity	
		Fuel Mix % NG	Fuel Mix % Coal	Fuel Mix % Biomass	g CO_2e/ MMBtu	g CO_2e/MJ
ICF: 2022 Build-Blocks Scenario: Dry Mill w/ Extraction - Biomass	**2.95**	**0%**	**0%**	**100%**	**9,694.80**	**9.2**
Dry Mill w/o Extraction - NG	2.93	100%	0%	0%	31,619.65	30.0
Dry Mill w/ Extraction - NG	2.95	100%	0%	0%	31,106.97	29.5

Table 4-6: Fuel Production Emissions

	Emissions Impacts (g CO_2e/MMBtu)
ICF: 2022 BAU Scenario—Dry Mill with corn oil extraction and natural gas fuel	31,006
ICF: 2022 Building-Blocks Scenario—Dry Mill with corn oil extraction, biomass fuel, and increased ethanol yield	9,695

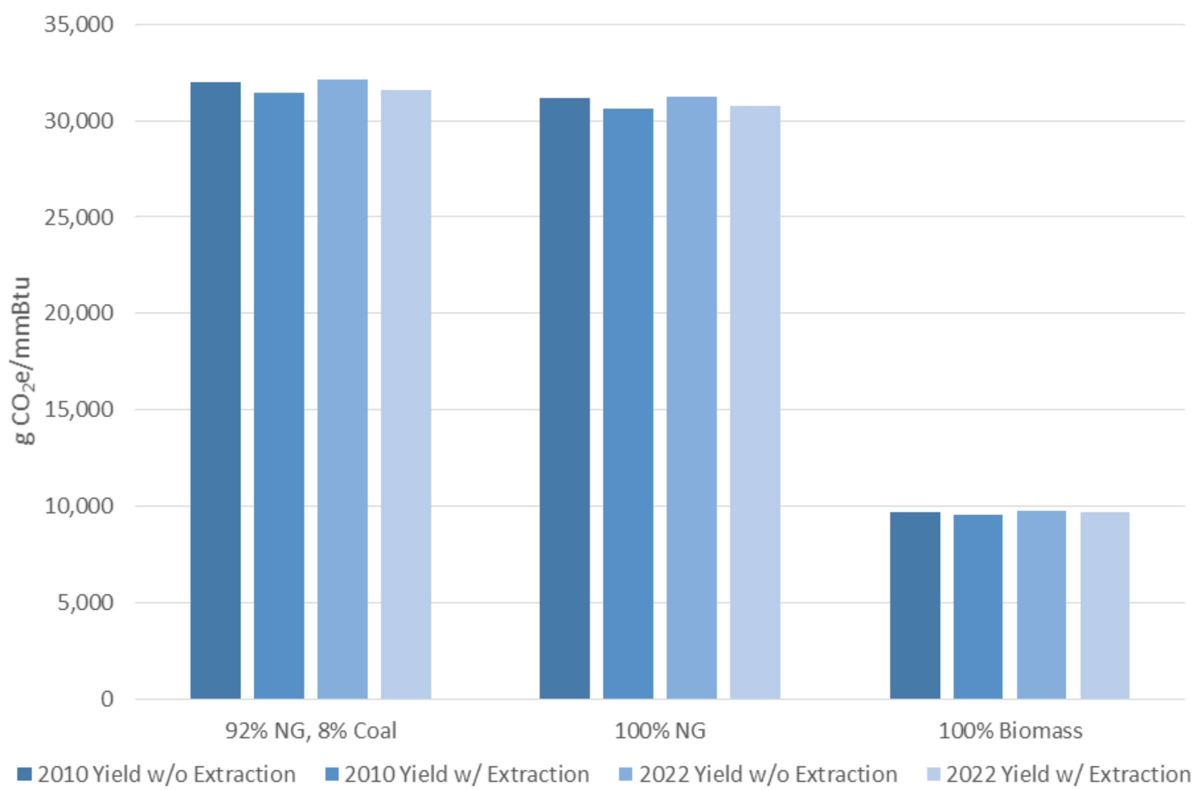

Figure 4-2: Fuel Production Emissions for ICF Emission Reduction Scenarios (Note: The horizontal axis reflects share of fuel mix.)

