THESIS

EVALUATING THE SUSTAINABIITY PERFORMANCE OF U.S. BIOFUEL IN 2017 WITH AN INTEGRATED TECHNO-ECONOMIC AND LIFE CYCLE ASSESSMENT FRAMEWORK

Submitted by

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ABSTRACT

EVALUATING THE SUSTAINABILITY PERFORMANCE OF U.S. BIOFUEL IN 2017 WITH AN INTEGRATED TECHNO-ECONOMIC AND LIFE CYCLE ASSESSMENT FRAMEWORK

The United States produced more than 66.2 million m^3 of biofuel for the transportation industry in 2017. Most of that volume (60.6 million m^3) was produced in the form of corn ethanol and the majority of the remaining volume (4.2 million m^3) was produced in the form of soybean-based biodiesel. Numerous works have assessed the economic and environmental performance of these two biofuel types. However, no work exists which evaluates both the economic and environmental outcomes of these two fuels with adequate geospatial resolution and national scope. In this study, a model framework is constructed that performs concurrent Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) using high-resolution input datasets to provide a granular estimation of sustainability performance of every county in the United States. This work presents results that include sector wide estimates and highlights the importance of capturing geographic heterogeneity. Results show a total emission volume of 55 MMT $CO_{2\text{-eq}}$ produced by the 2017 US biofuel industry, with 7 MMT $CO_{2\text{-eq}}$ of that amount resulting from Land Use Change effects. Nationwide weighted mean Global Warming Potential results are 38 $gCO_{2\text{-eq}}$/MJ and 37 $gCO_{2\text{-eq}}$/MJ for corn ethanol and soybean biodiesel, respectively, when Land Use Change emissions are included. Minimum Fuel Selling Price results are $0.0208/MJ ($2.52/GGE) and $0.0225/MJ ($2.72/GGE) for corn ethanol and soybean biodiesel, respectively. A Zero-Emissions Cost (ZEC) metric is applied, which combines the economic and environmental performance of a fuel into its analysis. Specifically, the cost associated with offsetting all fuel production and use emissions through Direct Air Capture (DAC) is added to the standard price of the fuel. Mean ZEC results are $0.037/MJ ($4.53/GGE) for corn ethanol and $0.039/MJ ($4.69/GGE) for soybean biodiesel which are lower than the ZEC of conventional gasoline of $0.062/MJ ($7.45/GGE). Finally, the cost of Direct Air Capture which results in ZEC parity between each biofuel and its petroleum-based counterpart is assessed to be $49/MT $CO_{2\text{-eq}}$.

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DEDICATION

For Jenna, who makes every day so full.

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1. INTRODUCTION

The passage of the Energy Policy Act of 2005 established the Renewable Fuel Standard program and accelerated biofuel production in the United States[1]. Domestic biofuel output more than doubled between 2005 and 2008[2] and the US industry production capacity has reached 79.5 million m^3 (21 billion gallons) of biofuel per year, which is about 2% of total US energy usage[3]. Corn ethanol constitutes the majority of annual production, with nearly 61 million m^3 (16 billion gallons) being produced in 2017[2-3]. Biodiesel makes up most of the remaining quantity with annual production reaching 6.1 million m^3 (1.6 billion gallons) in 2017[2-3]. The primary feedstock used for biodiesel production is soybean, and about 4.2 million m^3 (1.1 billion gallons) of annual production can be attributed to this crop/fuel combination[3]. Numerous other niche producers constitute about 2% of biofuel production in the US[2]. The largest players in the remaining market share include biodiesel produced from canola and corn oil[3], and renewable diesel produced from a handful of oil-based feedstocks[3]. Biofuels are most frequently blended with conventional fuels for consumption as this improves the emission profile of the consumed fuel without causing reduced engine performance[4]. Corn ethanol is typically blended with gasoline at a rate of 10-15% by volume (E10, E15) and biodiesel is typically blended with conventional diesel at a rate of 5-20% by volume (B5-B20)[4].

Both of these biofuel types (pathways) represent emission reducing systems with development supporting a reduction in the environmental consequences that are associated with the transportation industry[4]. These pathways are categorized as conventional biofuels because the feedstock used to produce the fuel is a food product. Conventional biofuels have been the subject of contention for many years. Specifically, concerns regarding the dedication of a food resource for the transportation industry (the Food-vs-Fuel debate) and the uncertainty associated with the accurate quantification of life cycle emissions has called into question the sustainability of the industry. Lark et. al.[5] recently evaluated the emissions impact of the corn ethanol industry to be worse (i.e., higher) than that of conventional gasoline, and other studies have identified the conversion of unused land for the purpose of feedstock production (Land Use Change) as being generally detrimental to the emission profile of biofuels[5-6].

Stakeholders have assessed the environmental performance of corn ethanol and soybean biodiesel to determine if the intended emission improvements are being achieved[7-16]. However, most of these publications do not incorporate economic evaluation into their analysis[7-14]. Economic outcomes are critical considerations to include when reviewing biofuel sustainability performance[17]. Specifically, including both dimensions in analysis enables the combination of both outcomes into a single metric, and can inform stakeholders of the effective cost of avoided emissions[18]. Beyond economic considerations, only a handful of publications[19, 15-16] characterize geospatial heterogeneity within their assessment. Capturing this geographic variation has been demonstrated to illustrate regional tradeoffs which would not be identified in aggregated analysis [15, 19-20]. No study exists which incorporates economic and environmental performance analysis with geospatial resolution and national scope for both corn ethanol and soybean biodiesel.

This work is centered around the construction of a model that concurrently evaluates the environmental impact and economic viability of corn-based ethanol and soy-based biodiesel through the incorporation of geospatial data. The model framework integrates Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) modules which provide Minimum Fuel Selling Price (MFSP) and Global Warming Potential (GWP) metrics, respectively. Country-wide and county-scale input datasets are incorporated in order to deliver a solution set which characterizes the sustainability performance of both biofuel types in counties across the US. Results are generated which describe, county-to-county, the specific GWP and MFSP metrics of the national biofuel industry. These sustainability metrics are weighted by biofuel production share in order to deliver sector-wide impact quantification. Solution sets both identify regionally specific impacts, such as Land Use Change emissions, and enable a high-resolution characterization of industry performance to be achieved. Analysis also applies the Zero-Emissions Cost (ZEC) metric proposed by Beal and King[18] to evaluate the combined environmental and economic performance of the two fuel pathways. Finally, the breakeven cost of Direct Air Capture (DAC) that results in ZEC parity between biofuels and their conventional counterparts is evaluated at a county level.

2. METHODS

This work developed a model that consumed geospatial data to evaluate the US biofuel industry in terms of economic viability and environmental impact. The model framework integrated several components in order to characterize the 2017 biofuel industry, and the following subsections provide a detailed exploration of each component. First, section 3.1 illustrates the general model structure. Second, section 3.2 discusses the construction of the Process Models. Third and fourth, sections 3.3 and 3.4 describe Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) methodologies, respectively. Fifth, section 3.5 discusses the geospatial datasets which the model integrates. Sixth, section 3.6 discusses the Monte-Carlo Analysis techniques that the framework applies to its analysis. Seventh, section 3.7 discusses the Zero-Emissions Cost metric and finally section 3.8 discusses model validation.

2.1 MODEL STRUCTURE

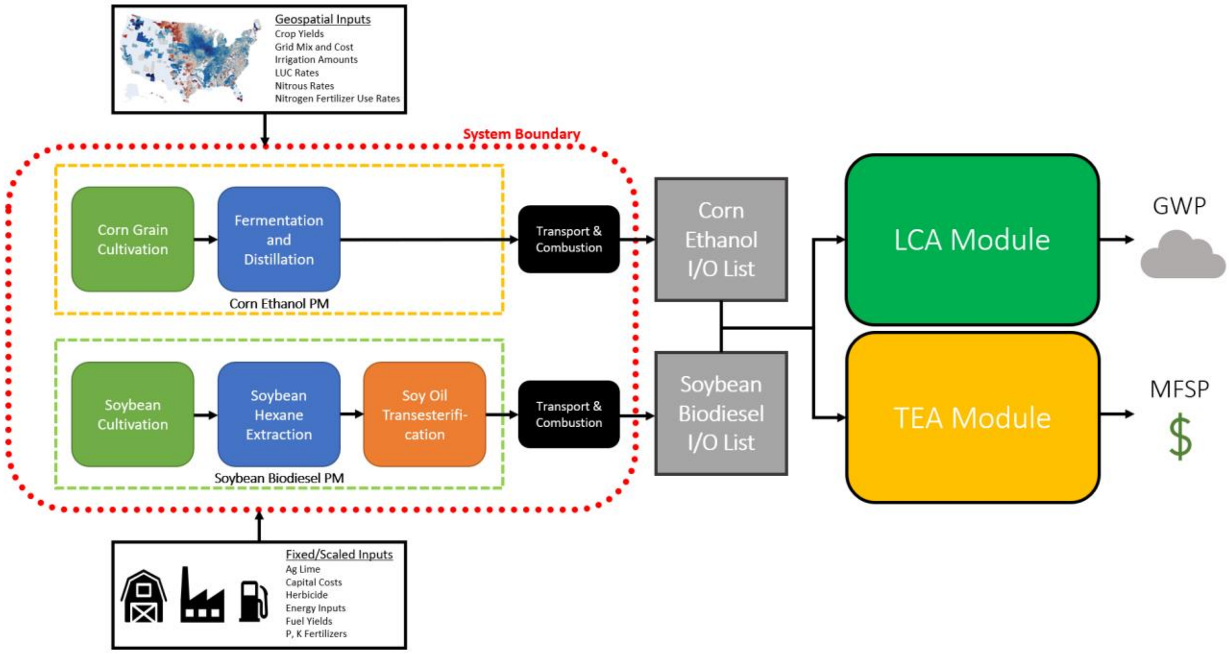

Figure 1 - Process Flow Diagram of primary model components. Geospatial Input datasets are integrated with Fixed/Scaled inputs to produce Process Models for corn ethanol and soybean biodiesel pathways. Process Models characterize aggregated flows associated with fuel production (Input/Output or I/O list). The I/O list feeds into the LCA and TEA modules in order to produce GWP and MFSP results, respectively.

The primary model components are depicted in Figure 1. The foundational units of the framework – the Process Models – were constructed to characterize the corn ethanol and soybean biodiesel pathways. Section 3.2 provides a deeper exploration of these components, but the fundamental task of the Process Models was to quantify mass, energy, and economic amounts (flows) that came into or went out of the system during fuel production. These flow quantities were defined by values retrieved from published literature, and the Process Models produced an aggregated list of all life cycle flows. The Process Models passed this totaled list, referred to as the Input/Output (I/O) list, to the TEA and LCA Modules which performed economic and environmental performance analysis. The TEA module produced the Minimum Fuel Selling Price (MFSP) result based on a discounted cash flow rate of return analysis (section 3.3) and the LCA module produced the Global Warming Potential (GWP) metric based on ISO standards for life cycle accounting (section 3.4). Together, these two quantities constitute a measure of sustainability performance[17]. This action produced the base-case result for both pathways if no geospatial input data was provided to the Process Models. A comparison of these base-case outcomes to other published literature values is presented in section 3.8 and in the Supporting Information. In order to evaluate sustainability performance for different counties, the Process Models consumed different geospatial datasets (section 3.5) which updated the geographically specific flows that correspond to a particular county. In this way, the model was able to determine how each county performed economically and environmentally across the US in a consistent manner.

2.2 PROCESS MODELS

The Process Models were constructed in order to track all flows associated with the production of either fuel. The framework applied two branches in order to accomplish this, with each branch constituting either fuel production pathway. The next subsections explore the pathway-specific considerations that went into the construction of the two branches, but first it presents an explanation of the components which the two branches share.

Model Independent Variables (MIVs) are referenced from literature values and are used to quantify all flows[21-30]. These MIVs may be fixed, in which case they are static and do not vary from county to county; they may be geospatial, in which case they represent the flow amount that is assumed to be produced or consumed in a particular county; or they may be scaled, in which case they define a flow's quantity as relative to another. Each process model branch consists of numerous MIVs which include instances of all three types. The Supporting Information presents an exhaustive list of the specific MIVs used in both pathways.

The Process Model branches were used to characterize the entire life cycle of the products in terms of energy and mass. Thus, the system boundary – a demarcation of what steps are included in the model characterization[31] – extended from before agricultural production of the biomass to beyond the point of fuel use (combustion).

2.2.1 CORN GRAIN ETHANOL

The primary components of the corn grain fermentation to ethanol pathway are presented as a process flow diagram in Figure 2. The pathway possessed two primary process steps, agricultural cultivation and fermentation, and yielded two products, ethanol and Dried Distillers' Grains with Solubles (DDGS). Figure 2 constitutes a more detailed view of the dashed-outline box (labeled "Corn Ethanol PM") in Figure 1, and it quantifies the base-case flow amounts that are assumed in the Process Model branch. The transportation energy requirements of intermediate and final products are not depicted as distinct process steps in the figure but are included in the analysis.

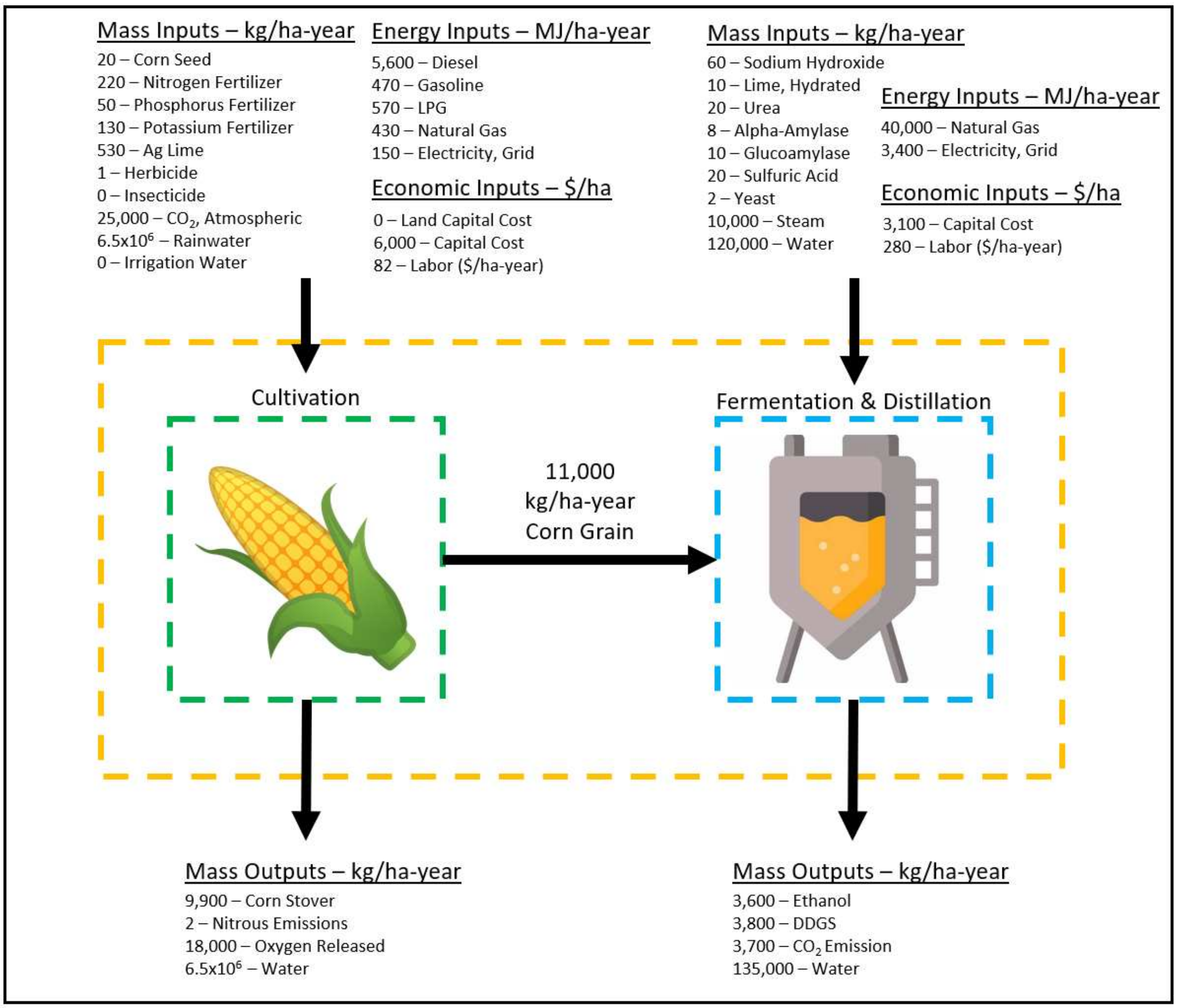

Figure 2 - Process Flow Diagram of the corn grain fermentation to ethanol pathway. All mass, energy and economic flows are enumerated for each distinct process step. Mass outputs from the conversion step are combusted (ethanol), consumed (DDGS) or emitted (CO_2) before the end of the Life Cycle Analysis system boundary in steps that are not included in the scope of this depiction (section 3.4).

The corn to ethanol pathway was based on values provided by NREL's Simplified Starch Fermentation Model[32]. It represented the inputs and yields that are associated with a dry mill corn ethanol plant. Though some 10% of the industry produces ethanol from corn grain plants with the wet mill process[2, 4], similar economic and environmental metrics are observed for the two types [Boland]. Moreover, no wet mill fermentation plants have been constructed after 2005 due to the high capital thresholds required with their construction[4, 33]. Thus, the model characterized national corn fermentation with the dry mill configuration.

Dried Distillers' Grains are produced as a result of the fermentation step and constitute a high-volume co-product to the ethanol pathway[4, 32, 34]. DDGS are assumed to be sold as a ruminant feed supplement, as other analyses have done previously[4, 34]. Gasoline is added to the final, high-concentration ethanol in order to denature it before distribution and use[32]. The model assumed that 5% gasoline by mass was added to the final product. A detailed inputs table is presented in the Supporting Information section.

2.2.2 SOYBEAN BIODIESEL

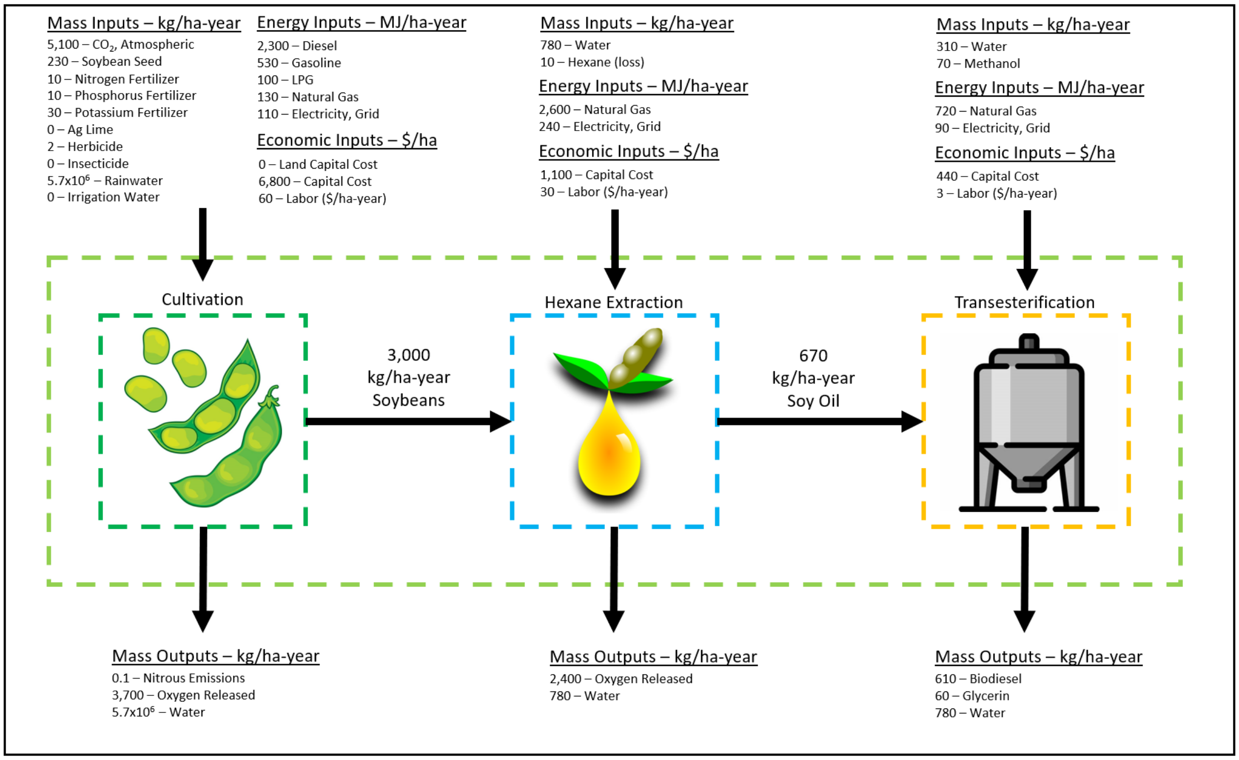

Figure 3 - Process Flow Diagram for the soybean lipid-extraction to biodiesel pathway. All mass, energy and economic flows are enumerated for each distinct process step. Mass outputs from the upgrading process are assumed to be combusted (biodiesel) or consumed (soymeal, glycerin) before the end of the Life Cycle Assessment system boundary in steps that are not included in the scope of this depiction (section 3.4).

The soybean biodiesel pathway was constructed from the values reported in Beal[21] and Chen[27]. Conversion facilities in the US typically apply one of two distinct methods to the extraction of soybean oil: mechanical separation or solvent extraction[35-36]. Nearly all (98%) of soybeans undergoing oil-recovery in the US apply solvent extraction methods, and Hammond[36] cites n-hexane and its isomers as the only solvent currently used[36]. The produced oil is then most frequently converted to biodiesel via a transesterification process[37]. Thus, national soybean biodiesel production was characterized using hexane extraction and transesterification process steps. These two steps, along with the cultivation process, are depicted in Figure 3. The transportation energy requirements of intermediate and final products are not depicted as distinct process steps in the figure. However, both these energy requirements and the emissions associated with the use of the final products are included in the analysis. A detailed inputs table is presented in the Supporting Information section.

2.3 TECHNO-ECONOMIC ANALYSIS

A techno-Economic Analysis (TEA) evaluation methodology[34, 38-40] was applied to assess the relative economic competitiveness of the production of the two fuels in question. The constructed TEA block, along with the LCA module, consumed the same I/O list of aggregate flows generated by the Process Models and produced the evaluated Minimum Fuel Selling Price (MFSP) metric in units of $/MJ delivered fuel.

Operation Expenditure (OPEX) was calculated by scaling the input flows by their assumed priced quantity, and Capital Expenditure (CAPEX) was defined from literature values for each production step (Supporting Information). N^{th} of a Kind (NOAK) capital cost assumptions were applied as defined by the National Renewable Energy Lab (NREL) and the Department of Energy's Bio-Energy Technologies Office (DOE BETO) for all process steps[41]. This is a reasonable assumption to make, as both the corn ethanol and soybean biodiesel industries are well-established, and hundreds of conversion plants of each type were operating in 2017[2]. The Supporting Information section includes an exhaustive list of all NOAK values.

TEA was performed with a 30-year Discounted Cash Flow Rate of Return (DCFROR) model that assessed the minimum price at which the final product must be sold in order to produce a net-present value of zero. This amount is referred to as the Minimum Fuel Selling Price (MFSP). A 10% Internal Rate of Return and seven-year MACRS equipment depreciation schedule was applied in accordance with the established practice dictated by DOE BETO and present in numerous biofuel analyses[30, 42-43]. Prices of all material inputs were pulled from established models and literature values wherever possible. A detailed list of all input prices (e.g., the cost of corn seed) and all OPEX/CAPEX assumptions is provided in the Supporting Information section.

2.4 LIFE CYCLE ASSESSMENT

Life Cycle Assessment (LCA) is an evaluation methodology[38-40, 44] which the model implemented in order to assess the environmental consequences of the production of the two fuels in question. It applied a well-to-wheels system boundary to its analysis of both pathways. This allowed for a holistic characterization of the associated greenhouse gases, as such analysis characterizes both the biogenic carbon uptake which occurs during crop cultivation, embodied emissions in consumables direct emissions from the process and the emissions associated with the end-use of all products. Combustion emissions were accounted for in the same manner as in GREET[45] and a detailed exploration of the assumed carbon amounts is provided in the Supporting Information section.

As the primary purpose of these two pathways is to provide a high-energy liquid fuel, and the energy content of that delivered fuel is critical to its usefulness, the LCA module normalized GWP results against a functional unit of Megajoule liquid fuel. This functional unit is a frequently selected value to normalize impacts against when assessing the environmental outcomes of a liquid biofuel[12,14]. The model performed co-product burden attribution through energy-based allocation methods[34].

The model integrates Life Cycle Inventory (LCI) data from the EcoInvent 3.1 Database accessed through the OpenLCA 1.10.2 platform. LCI values with consistent regions were integrated wherever possible, and inventories of the market type were prioritized. This was done as the market LCI data include the emissions associated with the transportation of a flow to the point of consumption as well the different market shares possessed by distinct products in their analysis[46]. LCI data of the Cutoff type was selected where available.

These LCI values apply the TRACI v2.1 impact assessment methodology in order to provide flow specific metrics of environmental impact. This particular impact assessment methodology assesses the greenhouse gas impacts of emissions on a 100-year timeline. Because different gases possess different greenhouse gas impacts, GWP results are presented in units of carbon dioxide equivalence ($CO_{2\text{-eq}}$), where the total global warming potential of other greenhouse gases are normalized to the equivalent amount of carbon dioxide emissions which would produce the same effect. The gas specific equivalence factors are 1 $gCO_{2\text{-eq}}/gCO_2$, 25 $gCO_{2\text{-eq}}/gCH_4$, and 298 $gCO_{2\text{-eq}}/gN_2O$ as are specified by the Intergovernmental Panel on Climate Change[29].

Finally, the Life Cycle Assessment module is constructed to consume data regarding Land Use Change (LUC) emissions. LUC impacts are typically separated into two categories: direct LUC and indirect LUC[6, 47]. Direct Land Use Change (DLUC) quantifies the soil organic carbon emissions which are physically released at the farm when previously unused land is converted to support agricultural cultivation[47]. Indirect Land Use Change, sometimes referred to as Induced Land Use Change, quantifies the emissions which are associated with a nontrivial increase in demand for a crop; previously unused land is converted to meet the higher demand and DLUC emissions occur at this point[47]. ILUC is very difficult to quantify, and a high level of uncertainty regarding its assessment has resulted in corn ethanol GWP results ranging from 104 $gCO_{2\text{-eq}}/MJ$ to 6 $gCO_{2\text{-eq}}/MJ$[6, 48]. Soy biodiesel results have ranged similarly, and many life cycle practitioners elect to disregard the effects of ILUC in assessing environmental outcomes; a choice which is replicated here[19,21]. LUC, in the context of this analysis, refer to the DLUC emissions which results from the change in the soil organic carbon profile of a particular plot of land. Quantified LUC emissions were brought into the model at a county scale, and a more thorough discussion of these data are provided in section 3.5.

2.5 GEOSPATIAL INPUT DATA

In order to accurately capture geospatial variability, county-level data was integrated with the foundational sustainability modeling. These input datasets are listed in the primary model graphic (Figure 1). They include characterizations of the areal crop yield (kg/ha), cost of electricity ($/kWh), emissions from electricity ($gCO_{2\text{-eq}}/kWh$), nitrogen fertilizer application rate (kg/ha), irrigation rates (kg/ha), Land Use Change emissions rates (kg/ha), and the N_2O emission rates (kg/ha) present in every corn or soy producing county. The model framework references these particular values in its county-to-county analysis.

The United States Department of Agriculture National Agricultural Statistics Service[22] provided county-level crop production and acreage dedication statistics for both the corn grain and soybean industries in 2017, the most recent year for which this data was available. From these two sets, the model obtained a county mean kg/ha areal crop yield. Electricity grid emissions and cost quantities were retrieved from the Environmental Protection Agency's eGrid service and from the Energy Information Administration (EIA), respectively[49-50]. Finally, Pelton offers county-level datasets which include nitrogen fertilizer application rates (kg/ha), irrigation rates (kg/ha), emissions due to Land Use Change (LUC) (kg/ha), and irrigation rates (kg/ha) at a county-level for most of the contiguous US. A detailed explanation of how these values were obtained is available in Pelton[20] and the Supporting Information section. By integrating these datasets, the model achieved a decoupled set of geospatial inputs that are independent of the county-specific biomass produced.

Each of these input sets is incorporated into the national sustainability assessment, and the county-to-county solution produced from this analysis illustrates the economic viability and environmental impact of a marginal component of biofuel production in each county. In this way, locations that possess different geographic characteristics may be compared to one another in a consistent manner. This set does not, however, provide an accurate characterization of the biofuel sector as a whole, as both crop and biofuel production are concentrated in particular regions rather than evenly distributed across the nation. In order to characterize the biofuel sector, county results are weighted based on relative production fraction. The industry is characterized by numerous and complex commodity flows that govern where produced biomass is converted to fuels. This makes the characterization of county-to-county corn grain and soybean destination tracking problematic. Only Pelton has addressed this behavior in the context of an LCA. Such analysis is beyond the scope of this work. Instead, data was retrieved from the United States Department of Agriculture's Economic Research Service (USDA-ERS) which quantifies state-to-state biofuel production volumes of each type. Illinois, for instance, is assumed to have produced 5,606 m^3 (1.5 million gallons) of corn ethanol in 2017[51]. The model assumes that the biomass required to produce this volume (about 100 MMT of corn grain, in this example) is sourced from the state in which the conversion facilities are located. This is not always feasible, as a few states exist which require either more than, or a vast majority of, the total biomass produced in the state for biofuel production. It is unreasonable to assume that all of a state's domestic crop production is dedicated to the fulfillment of a single downstream sector (namely, biofuel production). Instead, the model limits the total available biomass for biofuel production to be 50% of the total biomass produced in that state. In instances where the biomass demand cannot be met by this capacity, the model assumes that the additional input needed is sourced from another major crop producing state with a major excess of produced biomass (typically Iowa, as it produces more corn grain and soybean than any other state). This sourcing behavior replicates the relative crop production share present in over-producing states, and a more thorough explanation of this assumption is available in the Supporting Information section.

2.6 MONTE CARLO ANALYSIS

Monte-Carlo Analysis (MCA) is frequently applied to process model design in order to provide context as to the relative certainty associated with produced answers[52-54]. The model framework integrates an MCA module to stochastically assess the stability of produced results, and relative likelihood distributions (Probability Density Functions, or PDFs) were applied to several different MIVs. Sensitivity analysis results are presented in the Supporting Information section and serve as the starting point for this MCA. MIVs to which results demonstrate high sensitivity were fitted with PDFs in order to provide a characterization as to the potential range of answers that might be achieved as a result of statistical variance in real-world applications. Convergence testing was performed in order to ascertain how many executions were required before a stable answer was achieved. A 10,000-execution simulation was completed and assessed to determine the point at which the rolling average ceased to vary appreciably (i.e., where the solution had converged). A minimum required threshold of 1,000 executions was selected as a result of this convergence test, and all result simulations performed 1,000 random-walks in order to characterize both the answer and the associated uncertainty. Difficulty arises in the application of MCA when considering the mass-balance logic which the process models are predicated upon. Specifically, if the MIV which defines the ethanol yield that is obtained from corn grain input is fit with a PDF, which in turn will change that particular value during each of its random-walks, the net mass-in mass-out balance may be violated. This problem is addressed by performing a coupling calculation after a Monte-Carlo variate is selected for all co-product flows, in order to ensure that mass is conserved. Results from the MCA are presented in the Supporting Information section.

2.7 ZERO-EMISSIONS COST METRIC

Assessing the sustainability performance between biofuels and their petroleum-based counterparts is inherently problematic. Conventional fuels typically exhibit low economic costs and high emissions impacts, and biofuels typically exhibit high relative economic costs and low relative emissions impacts. Numerous techniques have been applied in the literature to perform this comparison in a consistent manner. Beal and King proposed a Zero-Emissions Cost (ZEC) metric which helps clarify this comparison[18]. ZEC consists of two components – the standard cost of the fuel (e.g., the $2.50/Gal that consumers spent at the gas pump in 2017) and the cost of running Direct Air Capture technology to offset all emissions associated with the fuel. In this way, the ZEC outcome allows for consistent comparison between renewable and conventional fuel types. The cost of DAC is assumed to be $440/Tonne $CO_{2\text{-eq}}$ and is taken from[55]. Equation 1 below demonstrates this formulation, and a further explanation of this metric is available in the original publication[18].

$$MFSP\left(\frac{\$}{MJ}\right)+\frac{GWP\left(\frac{g\ CO_{2-eq}}{MJ}\right)\times DAC\left(\frac{\$}{MT\ CO_{2-eq}}\right)}{1{,}000{,}000\left(\frac{gCO_{2-eq}}{MT\ CO_{2-eq}}\right)}\ =\ ZEC\left(\frac{\$}{MJ}\right)$$

MFSP represents the Minimum Fuel Selling Price of the fuel that is being assessed in $/MJ. GWP represents the Global Warming Potential of the fuel that is being assessed in $gCO_{2\text{-eq}}$/MJ. DAC constitutes the cost of Direct Air Capture technology in $/MT $CO_{2\text{-eq}}$. The denominator of the second term constitutes a unit conversion from $gCO_{2\text{-eq}}$ to MT $CO_{2\text{-eq}}$. Finally, the ZEC variable above represents the assessed Zero-Emissions Cost outcome of the fuel in $/MJ.

Direct Air Capture is a relatively unproven technology, and little consensus has been achieved regarding current costs required for operation. Additionally, most estimates expect this value to be dramatically lower several years in the future, as the industry matures[55], and all of these factors contribute to a high level of uncertainty associated with the $440/MT $CO_{2\text{-eq}}$ assumption applied. A new metric, the Breakeven Cost of Direct Air Capture (BEC-DAC), was used in order to address this uncertainty. This variable assesses the cost at which Direct Air Capture must be priced at in order to result in ZEC parity between the biofuels and their conventional, petroleum-based counterparts.

2.8 MODEL VALIDATION AND LITERATURE RESULTS

Base case process model results were compared to other published Life Cycle Assessments and Techno-Economic Analyses for both biofuel types. This comparison demonstrated strong parity with base case outcomes to other results. The process model's base GWPs were 45.8 $gCO_{2\text{-eq}}$/MJ for corn grain ethanol and 22.1 $gCO_{2\text{-eq}}$/MJ for soybean biodiesel, and the process models' base MFSPs were $0.0217/MJ ($2.62/GGE) for corn grain ethanol and $0.0298/MJ ($3.61/GGE) for soybean biodiesel. A brief discussion of the GWP and MFSP comparisons is provided below.

Seven corn ethanol Life Cycle Assessments were referenced[33, 44, 56-60]. These publications ranged in their assessment from 41.2 $gCO_{2\text{-eq}}$/MJ[56] to 56.5 $gCO_{2\text{-eq}}$/MJ[33] when Land Use Change effects are not included. The mean GWP of corn ethanol across these works is 48.4 $gCO_{2\text{-eq}}$/MJ, aligning well with the base case results of the process model constructed here. LUC effects were not included in the comparison to the base case results as the process model default assumption is that corn is sourced from an established farm. Six soybean biodiesel Life Cycle Assessments were referenced[27, 44, 61-64]. GWP results cited in these publications ranged from 16.9 $gCO_{2\text{-eq}}$/MJ[61] to 49.1 $gCO_{2\text{-eq}}$/MJ[64] when Land Use Change effects are not included. The mean GWP of soybean biodiesel across these works is 29.5 $gCO_{2\text{-eq}}$/MJ, which is slightly higher than the base case result reported by the constructed process model. However, these referenced soybean biodiesel results constitute a wider range of answers than was observed during the corn ethanol literature review, and the base case outcome produced by the model still resides within this range.