4.4.3. 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.

4.4.4. References: Fuel Production

Boland, S. and Unnasch, S. 2014. Carbon Intensity of Marginal Petroleum and Corn Ethanol Fuels. Life Cycle Associates Report LCA.6075.83.2014, Prepared for Renewable Fuels Association.

EIA. 2015. Corn Ethanol Yields Continue to Improve. Accessed June 6, 2016. U.S. Energy Information Administration. http://www.eia.gov/todayinenergy/detail.cfm?id=21212

4.5. Fuel and Feedstock Transportation

The ICF current conditions LCA used the most recent literature available to update the emissions associated with the transportation of corn to refineries and ethanol to distributors. In developing the

BAU and Building-Blocks scenarios, this analysis considers improved fuel efficiency in trucking, increased use of less carbon-intensive transportation fuels, and reduced co-product transportation requirements.

4.5.1. Methodology

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

- ICF: 2022 BAU Scenario—incorporates increased trucking fuel economy and substitution of liquid natural gas (LNG) for diesel fuel heavy duty trucks; and
- ICF: 2022 Building-Blocks Scenario—incorporates the BAU scenario modifications with eliminating emissions related to transporting dried distillers grains (DDGS) (assumes location of a Confined Animal Feeding Operation (CAFO) in close proximity to the ethanol plant).

The analysis started with the GREET 2015 emission factors for LNG and renewable liquified natural gas (RLNG) used in transportation by trucks. The improved trucking 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 4-7 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 in all other segments.

Table 4-7: Emission Factor Variations for Fuel and Feedstock Transportation Pathways

Fuel and Technology	g CO_2e/MMBtu of Fuel Transported		
	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
RLNG w/ Improved Fuel Economy	3.87	7.07	1.44

Our analysis also included these fuel economy and new fuel variations in our assessment of corn oil transportation. Fuel types and fuel economies for rail and barge remained the same as in the ICF current conditions LCA. Transportation distances and mode allocations, outside of the removed DDGS transportation for the Building-Blocks scenario, were unchanged as well (see Chapter 3, Table 3-59).

4.5.2. Fuel and Feedstock Transportation Results

Table 4-8 and Figure 4-3 show the results of both the BAU and the Building-Blocks scenarios, as well as the ICF LCA developed in Chapter 3.

Table 4-8: Fuel and Feedstock Transportation Emissions for ICF: 2014 Current Conditions, ICF: 2022 BAU, and ICF: 2022 Build-Blocks Scenarios

Scenario	g CO_2e/MMBtu				
	Feedstock	Fuel	DDGS	Corn Oil	TOTAL
ICF: 2014 Current Conditions	1,965	1,156	286	20	**3,427**
ICF: 2022 BAU Scenario	1,224	1,118	286	13	**2,641**
ICF: 2022 Building-Blocks Scenario	322	910	N/A	6	**1,237**