Five corn ethanol Techno-Economic Analyses or pricing sources were referenced[30, 65-68]. These sources ranged in their reported corn grain ethanol MFSP from $0.0162/MJ ($1.96/GGE)[30] to $0.0304/MJ ($3.68/GGE)[67]. The mean MFSP of corn ethanol across these references is $0.0236/MJ ($2.85/GGE), which shows good parity with the constructed process model's base case outcome. Four soybean biodiesel Techno-Economic Analysis or pricing sources were referenced[68-71]. MFSP values ranged in these sources from $0.0210/MJ ($2.54/GGE)[69] to $0.0338/MJ ($4.09/GGE)[70], and the mean MFSP is $0.0264/MJ ($3.20/GGE). The constructed process model's MFSP outcome again resides within the range of reported results, if being slightly off of the mean.

3. RESULTS AND DISCUSSION

3.1 SUSTAINABILITY PERFORMANCE RESULTS

Sustainability performance results, which include environmental impacts (GWP) and economic outcomes (MFSP), are provided for all counties that were reported by the agricultural census to have produced either corn grain or soybean in 2017[22]. Figure 4 presents these economic and environmental results for both biofuel pathways across the United States. These results are not weighted by production; they report the MFSP and GWP results of each pathway in every location that corn grain or soybean was produced. Counties which are inactive in the maps below (i.e., those which are grayed out) did not report any production of the assessed crop in 2017[22].

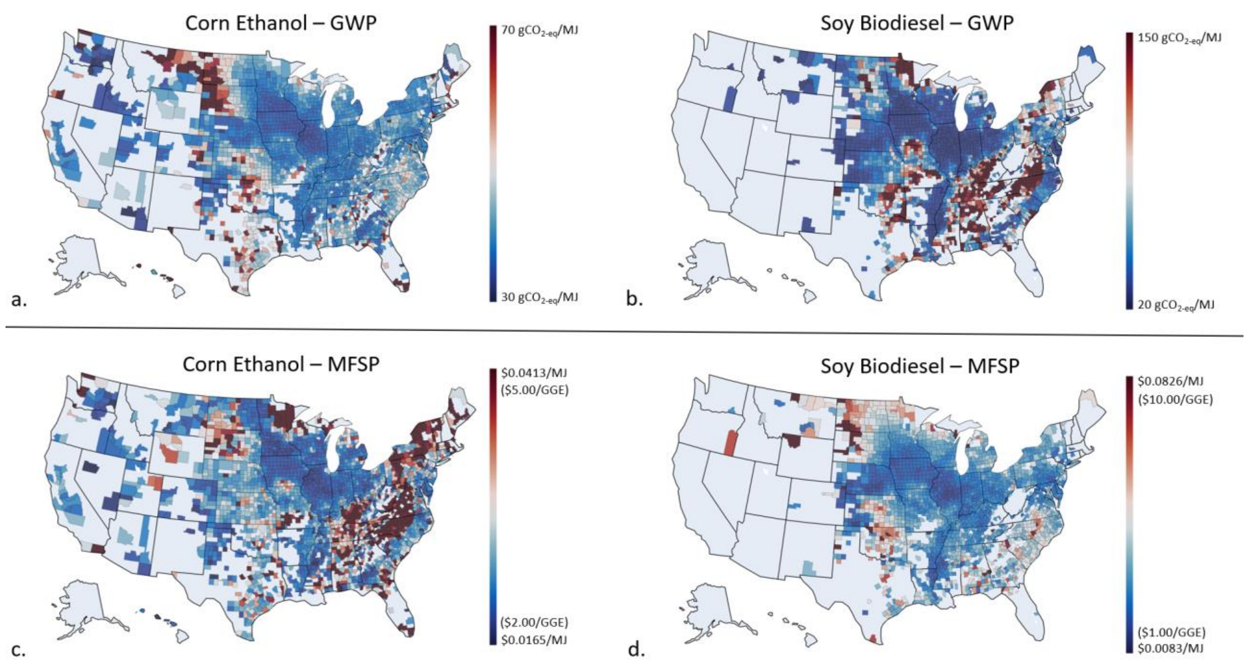

Figure 4- Global Warming Potential (GWP) and Minimum Fuel Selling Price (MFSP) of both biofuel pathways. GWP results (maps 'a' and 'b' for corn ethanol and soybean biodiesel, respectively) are presented in gCO_{2-eq} /MJ. MFSP results (maps 'c' and 'd' for corn ethanol and soybean biodiesel, respectively) are presented in \$/MJ. Equivalent \$/GGE values are indicated in parenthesis for the lower and upper legend bounds for these plots.

Results are grouped into three separate regions for discussion purposes: the corn belt region, the 100th meridian states, and the Appalachian region. The corn belt region includes Iowa, Illinois, Indiana, Minnesota, Missouri and Wisconsin and constitutes 61% and 71% of corn ethanol and soybean biodiesel production, respectively. The 100th meridian states include North Dakota, South Dakota, Nebraska, Kansas, Oklahoma and Texas and they account for 29% and 7% of corn ethanol and soybean biodiesel production, respectively. The Appalachian region includes Kentucky, North Carolina, South Carolina, Tennessee, and Virginia and accounts for 2% and 6% of corn ethanol and soybean biodiesel production, respectively. While other states which are not listed above also produce corn and soy, these three regions together constitute 92% of the total production of corn ethanol and 83% of the total production of soybean biodiesel.

Economic (MFSP) and environmental (GWP) outcomes in the following subsections (4.1.2 and 4.1.1) are presented as the mean amount assessed across a region. Each county is weighted equally, regardless of production share or relative area. This is done in order to illustrate the sustainability outcomes of the two pathways that are present in a particular geographic location. Sector-wide, weighted impact results are presented in section 4.2, and these two sections together serve as a strong characterization of the biofuel industry: section 4.1 quantifies the sustainability performance of a marginal component of biofuel production in every county, and section 4.2 assesses the sustainability outcomes of the entire industry when regional volumes and concentrations are considered.

3.1.1 ENVIRONMENTAL PERFORMANCE RESULTS

National mean Global Warming Potential is 51 $gCO_{2\text{-}eq}$/MJ for corn ethanol and 78 $gCO_{2\text{-}eq}$/MJ for biodiesel. The analysis in this particular section does not weight results based on relative industry share; discussion will not focus on the qualitative conclusions which should be drawn from the national mean results (section 4.2). Instead, this section explores the major contributors to life cycle emissions impact that vary from region to region. Numerous factors contribute to the environmental performance of a county, but the two primary constituents are the areal yield and the emissions due to Land Use Change. Both of these considerations are responsible for soybean biodiesel's assessed GWP being substantially higher than the base case pathway result, and both are discussed more thoroughly below.

The areal yield achieved is the primary driver of environmental performance and varies based on location. In general, counties with low yield will have high GWP results and counties with high yield will have low GWP results. This behavior is due to the several agricultural inputs that are decoupled from the observed yield amount (such as the quantity of fertilizer applied). In instances where moderate to low biomass output is achieved the decoupled input emissions are concentrated onto a smaller quantity of final product: the inputs that are independent of the achieved yield apply their emissions burden over a lower final total energy output. This particular behavior is apparent when regional means are compared against their associated areal yields. Corn belt states, which show the highest national areal yields (11 - 14 Mg/ha for corn 4 - 5 Mg/ha for soy) also possess the lowest GWP results in the nation (36 $gCO_{2\text{-}eq}$/MJ and 29 $gCO_{2\text{-}eq}$/MJ). The 100th meridian states exhibit low areal yields (4 - 7 Mg/ha and 1 - 2 Mg/ha) and show poor GWP results (42 $gCO_{2\text{-}eq}$/MJ and 73 $gCO_{2\text{-}eq}$/MJ). States in the Appalachian region possess moderate areal yields (7 - 9 Mg/ha and 2 - 3 Mg/ha) and this region shows the highest environmental consequences in the nation (53 $gCO_{2\text{-}eq}$/MJ and 78 $gCO_{2\text{-}eq}$/MJ).

Emissions from Land Use Change exhibit similar high geographic variability by location, and the GWP results in turn show high sensitivity to LUC emission quantities (section 4.2.3). The corn belt region constitutes well-established cultivation and most land suitable for crop production is already dedicated. Thus, the instances of Land Use Change are low for the region (2,000 $kgCO_{2\text{-}eq}$/ha for both pathways), with the notable exceptions of Missouri and the north-eastern corner of Minnesota. Missouri exhibits mean LUC emissions of 4,800 $kgCO_{2\text{-}eq}$/ha for both crop types, and the counties in north-east Minnesota exhibit mean LUC emissions of 4,000 $kgCO_{2\text{-}eq}$/ha and 2,600 $kgCO_{2\text{-}eq}$/ha for the corn ethanol and soybean biodiesel pathways respectively. Instances of Land Use Change are high in these areas as they constitute the border of where production of both crop types is concentrated, and this behavior is most apparent when maps which depict total LUC emissions and total crop production are viewed together (Supporting Information). The 100th meridian states have low emissions due to land use change, with mean LUC emissions of 1,300 $kgCO_{2\text{-}eq}$/ha for corn grain and 1,000 $kgCO_{2\text{-}eq}$/ha for soybean, as land that is being converted is of the lower-impact grassland type. Finally, the Appalachian region exhibits very high LUC emissions, with regional means reaching 8,700 $kgCO_{2\text{-}eq}$/ha for corn grain and 7,100 $kgCO_{2\text{-}eq}$/ha for soybean. In this region, LUC emissions are substantially higher than in the rest of the nation as a greater portion of the land converted for production is forested, and thus contains more sequestered carbon than the grassland cover which is present in the 100th meridian and corn belt states[20]. In all, LUC emissions constitute a serious contributor to the carbon balance of biofuel production and show high variation from region to region.

3.1.2 ECONOMIC PERFORMANCE RESULTS

The national mean MFSP results for corn ethanol and soybean biodiesel are $0.0246/MJ ($2.98/GGE) and $0.0306/MJ ($3.70/GGE), respectively. Analysis in this particular section does not weight results based on relative industry share and thus discussion will not focus on the qualitative conclusions which should be drawn from the national mean results (section 4.2). Instead, this section explores the major contributor to economic performance: the areal yield.

As was the case with the environmental performance of both biofuel types, economic outcomes are most sensitive to the areal yield that is present in a particular county. This relationship is more pronounced than that observed for the GWP results, as there is a greater relative share of total expenditure which are decoupled (i.e., fixed) from specific biomass production. Additionally, other geospatially varying inputs (fertilizers, irrigation, LUC, etc.) constitute marginal players in the economic balance. Thus, the produced economic performance result maps look nearly identical to the areal yield maps for each pathway's respective crop (Supporting Information). This demonstrates that the decoupled, geospatially varying costs (fertilizer, irrigation, electricity grid cost, etc.) do not possess the same leverage over the MFSP results as the capital, per hectare expenditure that is associated with agricultural equipment. Corn belt states, which show the highest national areal yields (11 - 14 MT/ha for corn 4 - 5 MT/ha for soy) also possess the lowest MFSP results in the nation ($0.0198/MJ and $0.0204/MJ). The 100th meridian states possess the lowest areal yields in the nation (4 - 7 MT/ha and 1 - 2 MT/ha) and show the highest MFSP results ($0.0225/MJ and $0.0410/MJ). Finally, the Appalachian region possess moderate areal yields (7 - 9 Mg/ha and 2 - 3 Mg/ha) and show poor MFSP results ($0.0224/MJ and $0.0293/MJ). States in the 100th meridian region and in Appalachia produce Minimum Fuel Selling Price values which are higher than the 2017 mean cost of petroleum-based gasoline ($0.0207/MJ, or $2.50/GGE) and diesel ($0.0210/MJ, or $2.65/GGE), demonstrating that biofuels produced from feedstocks grown in these locations are not cost competitive solutions. However, both corn ethanol and soybean biodiesel produced in the corn belt region show, in the mean, a lower $/MJ cost than their conventional, petroleum-based counterparts. While the cost of petroleum-based fuel is volatile and the MFSP evaluation performed here may be under-representing the total cost of production, the parity demonstrated in these results show that, in locations where areal yield is high, both biofuel types constitute a cost competitive alternate fuel solution.

3.2 AGGREGATED IMPACT RESULTS

The results from section 4.1 provide a county-to-county evaluation of environmental and economic performance of both biofuel types. However, in order to produce a characterization of the entire sector, relative production fractions must be considered and brought into the analysis. County specific results from the sustainability performance analysis (section 4.1) are weighted by that county's fraction of national production, and this produces results that represent the total industry emissions and expenditure. Results are presented in Figure 5 that depict the total emissions (in Metric Tonnes $CO_{2\text{-eq}}$) and total expenditure (in dollars) associated with corn ethanol and soybean biodiesel production in 2017. Some areas which were active in the maps presented in Figure 4 are inactive in Figure 5, as not all counties dedicate biomass to fuel production.

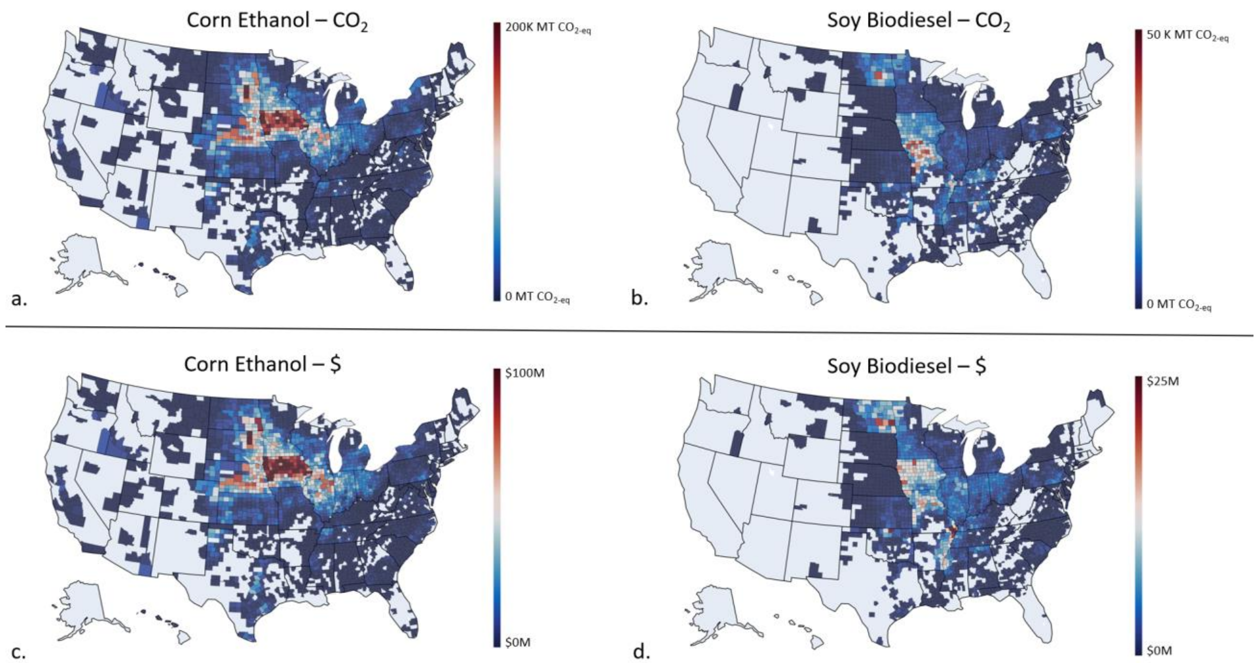

Figure 5- Total Expenditure and Emissions for corn ethanol and soybean biodiesel. Values calculated by weighting county-specific economic and environmental performance with production share. Emissions maps ('a' and 'b') present results in Metric Tonnes $CO_{2\text{-eq}}$ and expenditure maps ('c' and 'd') present results in total dollars spent for corn and soy, respectively.

3.2.1 TOTAL EMISSIONS QUANTITIES

Results show a total of 55 MMT of $CO_{2\text{-eq}}$ are released due to the production of corn ethanol (48 MMT $CO_{2\text{-eq}}$) and soybean biodiesel (7 MMT $CO_{2\text{-eq}}$) in 2017. Several of the most substantial contributors to the total emission volume are related to the corn ethanol pathway specifically. These emissions include direct CO_2 emissions from yeast respiration during corn grain fermentation (13 MMT $CO_{2\text{-eq}}$), emissions from natural gas use during ethanol distillation (7 MMT $CO_{2\text{-eq}}$), and diesel use at the farm (3.6 MMT $CO_{2\text{-eq}}$). All of these contributors remain relatively constant with respect to geographic location, and regional variation of these quantities only occurs as a result of the unique yield present in a particular county. Pathway modifications can be targeted to improve these particular flows as they represent the most significant sources of emission in the biofuel industry. Corn fermentation plants, for instance, could be retro-fitted with carbon-capture technology in order to store the 13 MMT of CO_2 that is emitted from the fermentation process nation-wide every year[72]. Techno-economic work has been done to show this is not an economically viable pathway for emissions reduction in the absence of a carbon-based credit[72].

In addition to these high quantity contributors which do not vary based on location, a number of moderate emission contributors exist for both biofuel pathways which vary geospatially and can be regionally targeted for improvement. These particular contributors include Land Use Change emissions and impacts due to irrigation practices. Total Land Use Change emissions are assessed to be 3.6 MMT $CO_{2\text{-eq}}$ and 3.2 MMT $CO_{2\text{-eq}}$ for the corn ethanol and soybean biodiesel pathways, respectively. It is unsurprising that both crop types exhibit similar total national volumes of emissions from LUC effects, as corn and soybean are typically grown in rotation with one another and, for some given year, roughly the same area of land might be converted to support additional demand. These quantities show high variation from region to region; for example, corn belt states, which produce 61% of the national corn ethanol volume and 71% of the national soybean biodiesel volume, contribute to 28% and 55% of total LUC emission quantities, respectively. The Appalachian region, which produces 2% of national corn ethanol and 6% of soybean biodiesel, contributes 9% and 21% of total LUC emission volume for the corn ethanol and soybean biodiesel pathways, respectively. These emission quantities constitute more than 12% of the national total volume and this particular contributor possesses serious influence over the GWP performance of the industry (4.2.3). These results show that the conversion of previously unused land for cultivation of biofuel does not make sense, emissions-wise, and numerous works have identified this particular practice as being generally detrimental to the environmental performance of the industry[5, 20].

Another input which shows similar sensitivity to geographic location is irrigation. Irrigation impacts are concentrated in Nebraska and contribute primarily to the corn ethanol production pathway. The state constitutes 13% of national corn ethanol production but is responsible for 67% (0.9 MMT $CO_{2\text{-eq}}$) of the 1.3 MMT $CO_{2\text{-eq}}$ attributable to nationwide irrigation practices. However, it is difficult to gauge the holistic impact that this process has on life cycle greenhouse gas performance as the additional water application in these counties is clearly responsible for additional biomass production. Corn grain yields in all other 100th meridian states which do not irrigate range between 4 - 6 Mg/ha (in the western half of the states) to 8 - 10 Mg/ha (in the eastern half of the states); Nebraska achieves yields of 11 - 13 Mg/ha in almost every county. In addition to these considerations, different impacts are associated with irrigation water that is sourced from surface reservoirs and that is sourced from sub-surface aquifers. Analysis that can characterize and address the interaction between irrigation emissions and improved yield is beyond the scope of this study. However, while the emission balance associated with irrigation of corn is complicated, the water balance is not. Numerous studies have identified the frequency of irrigation over the Ogallala aquifer to be unsustainable regarding water impacts[73-75].

3.2.2 TOTAL ESTIMATED EXPENDITURE QUANTITIES

Total expenditure is estimated for the industry by taking the product of the assessed MFSP with the total assumed fuel production. Estimated expenditure results show a total of $30.5 billion spent on the production of corn ethanol ($26.5 billion) and soybean biodiesel ($4 billion) in 2017. Corn ethanol constitutes the majority of the total biofuel production volume and, as such, the highest individual contributors of national financial outflow are related to the pathway. Specifically, $7.9 billion is attributable to natural gas for starch conversion (fermentation and distillation), $4 billion is attributable to capital expenditures (farm and conversion facility equipment), and $2.8 billion is attributable to corn seed. These constituents vary geographically only as a result of the specific yield present in a county, as is the case for most contributors to economic outflow. While nitrogen fertilizer inputs are geospatially defined and are thus independent of yield, application rates show relative consistency across the nation. Additionally, this flow constitutes about 6% of total expenditure, and it is difficult to draw economic conclusions as the interaction between fertilizer application and achieved yield is intricate and complex. Similar behavior is observed regarding the estimated economic outflow from irrigation, which constitutes less than 1% of national total expenditure. Grid electricity cost, which constitutes about 5% of national total expenditure, does not vary substantially in regions where production is concentrated.

3.2.3 SECTOR WIDE SUSTAINABILITY OUTCOMES

Results from the previous sections (4.2.1 and 4.2.2) are normalized over the aggregate biofuel production (in MJ) of both pathways. This delivers sector wide sustainability performance estimates for 2017 which capture the geospatial concentrations of the industry. These results represent the core product of this work. National, weighted mean GWP is 38 $gCO_{2\text{-}eq}$/MJ for corn ethanol and 37 $gCO_{2\text{-}eq}$/MJ for soybean biodiesel. MFSP results are $0.0208/MJ ($2.52/GGE) for corn ethanol and $0.0225/MJ ($2.72/GGE) for soybean biodiesel.

Industry wide GWP results show that corn ethanol and soybean biodiesel perform similarly, in the mean, in terms of environmental impact. The majority of published literature resources suggest that soybean biodiesel constitutes a lower life cycle emission pathway than corn ethanol. Specifically, while corn grain results show reasonable parity with published literature (Lee – 46 $gCO_{2\text{-}eq}$/MJ, RIA – 51 $gCO_{2\text{-}eq}$/MJ, etc. Kim 41 – $gCO_{2\text{-}eq}$/MJ), the soybean biodiesel results constitute a substantially higher impact than other reported values (Pradhan – 17 $gCO_{2\text{-}eq}$/MJ, Chen – 22 $gCO_{2\text{-}eq}$/MJ, Sheehan – 18 $gCO_{2\text{-}eq}$/MJ). The primary reason for this observed disparity is the disproportionate manner in which Land Use Change emissions affect the biodiesel pathway; when LUC impacts are not included in analysis, mean GWP results are 35 $gCO_{2\text{-}eq}$/MJ and 19 $gCO_{2\text{-}eq}$/MJ for corn ethanol and soybean biodiesel, respectively. This phenomenon is due to the lower biomass yield achieved by soybean plants: areal soy yield is, in the highest producing region, 5 Mg/ha. Corn yields are much greater, regularly reaching 12-14 Mg/ha output in the highest producing region. Additionally, the relative fuel yield to biomass input fraction is lower for the soybean biodiesel pathway than for corn ethanol (0.2 kg Biodiesel/kg Soybean compared to 0.33 kg Ethanol/kg Corn Grain). These factors conspire to make MJ/ha outputs low for the soybean biodiesel pathway and make fixed input emissions amounts (such as Land Use Change emissions) more influential regarding final GWP outcomes.

3.3 COMBINED EMISSIONS AND ECONOMIC RESULTS

Results in this section explore the performance of different counties under the Zero-Emission Cost (ZEC) metric and the Breakeven Cost of Direct Air Capture (BEC-DAC) for both biofuel pathways. The maps presented in Figures 6 and 7 portray the ZEC or BEC-DAC, in \$/MJ and \$/MT $CO_{2\text{-eq}}$, assessed for a particular county. However, national and regional mean reported values are based on the averaged results when weighted by county production fraction.

3.3.1 ZERO-EMISSION COST RESULTS

The Zero-Emission Cost results are presented in Figure 6, in \$/MJ (and \$/GGE in parenthesis), for the corn ethanol and soybean biodiesel pathways. Only counties that are assumed to contribute biomass for fuel production are active (i.e., are not grayed out) in the provided maps. Also included in Figure 6 is a marker which indicates the ZEC cost of conventional gasoline and diesel for the respective biofuel counterparts.

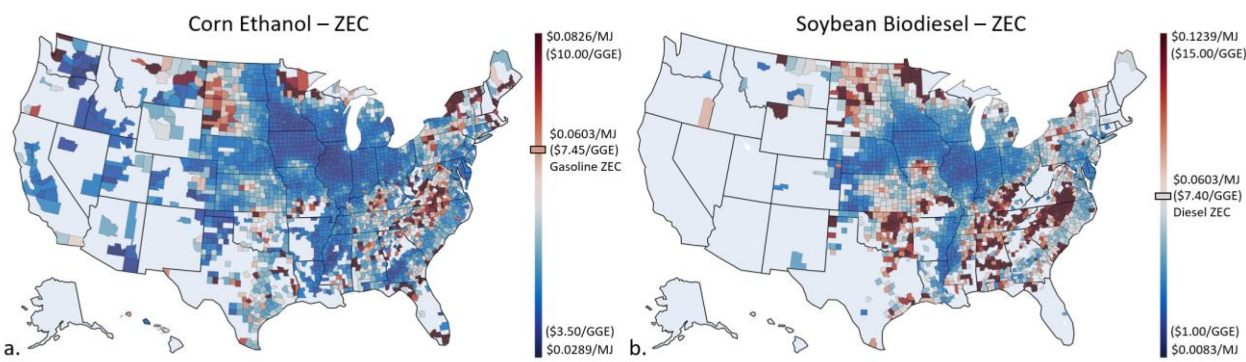

Figure 6 - Zero Emission Cost (\$/MJ and \$/GGE) results for corn ethanol and soybean biodiesel by county. The Zero-Emission Cost metric combines the fuel's traditional price with the cost of running Direct Air Capture (\$440/MT $CO_{2\text{-eq}}$) to offset the fuel's life cycle emissions. Conventional Gasoline's ZEC (\$0.0616/MJ, or \$7.45/GGE) and Diesel's ZEC (\$0.0612/MJ, or \$7.40/GGE) are indicated on the legend for context.

Corn ethanol weighted national mean ZEC is \$0.0374/MJ (\$4.53/GGE) and soybean biodiesel mean ZEC is \$0.0417/MJ (\$5.05/GGE). For the assumed DAC cost of \$440/MT $CO_{2\text{-eq}}$, both pathways represent a less expensive fuel than their conventional counterparts when emissions are included in analysis: the Zero-Emission Cost of conventional fuels is \$0.0616/MJ (\$7.45/GGE) for gasoline and \$0.0612/MJ (\$7.40/GGE) for diesel. The majority of corn ethanol Zero-Emissions Cost results are lower than those reported for soybean biodiesel, as ethanol is cheaper than biodiesel in nearly all counties.

However, in high-yield locations this difference in evaluated MFSP results of the two pathways becomes trivial. For instance, the corn belt weighted mean MFSP results for corn ethanol are $0.0198/MJ ($2.40/GGE) and are $0.0204/MJ ($2.47/GGE) for soybean biodiesel. In these cases, soybean biodiesel outperforms corn ethanol in terms of Zero-Emission Cost due to its improved environmental performance: $0.0342/MJ ($4.13/GGE) for soybean biodiesel to $0.0352/MJ ($4.26/GGE) for corn ethanol in the above example. Both pathways constitute marked improvements over their conventional counterparts for this assumed cost of DAC.

Direct Air Capture is a relatively unproven technology and consensus has not been achieved regarding current costs required for operation. Additionally, most estimates expect this value to be dramatically lower several years in the future, as the industry matures [McQueen], and all of these factors contribute to a high level of uncertainty associated with the $440/MT $CO_{2\text{-eq}}$ assumption applied. It is important to understand the sensitivity that the obtained ZEC results show to the cost of DAC assumption. The base-case assumption, DAC at $440/MT $CO_{2\text{-eq}}$, results in ZEC reductions of 38% and 36%, for corn ethanol and soybean biodiesel, respectively, when compared against the ZEC of their conventional counterparts. The most ambitious Direct Air Capture cost projections ($100/MT $CO_{2\text{-eq}}$) cause these ZEC reductions to drop to 17% and 12%. Conversely, conservative DAC cost projections ($1000/MT $CO_{2\text{-eq}}$) cause the ZEC reductions to jump to 47% and 46%. Because there is both a high level of uncertainty associated with the assumed cost of Direct Air Capture and a high sensitivity of ZEC results to this assumed cost of DAC, section 4.3.2 explores a separate evaluation method of the combined economic and emissions results.

3.3.2 BREAKEVEN COST OF DAC RESULTS

In order to address the sensitivity associated with the ZEC metric, this section presents the Breakeven Cost of Direct Air Capture (BEC-DAC). Specifically, this metric evaluates the cost at which DAC must be run in order to result in ZEC parity between the biofuel and its conventional petroleum counterpart. A number of counties are assessed across biofuel types to possess higher GWP results than the conventional fuels they displace. In all of these cases the associated MFSP is also higher than the cost of the conventional fuel, and thus no cost of Direct Air Capture exists which would make these fuels ZEC competitive. Figure 7 presents these particular counties as inactive (grayed out). The Supporting Information section contains maps which depict these counties for both biofuel types, explicitly. Similarly, there are many counties where the assessed biofuel MFSP is lower than the cost of its conventional petroleum counterpart. In all of these cases the associated GWP of the biofuel is also lower than the emission profile of the conventional fuel, and thus no cost of Direct Air Capture exists which would make these fuels ZEC non-competitive. Figure 7 presents these particular counties as possessing a breakeven DAC cost of \$0/MT $CO_{2\text{-eq}}$.

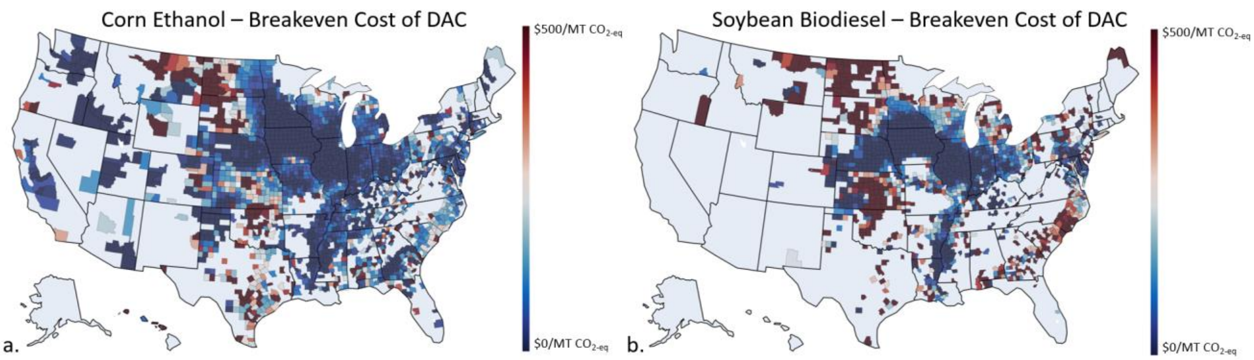

Figure 7- Breakeven cost of Direct Air Capture (DAC) technology for corn ethanol and soybean biodiesel when compared to the Zero-Emissions Cost of conventional gasoline. Results that indicate \$0/MT CO2-eq¬ have been assessed to be cheaper than gasoline, thus the biofuel is competitive in the absence of any carbon-related charge.

National weighted mean BEC-DAC is assessed to be \$49.00/MT $CO_{2\text{-eq}}$ for counties which present biofuel GWPs that are lower than their conventional counterpart's and MFSPs which are higher than their conventional counterpart's. This result is noteworthy, as it constitutes a competitive cost of avoided emissions when compared to that which is currently applied under the "Section '45Q' Carbon Capture and Sequestration Tax Credit"[76]. 45Q currently affords companies \$32/MT $CO_{2\text{-eq}}$ when CO2 is captured and stored in secure geological formations, with provisions to increase this amount to \$50/MT $CO_{2\text{-eq}}$ by 2026[76]. Most states in the corn belt region show BEC-DAC results of \$0/MT $CO_{2\text{-eq}}$ as the biofuel produced is assessed to be cheaper than gasoline or diesel. Corn ethanol exhibits this behavior in Iowa, Illinois and Minnesota, specifically, and soybean biodiesel exhibits this behavior in Iowa, Illinois and Indiana, specifically. The corn belt regional mean BEC-DAC is \$5/MT $CO_{2\text{-eq}}$ for corn ethanol and \$90/MT $CO_{2\text{-eq}}$ for soybean biodiesel. The 100th meridian states possess BEC-DAC results of \$46/MT $CO_{2\text{-eq}}$ for corn ethanol and \$450/MT $CO_{2\text{-eq}}$ for soybean biodiesel. Finally, the Appalachian region states show BEC-DAC results of \$37/MT $CO_{2\text{-eq}}$ for corn ethanol and \$888/MT $CO_{2\text{-eq}}$ for soybean biodiesel.

It is difficult to present regional means for this particular result type, as there are numerous confounding factors. Specifically, the majority of production is concentrated in areas where the BEC-DAC is zero, as the assessed MFSPs and GWPs are lower than that of petroleum-based gasoline or diesel. Additionally, there are a number of locations (Alabama, Kentucky, Texas and Virginia, specifically) where the weighted mean GWP of soybean biodiesel is higher than that of conventional diesel, and thus the BEC-DAC would be infinite. The results presented exclude both of these sets from the mean calculation in order to determine the Breakeven Cost of Direct Air Capture technology in locations where its determination is non-trivial. If the aggregated, national MFSP and GWP results are applied for both pathways to determine the BEC-DAC of the industry, a value of \$4.80/MT $CO_{2\text{-eq}}$ is assessed. This BEC-DAC is substantially lower than those reported above as it includes all of national production: numerous corn-belt counties which perform better than gasoline or diesel economically are now included in analysis. Though there are also numerous counties that perform worse than gasoline or diesel environmentally, the net effect of including both types is a reduction of the total BEC-DAC, as production is concentrated in well-performing regions. In all, these results show that both biofuel pathways constitute a less expensive means of emissions mitigation than most Direct Air Capture targets hope to achieve over the next several years[55].

4. CONCLUSION

County-level results for economic outcomes and environmental impacts indicate the importance of capturing geographic variability in sustainability assessment. Substantial variations in performance metrics are observed and characterized across the nation for several different inputs. National, sector-wide emissions are assessed to be 55 MMT $CO_{2\text{-eq}}$ and total estimated expenditure is \$31 billion. The weighted mean GWP for corn ethanol is 38 $gCO_{2\text{-eq}}$/MJ and 37 $gCO_{2\text{-eq}}$/MJ when Land Use Change emissions are included. These values are substantially lower than the life cycle GWP of conventional gasoline (93 $gCO_{2\text{-eq}}$/MJ) and diesel (92 $gCO_{2\text{-eq}}$/MJ). The weighted mean MFSP results are \$0.0208/MJ (\$2.51/GGE) for corn ethanol and \$0.0225/MJ (\$2.72/GGE) for soybean biodiesel. Both of the assessed pathways demonstrate competitive economic and environmental outcomes when compared against their conventional counterparts. Notably, the total emissions from Land Use Change constitute 12% of the national greenhouse gas volume produced by the industry in 2017. LUC effects also hold considerable influence over the environmental performance of the soybean biodiesel pathway specifically, as they constitute 50% of the assessed Global Warming Potential metric. Conversion of land is generally unsustainable regarding emission impacts and a moratorium on Land Use Change for crop production should be considered until more accurate characterization of the phenomenon can be achieved. 13 MMT of $CO_{2\text{-eq}}$ were emitted in 2017 due to the cellular respiration of yeast during the fermentation of corn ethanol. This particular flow represents a high-purity vent of carbon-dioxide and is suitable for capture and storage. Sequestration of this volume (about one-quarter of total emissions) would constitute a Global Warming Potential reduction of 25% (10 $gCO_{2\text{-eq}}$/MJ) when compared to current GWP performance. Combined economic and environmental metrics show biofuel to be a strong performer when compared to conventional fuels and existing negative emission technologies. The Zero-Emissions Cost metric results demonstrate that both corn ethanol (\$0.0374/MJ, or \$4.53/GGE) and soybean biodiesel (\$0.0387/MJ or \$4.69/GGE) constitute less expensive fuel solutions than their conventional counterparts (\$4.45/GGE and \$4.40/GGE for gasoline and diesel, respectively) with Direct Air Capture costs at current levels. Additionally, the breakeven cost result of Direct Air Capture technology for the production of biofuels (\$49/MT $CO_{2\text{-eq}}$) shows that the biofuel sector represents a cost-competitive emission mitigation technology.

5. FUTURE WORK

This work has identified areas where improved technology or management practices could deliver improved economic and environmental performance. Additionally, the toolset that is created can be applied to the analysis of future-states, such as in the evaluation of different next generation biomass feedstocks. A secondary purpose of this work was to calibrate the constructed model framework and lend credibility to further exploration of these future states.