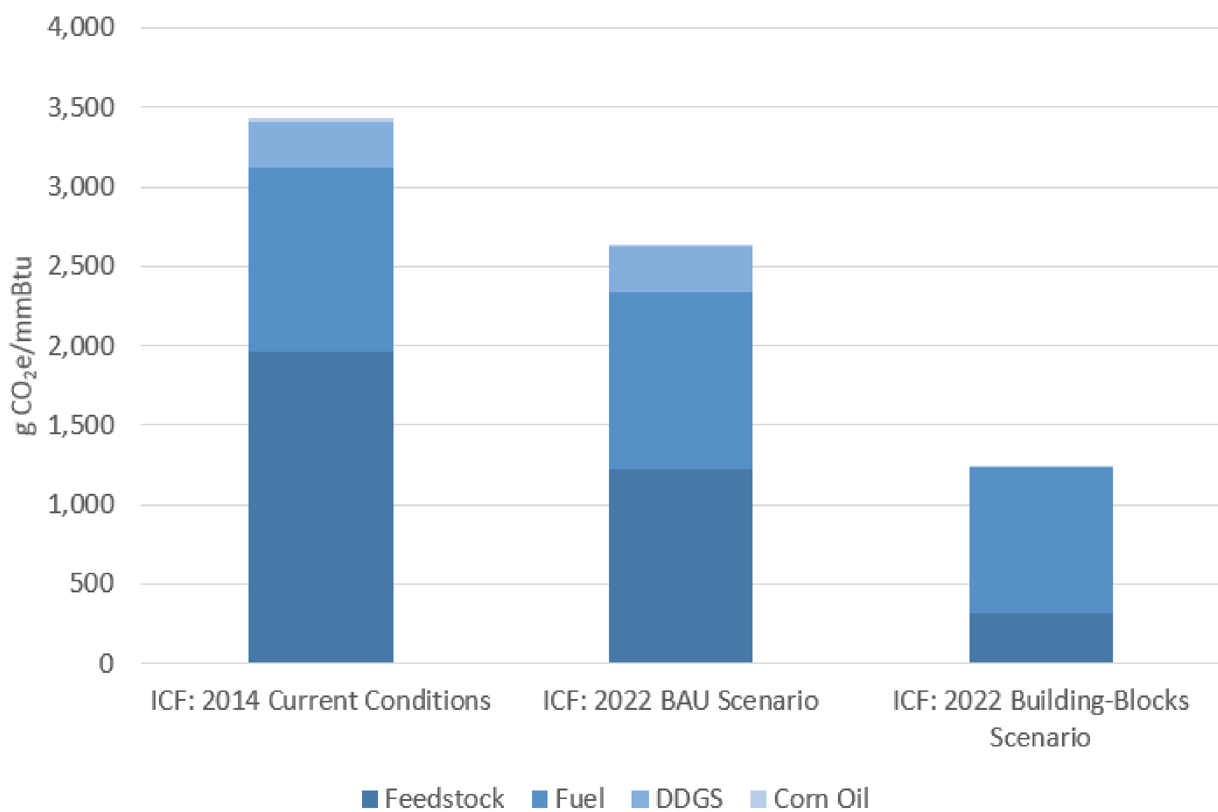

Figure 4-3: Fuel and Feedstock Transportation Emissions by ICF Scenario

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.

4.5.3. Limitations, Uncertainty, and Knowledge Gaps

This assessment focused on increasing trucking fuel efficiency and trucking technology improvements. The emissions 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 RLNG 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 GREET 2015. While these uncertainties could have significant effects on the emissions associated with the Fuel and Feedstock Transportation category, these emissions account for a very small share of the total life-cycle emissions of corn ethanol (see ICF LCA).

4.6. Summary of the ICF: 2022 BAU and ICF: 2022 Building-Block Scenarios Results

The results of the ICF: 2022 BAU and ICF: 2022 Building-Blocks Scenarios are compared against the 2005 Gasoline LCA, the EPA RIA: 2022 LCA, and ICF: 2014 Current Conditions LCA in Figure 4-4.

The EPA RIA: 2022 value for corn ethanol is 79,180 g CO_2e/MMBtu compared to 98,000 g CO_2e/MMBtu for gasoline (2005 Gasoline).

Our ICF: 2014 Current Conditions value of 55,731 g CO2e/MMBtu is a 43 percent GHG reduction compared to the 2005 Gasoline baseline and a 30 percent reduction compared to the EPA RIA: 2022 LCA.

The ICF: 2022 BAU Scenario value of 50,553 g CO_2e/MMBtu is a 48 percent GHG reduction compared to the 2005 Gasoline baseline, a 36 percent reduction compared to the EPA RIA: 2022 LCA, and a 9 percent reduction compared to the ICF: 2014 Current Conditions LCA.