Two sections are presented regarding potential future work. First, a section which identifies the areas in which improvements to the analysis of the 2017 case that would deliver better result characterization is presented. This section aims to identify potential weaknesses or deficiencies that are present in this analysis that could be addressed. Second, a section that describes potential future project directions presented.

5.1 FUTURE WORK – IMPROVED 2017 ANALYSIS

It is important to understand and highlight the areas in which this assessment might be deficient as this lends to a more holistic understanding of the presented results. No assessment is complete without a critical reflection on the areas where analysis could have been improved.

Land Use Change classification and quantification represents the foremost of these concerns. The LUC inputs that were brought in from the Pelton publication are not the results of analysis performed in this work. As such, while Pelton and Lark deliver careful, thorough work, it is difficult to claim categorically that all research methods and assumptions in their analysis align with those applied here. This uncertainty is made more relevant as one of the primary conclusions of this work (the LUC emission's influence on soybean GWP) is based on this input data. However, the behavior of the model demonstrates that LUC effects disproportionately influence the soy biodiesel pathway regardless of the actual quantity of LUC emissions that are assessed. This detail is important, as the final conclusion that was reached is not particularly sensitive to the specific LUC emission quantity assumed.

Calculation of areal yield constitutes the second area in which more detailed analysis could improve the obtained results. In order to predict the average areal yield that each crop achieved in every county, USDA-NASS data describing the total production of each crop type was divided by the total number of acres which are reported to grow that crop for each county. There is inherent uncertainty associated with these datapoints, as the agricultural census constitutes an enormous undertaking. Small discrepancies between the total production reported and the total dedicated acreage can have substantial influence over the calculated areal yield. Further work could assess, by field observation or targeted polling, the actual achieved yields for a number of representative locations across the United States. In this way, the derived areal yields from the USDA-NASS set could be validated or centered based on direct observation. As was the case with the previous assumption, the conclusions that were drawn from the results do not change substantially if these yield amounts are changed. The county-to-county economic and environmental comparisons, one of the main products of this work, still hold with different yield input values, and only the aggregated performance results which characterize the sector as a whole would require serious re-evaluation.

The way the model addressed the numerous different types of corn ethanol conversion facilities is another area in which this particular analysis is weak. While soybean biodiesel is almost always converted with the hexane-extraction and transesterification processes, ethanol can be produced from corn grain feedstocks in a myriad of different ways. The two most prolific conversion methods – dry and wet milling – are assessed in different works to possess serious environmental differences when non-conventional configurations are applied. The Environmental Protection Agency presents a list of all potential corn grain conversion technologies, and the reported GWP results swing from 48.4 $gCO_{2\text{-eq}}$/MJ (for a dry-mill Combined Heat and Power plant that extracts wet DGS and burns biomass for fuel) to 110.8 $gCO_{2\text{-eq}}$/MJ (for a wet-mill, coal-burning conversion plant)[77]. More than a dozen other configurations are presented, and while the majority of currently operational conversion plants are in the dry-mill configuration, the industry is far from homogenous. Further work could be done to include the different types of corn grain to ethanol conversion facilities and better characterize the landscape.

Finally, the way in which the Minimum Fuel Selling Price is evaluated for each county could be improved. The model assumes that the costs associated with the production of the crop (corn grain or soybean) is aggregated with the costs associated with the conversion to a biofuel and evaluated as though it were one, vertically integrated unit. In reality, the production and conversion of the crop are managed by separate entities; farmers sell their product to distributors and conversion facilities purchase it as a feedstock. Analysis, then, is predicated on the assumption that the MFSP that would be assessed for a conversion facility paying $X for corn as a feedstock is the same as the MFSP that would be assessed for a conversion facility covering the cost of producing the corn itself. This is a reasonable assumption as the cost of corn at the farm-gate presumably covers the cost of production plus some margin for the producer, and both of these considerations are included in the vertical integration analysis. However, crop prices in the United States are subsidized in order to ensure commodity price stability. As such, it is difficult to determine whether this assumption, then, accurately represents the costs associated with the feedstock. Future analysis could break apart these analysis steps, and separate entities could be modeled for the MFSP evaluation. This could also allow for a more formal treatment of conversion facility sizing and siting, which was beyond the scope of this particular analysis.

5.2 FUTURE WORK – PROSPECTIVE ENERGY SOLUTIONS

The two pathways considered in this work are first-generation biofuels; in both cases, a food resource is consumed as the primary biomass feedstock. Corn grain ethanol production has been capped by the Environmental Protection Agency, and the general consensus in the literature is that first-generation biofuels are not worth further pursuit[78-79]. Future applications of this toolset, then, are to be focused on second- and third-generation biofuel pathways. No second- or third-generation biofuel type is currently produced in a non-trivial quantity (corn stover ethanol production has stalled due to a number of factors). As such, holistic assessment of prospective energy solutions must address the numerous different potential pathways available as well as the likelihood of adoption of these technologies. It must also be able to assess the relative merits of each solution. Therefore, future work can be categorized in three distinct groups: construction of process models for new pathways, characterization of adoption/diffusion behavior, and evaluation of potential future states.

The construction of process models that characterize second- and third-generation biofuel types constitutes an extension of the work presented here. The established workflow could be adhered to in order to generate consistent, modular components for analysis. Feedstocks of interest include corn stover and other crop residues, energy grasses such as switchgrass and miscanthus, and microalgae cultivated on marginal land. Each of these biofuel types could be assessed across the United States with the same methodology that was applied to the analysis above. A solution set could then be produced that describes the relative economic and environmental performance of all potential biofuel types. In this way, the ideal biofuel pathway can be assessed for a given region.

Assessing the adoption behavior of biofuel types represents a complicated task[80]. Recent studies[80-81] have approached this characterization through the application of an Agent-Based Modelling (ABM) framework. ABM allows for interactions between discrete model constituents (such as conversion facilities, or farmers) and can characterize diffusion behavior in biofuel adoption settings[80]. Future work could integrate an ABM module that allows for such behavior to be captured.

Finally, the ability to compare prospective energy solutions can be addressed through the application of Multi-Objective Optimization. This optimization methodology allows for the consistent comparison of different metrics, such as GWP and MFSP results, and the delivery of granular, optimized results. An evolutionary algorithm could be applied to the assessment of the potential US biofuel production, and a solution set which defines the theoretically best possible energy portfolio could be delivered.

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APPENDICES

LITERATURE REVIEW AND COMPARISON

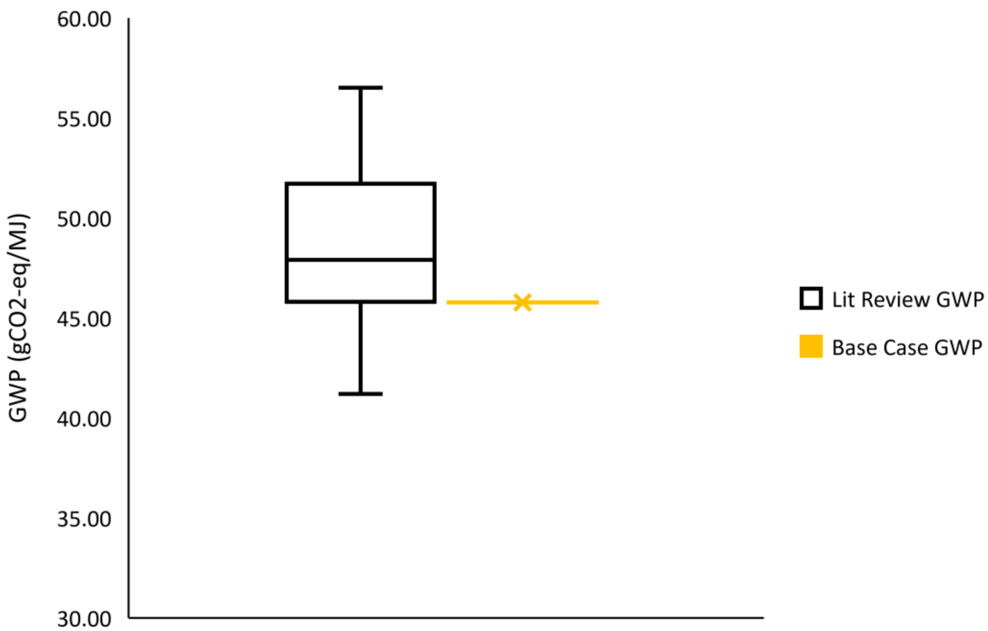

Figure 8 – Corn Ethanol Life Cycle Assessment results - comparison of base-case GWP outcomes for the pathway to reported literature values.

Literature values for corn ethanol GWPs range from 41.2 $gCO_{2\text{-}eq}$/MJ [Kim] to 56.5 $gCO_{2\text{-}eq}$/MJ [Boland] and are presented in Figure 8. The arithmetic mean of the cited values is 48.4 $gCO_{2\text{-}eq}$/MJ, and the model constructed produced a base-case GWP for corn ethanol of 45.6 $gCO_{2\text{-}eq}$/MJ. Seven works were referenced: Kim (41.2 $gCO_{2\text{-}eq}$/MJ), Lee (46.0 $gCO_{2\text{-}eq}$/MJ), Boland (56.5 $gCO_{2\text{-}eq}$/MJ), Unnasch (45.8 $gCO_{2\text{-}eq}$/MJ), Scully (50.0 $gCO_{2\text{-}eq}$/MJ), Lewandowski [2018] (47.9 $gCO_{2\text{-}eq}$/MJ), Lewandowski [2021] (51.7 $gCO_{2\text{-}eq}$/MJ).

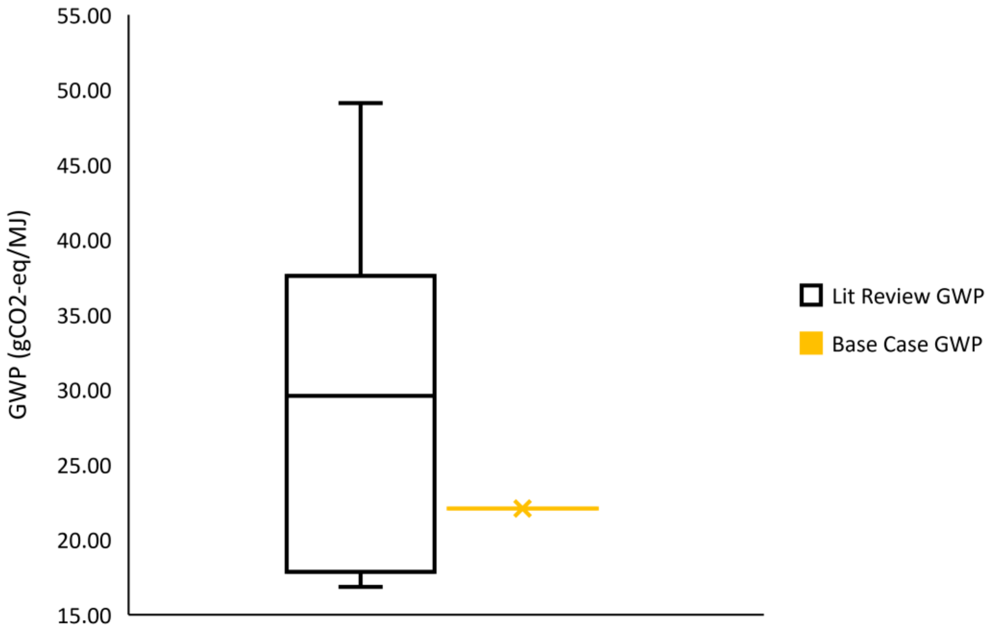

Figure 9 – Soybean Biodiesel Life Cycle Assessment results - comparison of base-case GWP outcomes for the pathway to reported literature values.

Literature values for soybean biodiesel GWPs range from 16.9 $gCO_{2\text{-}eq}$/MJ [Pradhan] to 49.1 $gCO_{2\text{-}eq}$/MJ [Hill] and are presented in Figure 9. The arithmetic mean of the cited values is 29.5 $gCO_{2\text{-}eq}$/MJ, and the model constructed produced a base-case GWP for soybean biodiesel of 22.1 $gCO_{2\text{-}eq}$/MJ. Six works were referenced: Chen (29.5 $gCO_{2\text{-}eq}$/MJ), Pradhan (16.9 $gCO_{2\text{-}eq}$/MJ), Sheehan (18.2 $gCO_{2\text{-}eq}$/MJ), GHGenius (29.7 $gCO_{2\text{-}eq}$/MJ), GREET (33.7 $gCO_{2\text{-}eq}$/MJ), and Hill (49.1 $gCO_{2\text{-}eq}$/MJ).

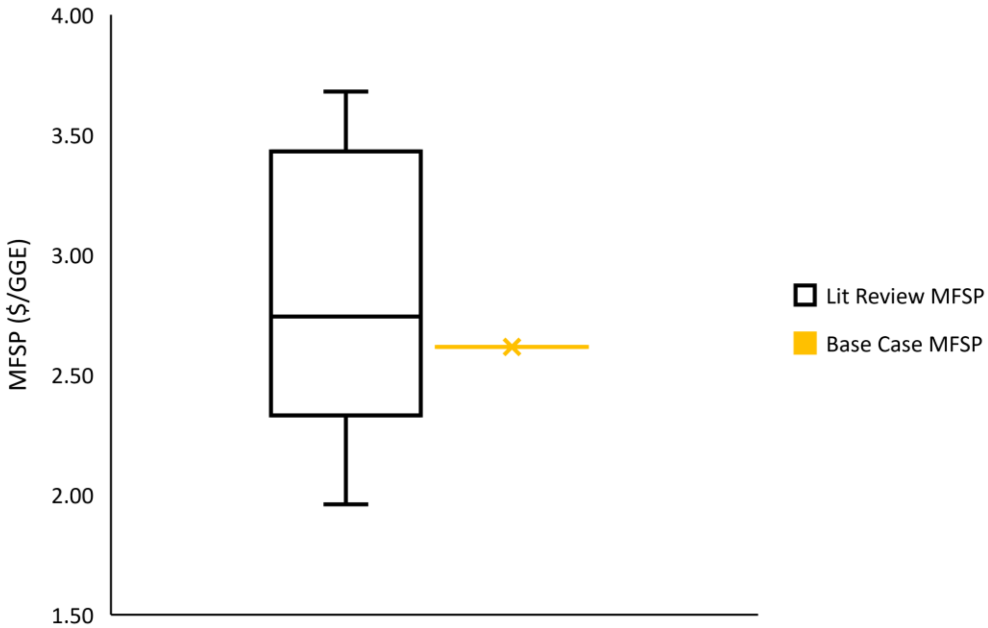

Figure 10 – Corn Ethanol Techno-Economic Analysis results - comparison of base-case MFSP outcomes for the pathway to reported literature values.

Literature values and other sources for corn ethanol MFSPs range from $0.0162/MJ or $1.96/GGE [Wallace] to $0.0304/MJ or $3.68/GGE [Zhang] and are presented in Figure 10. The arithmetic mean of the cited values is $0.0236/MJ or $2.85/GGE, and the model constructed produced a base-case MFSP for corn ethanol of $0.0216/MJ or $2.62/GGE. Five sources were referenced: Ou ($0.0263/MJ or $3.18/GGE), Huang ($0.0223/MJ or $2.70/GGE), Wallace ($0.0162/MJ or $1.96/GGE), Zhang ($0.0304/MJ or $3.68/GGE), and the EIA Quarterly Cost of Ethanol ($0.0227/MJ or $2.74/GGE). The EIA reported cost of ethanol in 2017 is for E85, and the determined cost of E100 above ($0.0227/MJ) was obtained with the cost of gasoline for the same time:

$$\mathrm{E}_{100} = \frac{\mathrm{E}_{85} - (0.15 \times \mathrm{Gas})}{0.85}$$

Where E_{100} is the cost of fuel-grade ethanol, E_{85} is the cost of an ethanol blended with gasoline at 85-15%, respectively, and Gas is the cost of gasoline.

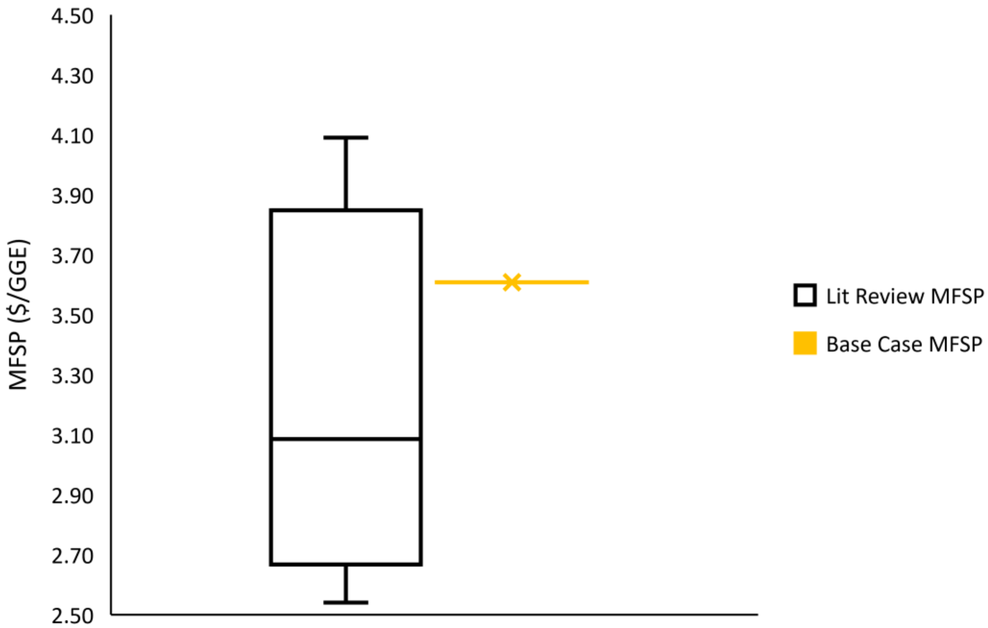

Figure 11 – Soybean Biodiesel Techno-Economic Analysis results - comparison of base-case MFSP outcomes for the pathway to reported literature values.

Literature values and other sources for soybean biodiesel MFSPs range from $0.0210/MJ or $2.54/GGE [Haas] to $0.0338/MJ or $4.09/GGE [Huang] and are presented in Figure 11. The arithmetic mean of the cited values is $0.0264/MJ or $3.20/GGE, and the model constructed produced a base-case MFSP for soybean biodiesel of $0.0298/MJ or $3.61/GGE. Four sources were referenced: Haas ($0.0210/MJ or $2.54/GGE), Huang ($0.0338/MJ or $4.09/GGE), USDA's Economic Marketing Service ($0.0252/MJ or $3.05/GGE), and the EIA Quarterly Cost of Biodiesel ($0.0258/MJ or $3.12/GGE). The EIA reported cost of biodiesel in 2017 is for B100, so no normalization was required. However, this cost of B100 likely includes the assessed price of biodiesel produced from other, non-soy feedstocks.

SENSITIVITY ANALYSIS RESULTS

Sensitivity Analysis plots are presented in Figures 12-16. Model Independent Variables (MIVs) were adjusted to be 20% greater than and less than their base-case amount in order to determine how sensitive the results (MFSP and GWP) are to each input. MIVs of the amount type specify the base-case input or output quantity that is associated with a particular substance. A few substances quantities are coupled, for mass balance purposes, to other substance amounts. In these cases, sensitivity analysis results show greater impact on the outputs, and can influence outcomes in indirect ways. For instance, the CO_2 which is produced from yeast respiration during the corn grain fermentation process (Corn Conv CO2 Emissions Amount, in figure 1) shows influence over the MFSP result, despite not being assigned an economic value.

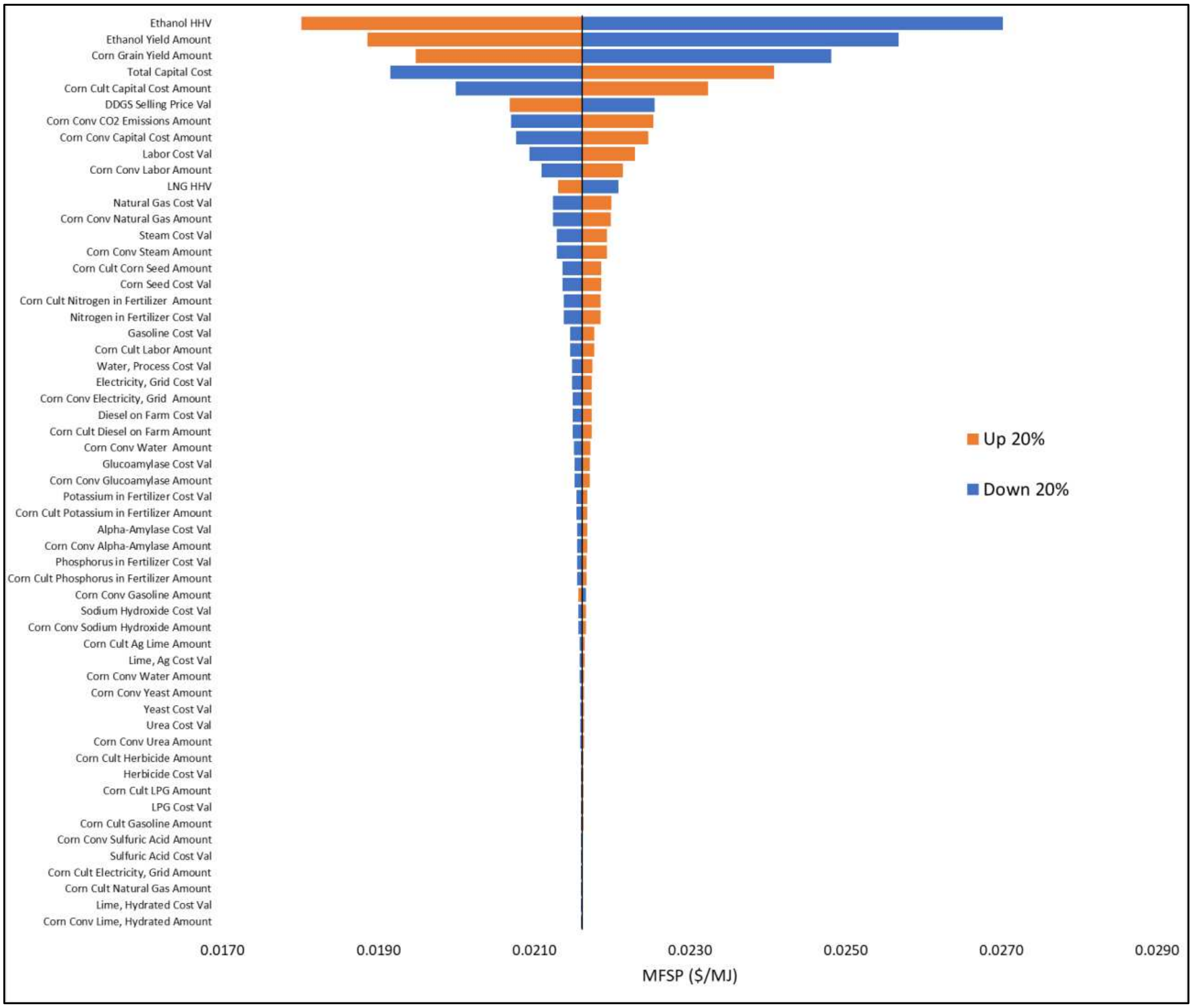

Figure 12 - Corn Grain Ethanol MFSP Sensitivity Analysis Results. Each Model Independent Variable was increased or decreased by twenty percent (orange and blue series, respectively) in order to determine the range of observed results due to these changes.

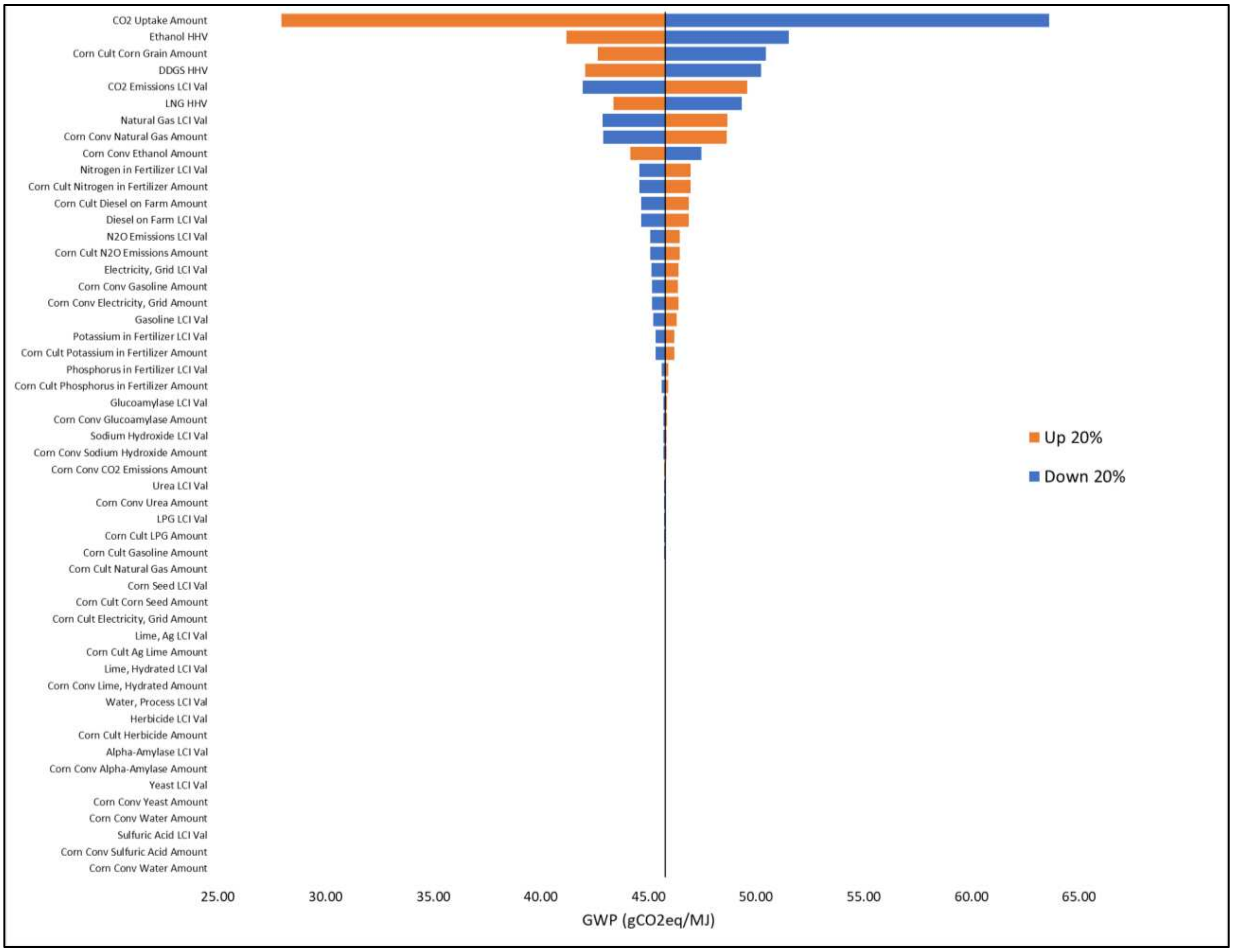

Figure 13 - Corn Grain Ethanol GWP Sensitivity Analysis Results. Each Model Independent Variable was increased or decreased by twenty percent (orange and blue series, respectively) in order to determine the range of observed results due to these changes.

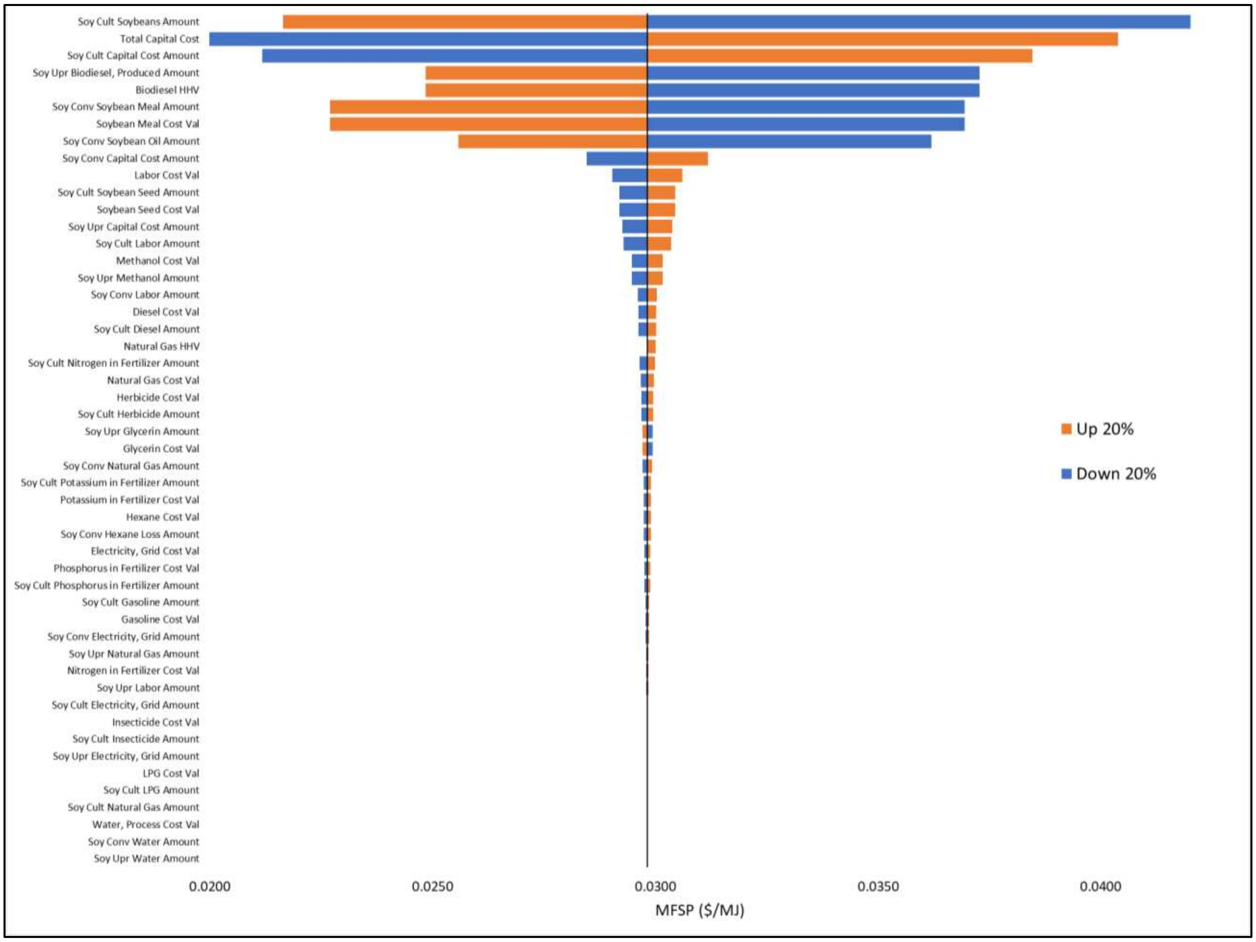

Figure 14 - Soybean Biodiesel MFSP Sensitivity Analysis Results. Each Model Independent Variable was increased or decreased by twenty percent (orange and blue series, respectively) in order to determine the range of observed results due to these changes.

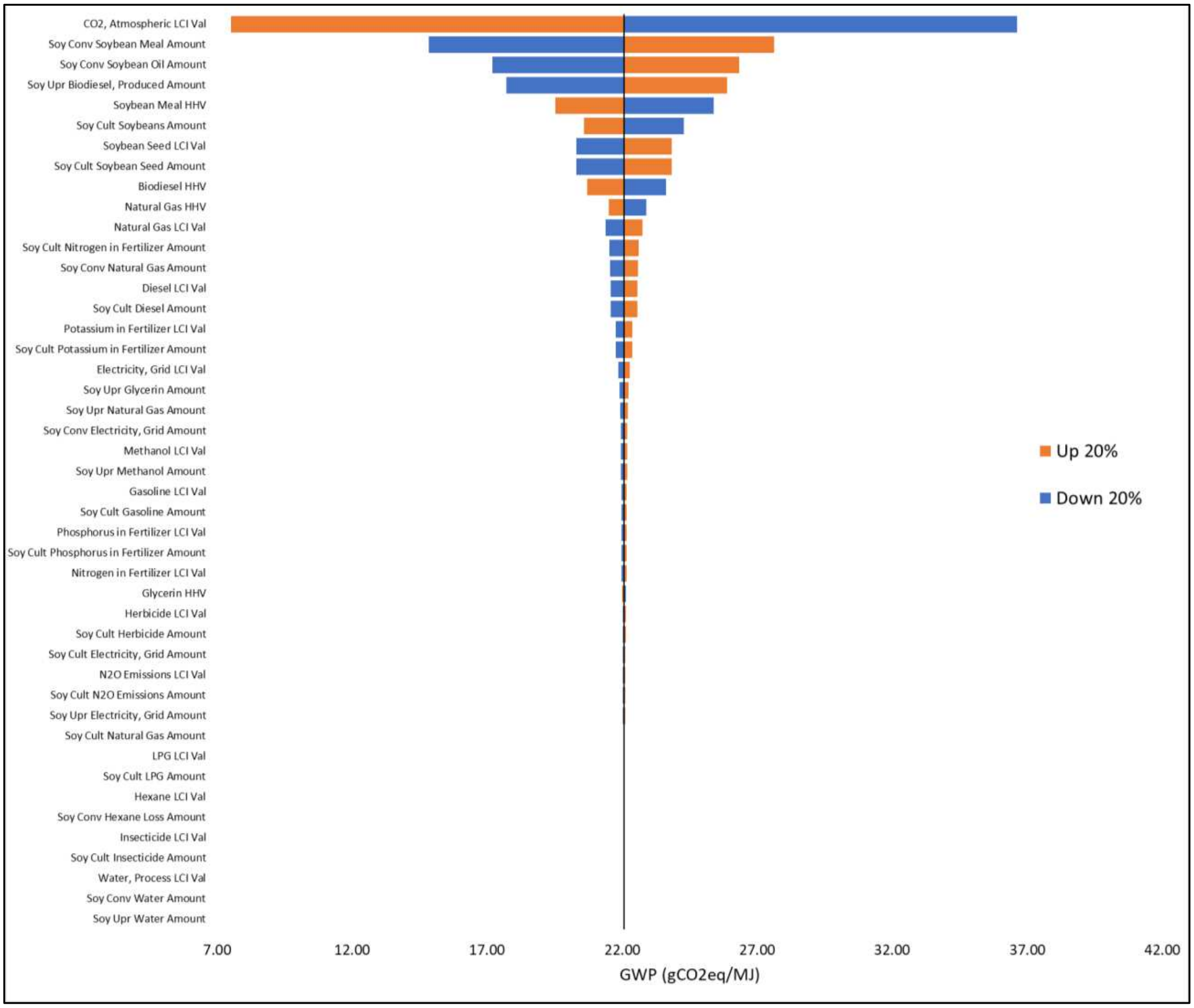

Figure 15 - Soybean Biodiesel GWP Sensitivity Analysis Results. Each Model Independent Variable was increased or decreased by twenty percent (orange and blue series, respectively) in order to determine the range of observed results due to these changes.

MONTE-CARLO ANALYSIS METHODS

This section presents the input Probability Density Functions (PDFs) and the associated data which was used to construct them. The next section (7.4) presents the results of the MCA trials in graphical form for select variables. A more exhaustive list of all MCA results is available in the Excel-based Supporting Information file. Several variables were fit with distinct Probability Density Functions (PDFs), and those are explored below.