The ICF: 2022 Building-Blocks Scenario value of 23,817 g CO_2e/MMBtu is a 76 percent GHG reduction compared to the 2005 Gasoline baseline, a 70 percent reduction compared to the EPA RIA: 2022 LCA, and a 57 percent reduction compared to the ICF: 2014 Current Conditions LCA.

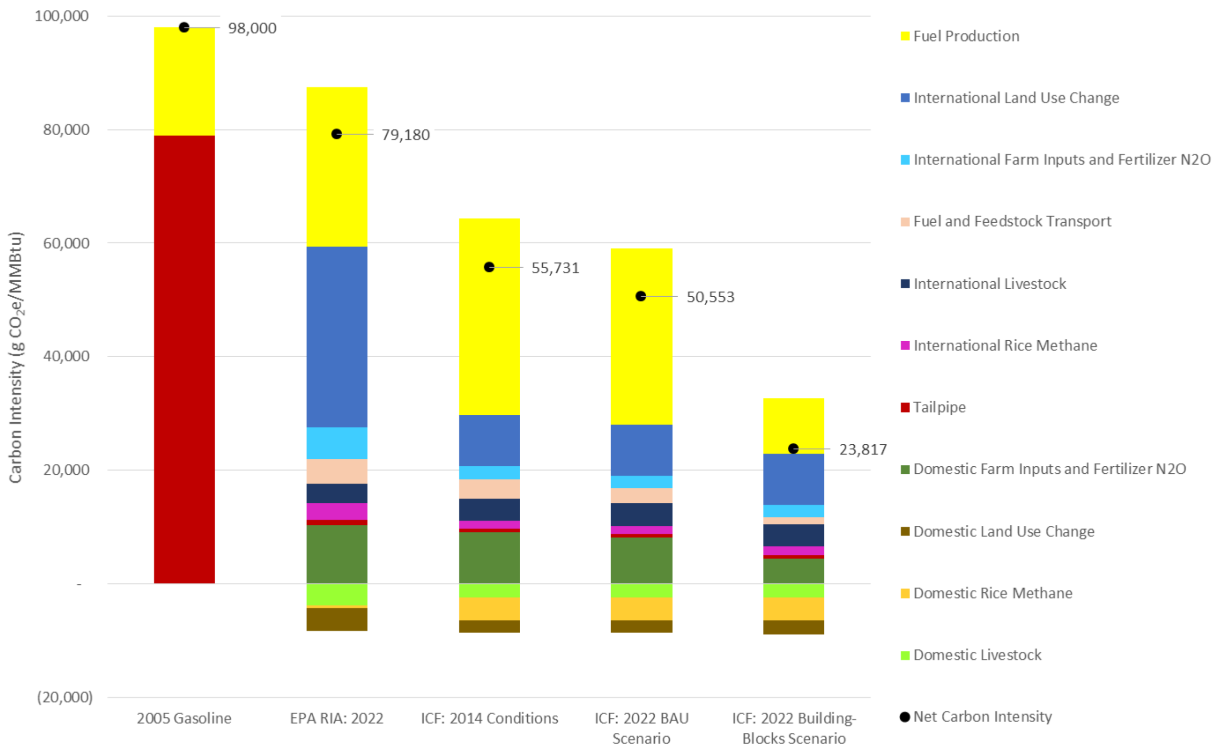

Figure 4-4: Full Life-Cycle Corn Ethanol GHG Results for the ICF: 2014 Current Conditions, ICF: 2022 BAU, and ICF: 2022 Building-Blocks Scenarios

The ICF: 2022 BAU and ICF: 2022 Building-Blocks Scenarios can be viewed as projections of the GHG emissions associated with corn ethanol production in 2022 given, respectively, a relatively passive and a relative aggressive effort to decrease corn ethanol's GHG footprint. While it is unlikely that all of the emission reductions estimated for the ICF: 2022 Building-Blocks Scenario would be achieved by 2022, the scenario does provide a lower bound for describing the potential reduced GHG emissions associated with ethanol, at least over the timeframe of the RFS2.

ICF