Monte-Carlo analysis was critical to apply to the crop yield amount reported for each county. This particular variable demonstrates significant real-world variability as a result of the numerous and complicated relationships that govern its quantity. Specific fields might suffer from pests, poor management, imprecise seed selection, negligence of care, improper irrigation, inadequate fertilization, non-optimized harvesting, etc., and thus might actually produce less than the assumed mean areal yield per county. Conversely, some fields might possess ideal characteristics for growth and perform better than the reported mean areal yield per county would suggest. Data was collected from the USDA NASS service – 5 years of historical crop yields were collected for each state. When completed, both distributions shared the same characteristics (skew, mean, standard deviation, specifically) when normalized against the base-case yield assumption. Thus, the same PDF was applied to both crop types:

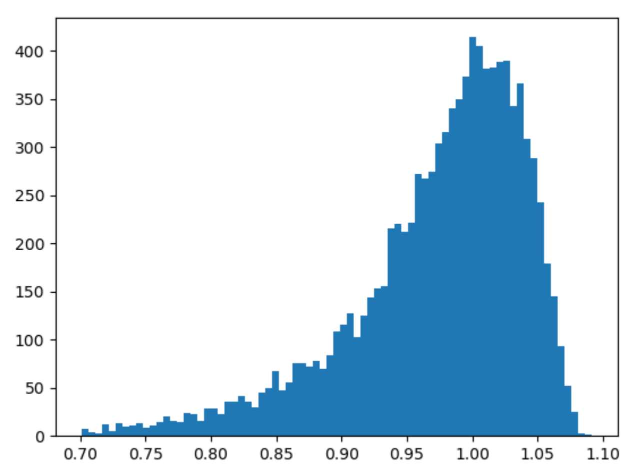

Figure 16 - Monte-Carlo input distribution for corn grain and soybean yield modifier. The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

Each Monte-Carlo random walk selects a value from the given PDF above, and then scales the reported, county-average yield by that amount. Over the numerous executions, this enabled results to capture how sensitive the results are to potential field-to-field variability. It does not, however, characterize the year-to-year, national variability that might occur as a result of drought conditions. Such analysis would require extensive alteration of the model flow, and – while future work is aimed at assessing this – no attempt was made to characterize yearly variability on a national scale: 2017 was not a drought year.

The fermentation process involves the digestion of starches within a given feedstock by yeast. In this case, starches present in the corn grain mash are converted to ethanol in the presence of *Saccharomyces Cerevisiae*, an ethanol-tolerant strain of yeast. The total quantity of sugar-to-ethanol conversion which can be achieved is subject to variability, and industry data regarding the total dedicated corn grain to total ethanol production was applied to produce a triangular PDF. The mode (right end) of this PDF constitutes the maximum theoretical ethanol yield for a kilogram of corn grain input. The MCA module applied this PDF to characterize variabilities which are inherent in the system. The DDGS (co-product) yield was coupled to the specific ethanol-yield variate for each random-walk in order to preserve the mass balance behavior.

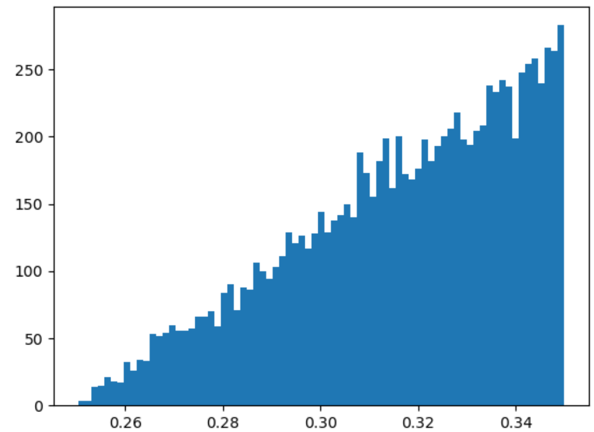

Figure 17 - Monte Carlo input distribution for ethanol yield from corn grain input (kg EtOH/kg Corn Grain). The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

The oil content of an individual soybean is subject to variability based on a number of factors, such as the growing conditions, time of harvest, et cetera. The USDA Soy and Soybean Products report was applied in order to determine the range and profile that this variation exhibited. Monthly data from 2010-2020 of soybean production and soy oil production was collected and the national average soy yield was derived from these values. The constructed PDF is a normal distribution, centered around 0.2 kg oil per kg soybean. As was the case with the ethanol and DDGS yields, the soybean meal yield is coupled with the soy oil variate in order to ensure mass-balance behavior.

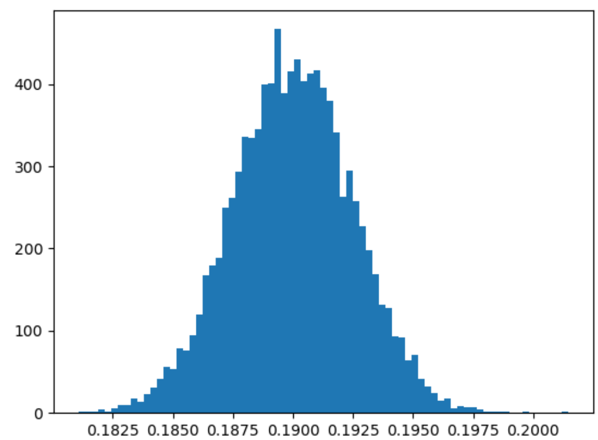

Figure 18- Monte Carlo input distribution for soy oil yield from soybean input (kg soy oil/kg soybean). The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

A PDF was constructed based on an assumed capital cost of a base plant, an economies of scale rule of 0.6, and the actual size of the plants that were operating in the US as of 2017. The reported facility sizes were normalized against the base case conversion facilities (50 MMGal/year for ethanol and 22 MMGal/year for soybean biodiesel) for both conversion facility types. The economies-of-scale 0.6 rule was applied to this distribution to produce a PDF which aims to characterize the effective, per kg feedstock capital cost that is associated with each facility for both pathways.

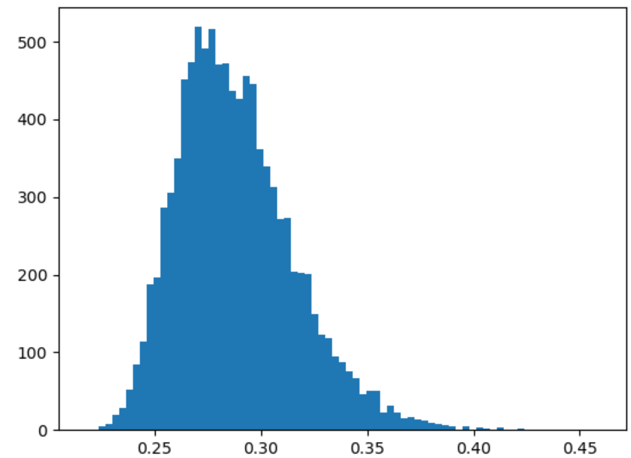

Figure 19- Monte Carlo input distribution for starch fermentation capital cost ($/kg corn grain). The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

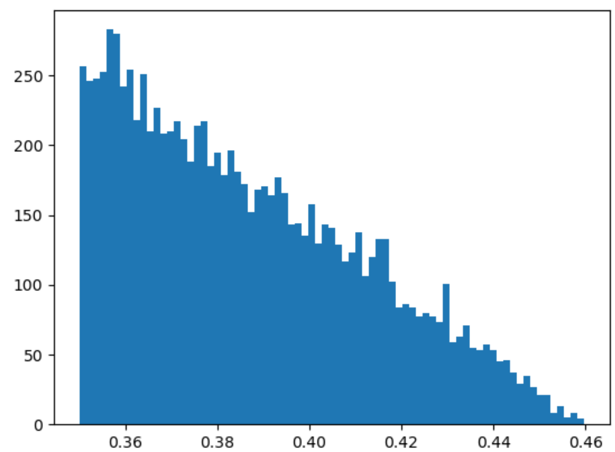

Figure 20- Monte Carlo input distribution for hexane extraction capital cost ($/kg soybean). The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

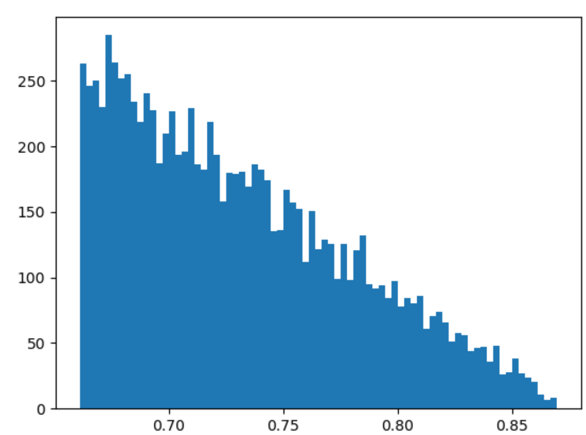

Figure 21- Monte Carlo input distribution for hexane extraction capital cost ($/kg soybean). The ordinate axis presents the total number of instances of a particular modifier value (on the abscissa) when applied over 10,000 executions.

Convergence testing was performed to determine how many minimum executions were required before the Monte-Carlo analysis achieved stable results. With the base-case assumptions and the above Monte-Carlo variates included, ten-thousand executions were run. The rolling average was then determined for each execution, the results are plotted below. The presented figure constitutes the highest volatility case (soybean biodiesel GWP results), and thus these results were used to set the convergence threshold.

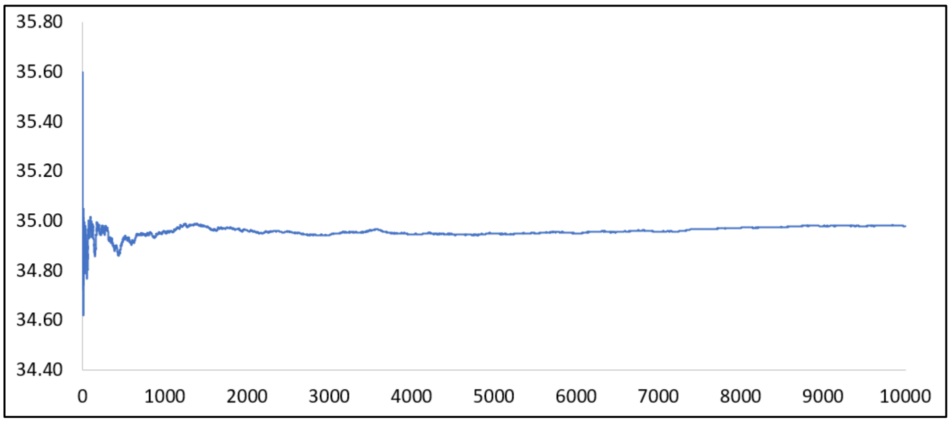

Figure 22 - Soybean Biodiesel GWP results of Convergence testing. The ordinate axis displays the rolling average GWP ($gCO_{2\text{-}eq}$/MJ), and the abscissa presents the number of random-walk executions. 1000 executions constitute convergence to less than 5% error on final result.

MONTE CARLO ANALYSIS RESULTS

This section presents graphic results of the Monte-Carlo Analysis. Specifically, eight maps are provided, which convey the standard deviation (normalized over the mean) of both pathways for MFSP and GWP, and the skew of the results of both pathways for MFSP and GWP. Numerical results are provided in the Excel Supporting Information file.

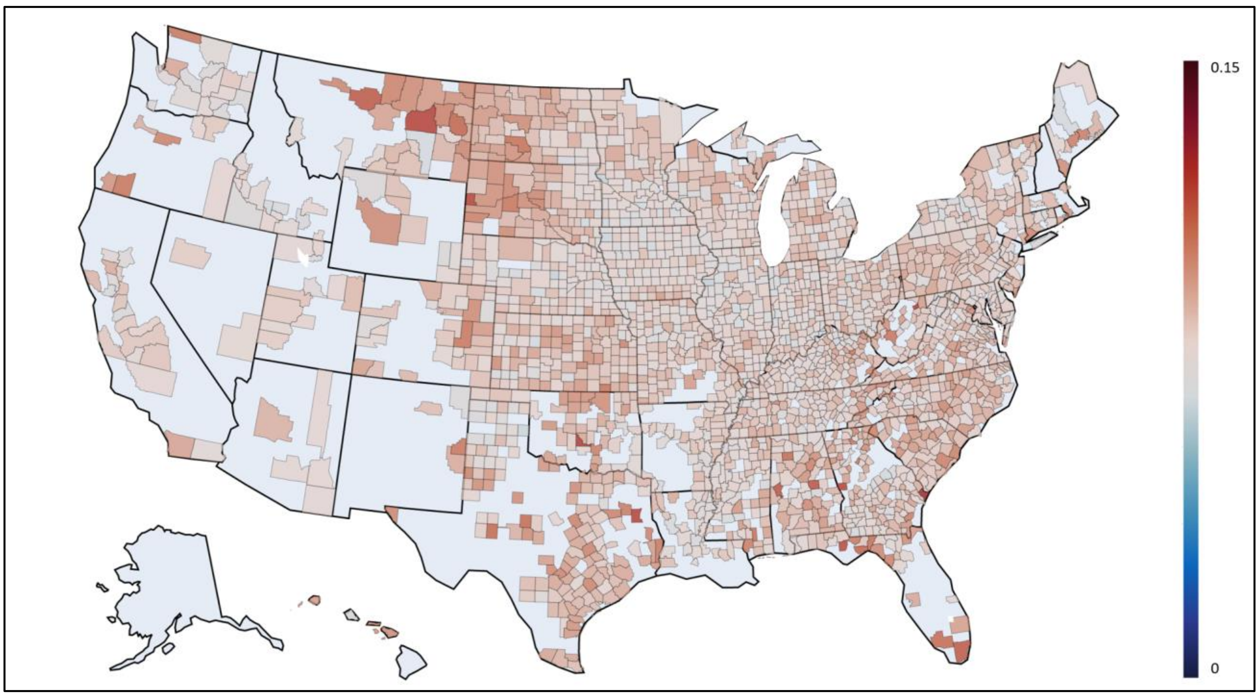

Figure 23 - Corn Ethanol Standard Deviation divided by the mean reported value for each county for MFSP results.

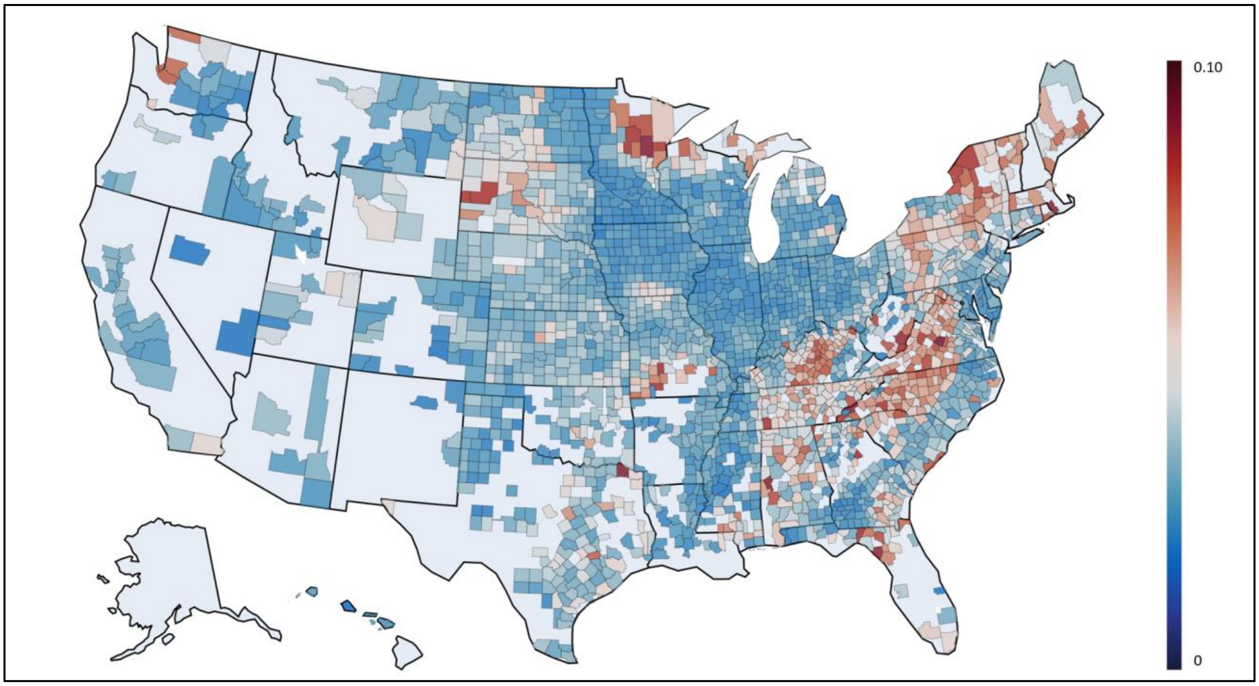

Figure 24 - Corn Ethanol Standard Deviation divided by the mean reported value for each county for GWP results.

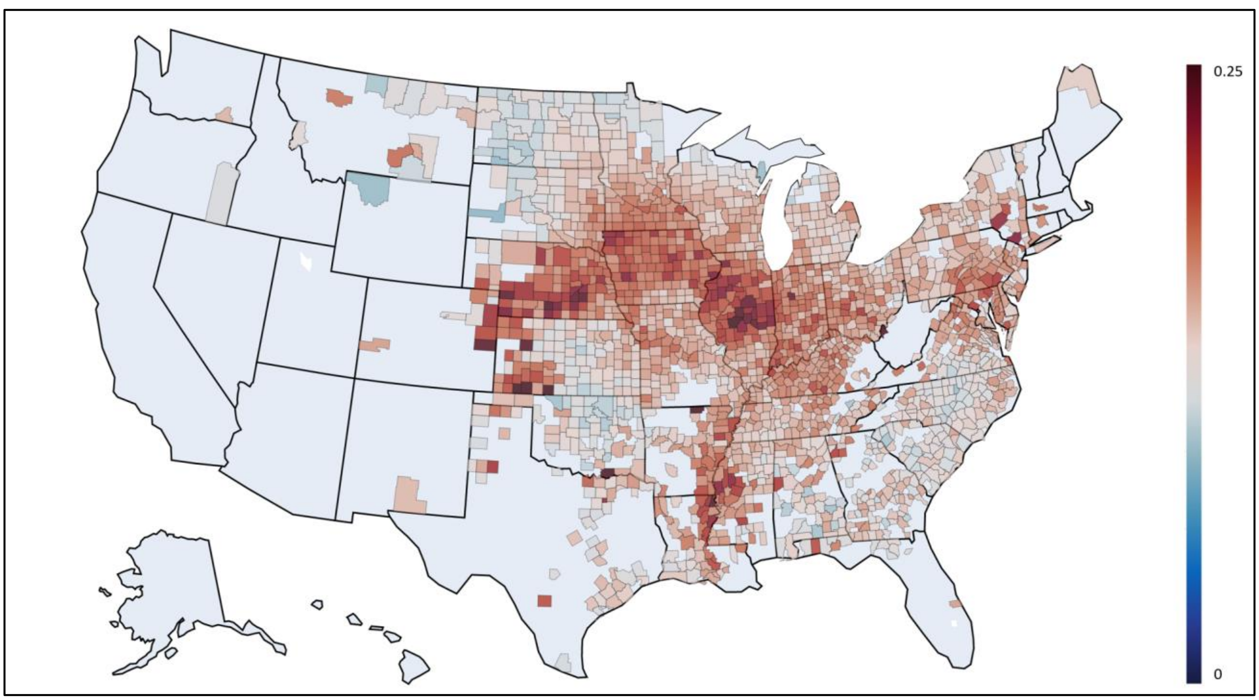

Figure 25 - Soybean Biodiesel Standard Deviation divided by the mean reported value for each county for MFSP results.

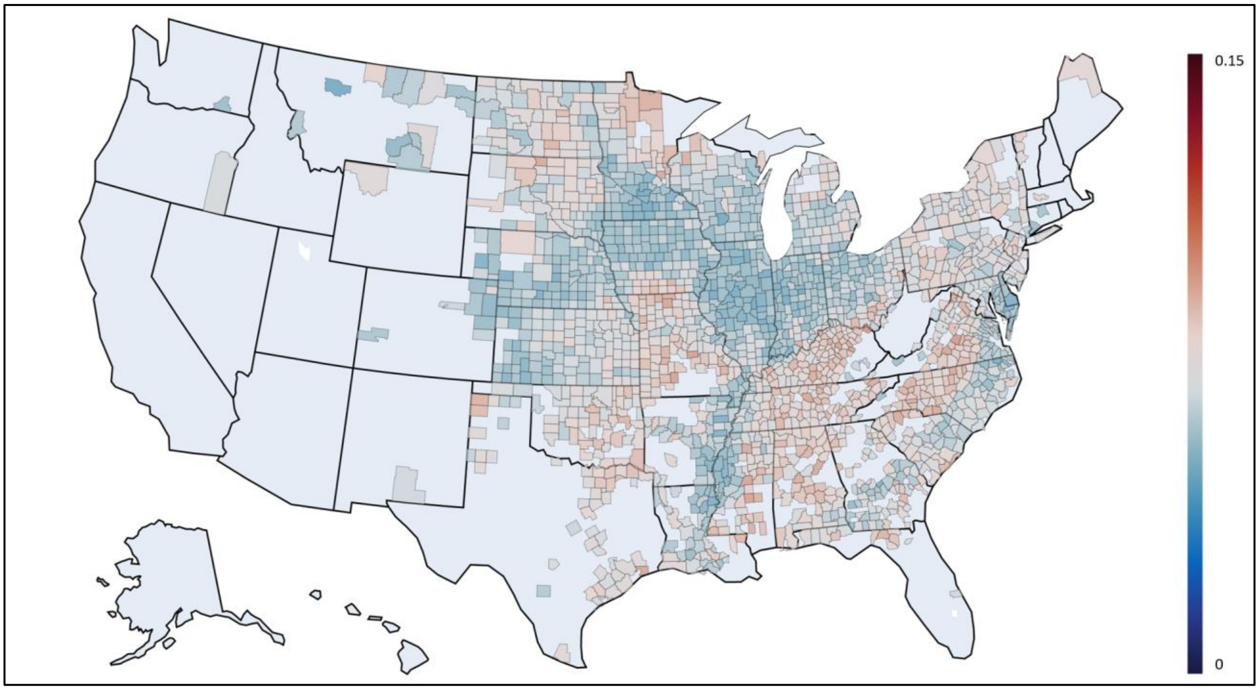

Figure 26 - Soybean Biodiesel Standard Deviation divided by the mean reported value for each county for GWP results.

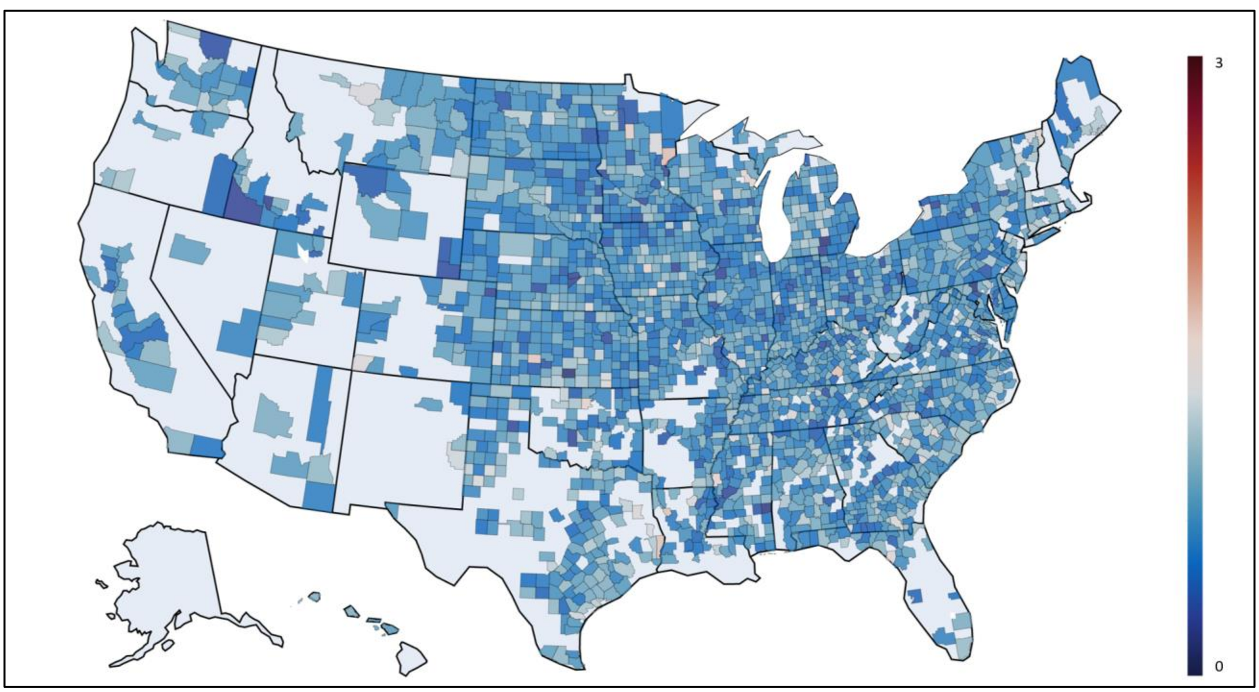

Figure 27 – Corn Grain Ethanol skew results for each county for MFSP results.

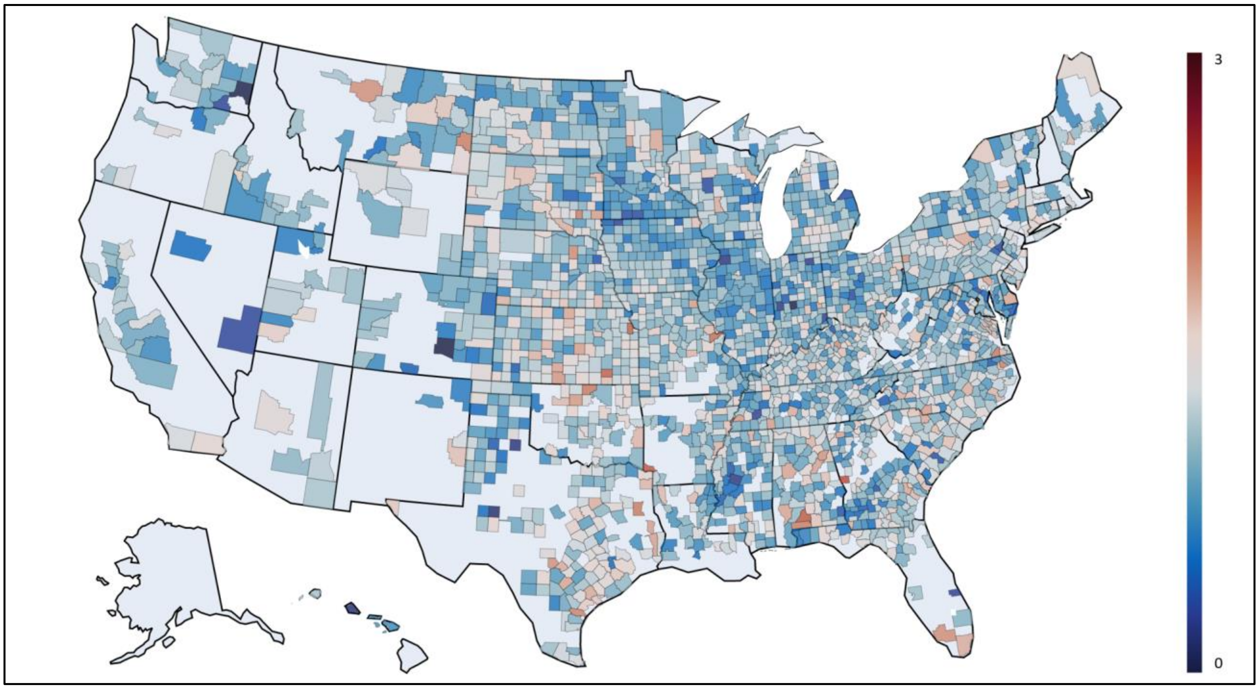

Figure 28 - Corn Grain Ethanol skew results for each county for GWP results.

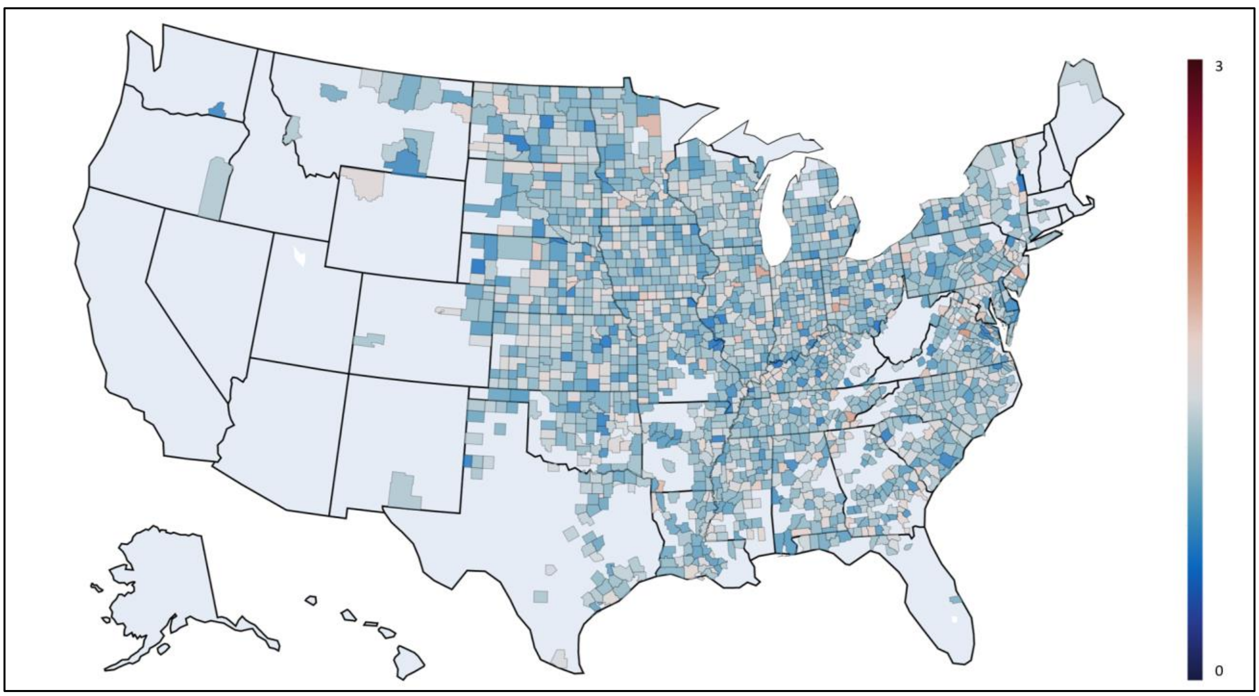

Figure 29 - Soybean Biodiesel skew results for each county for MFSP results.

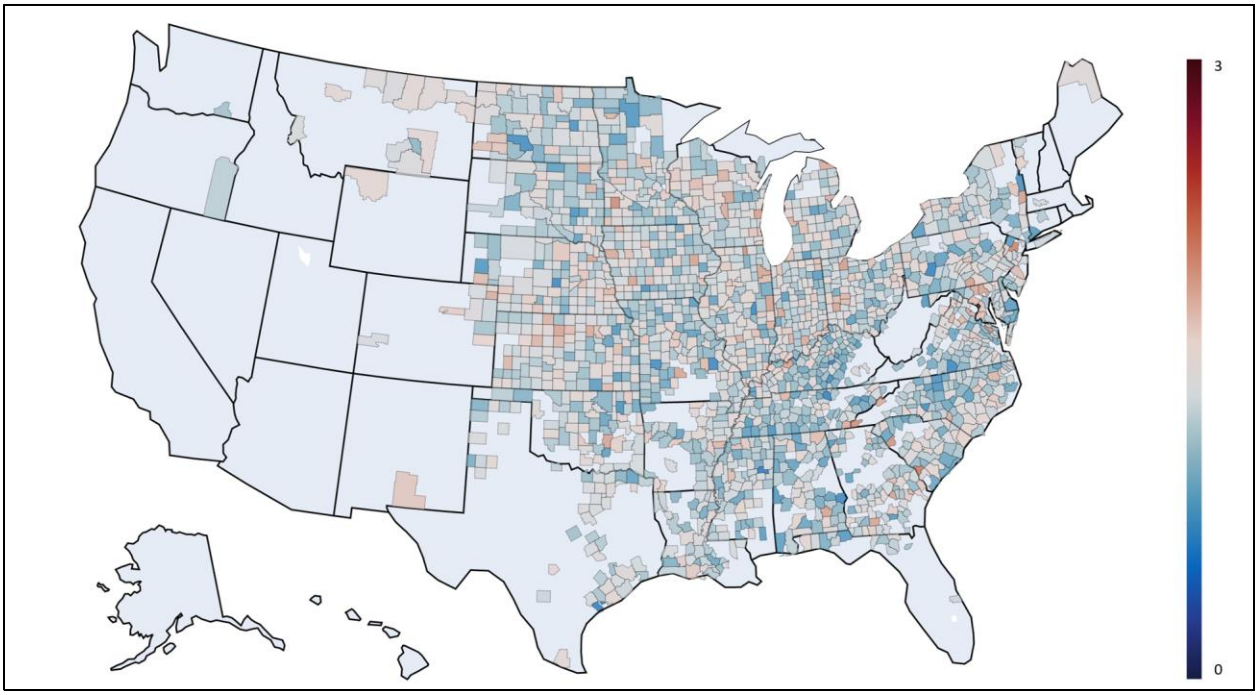

Figure 30 - Soybean Biodiesel skew results for each county for GWP results.

BIOFUEL DEDICATION FRACTION

Approximating the sourcing of corn or soybean for biofuel production is a complicated task. The model determined (from the USDA production data) the total amount of corn grain and soybean produced per state. From there, the EIA monthly ethanol and monthly biodiesel production capacity data was assessed. This provided a state-level description of total biofuel production capacity, and the datasets these estimates are based on may be referenced online[51], here and here.

The reported production capacities were used to determine the total ethanol and biodiesel production of each state. As an example, corn ethanol production capacity in Illinois was reported to be 1.5 billion gallons total for the 2017 year. The amount of corn grain needed to cover this particular volume quota (about 100 MMT) was then collected from each county that produces corn in the state. Specifically, each county dedicates 30% of its corn grain to ethanol production (this ratio is termed the biofuel dedication fraction). In this way, a state-level mean performance that is weighted by production is achieved for the GWP and MFSP performance of the two fuels.

Determining the soybean biodiesel biofuel dedication fraction requires an additional step; it is assumed that 60% of the biodiesel produced everywhere is produced from a soy-oil feedstock. This 60% correlates with the reported input ratio (soybean vs corn/canola/palm oils) that is presented in the EIA's Biodiesel Monthly Input Report. Biodiesel production is not uniform across all geographic regions, and soy-based biodiesel conversion plants are most likely concentrated in areas of high soybean production. In this case, the soybean biodiesel pathway would be assessed to show both lower GWP and lower MFSP than what has been reported in the primary article. However, this characterization would require a more detailed analysis of the actual supply chains which are associated with the biodiesel production industry – assessment which fell beyond the scope of this work. Thus, a consistent, simplifying assumption was applied as described above.

Not all states produce enough corn grain or soybean in order to fulfill their biofuel production quota. Texas, for instance, is reported to have produced 380 million gallons of biodiesel in the 2017 year

– nearly 15% of national production. However, the state does not produce the 43 MMT of soybean which would be required to fulfill this demand. In this instance, and in instances where more than fifty percent of the domestic crop production would need to be dedicated to fuel production in order to fulfill the assumed quota, the additional biomass (i.e., the biomass beyond the fifty percent provided by the state already) is sourced from the rest of the US by concentration. So, returning to the example of Texas, 24 MMT of the remaining soy comes from Iowa, 21 from Nebraska, 22 from Missouri, (and so on), as this relative share mimics the industry proportions. The biofuel dedication fraction for corn grain to ethanol is set to two-thirds for Iowa, specifically, as this state is reported to produce more than double the ethanol than the next largest producing state. Iowa constitutes the only exception to the 50% biomass dedication fraction rule.

Different scenarios were evaluated in order to determine how much the overall performance (in terms of GWP and MFSP) would change if this particular assumption were altered. In all, results show low sensitivity to this particular assumption for the corn grain to ethanol pathway. When the biofuel dedication fraction is set to be a constant value (0.394 kg corn grain to ethanol production for every kilogram of corn grain produced) that is uniform across the United States, the GWP result increases by 0.7% and the MFSP increases by 0.7%. This is primarily due to the fact that production is concentrated even more tightly in the well-performing corn belt region than the grain industry itself is. The base-case soybean biodiesel results also show reasonable parity with this uniform Biofuel Dedication Fraction assumption, as the GWP and MFSP results are reduced by 7.8% and 6.6%, respectively.

MODEL INDEPENDENT VARIABLES LIST

A copy of the Model Independent Variables which were applied during analysis is provided below. This file provides more context (such as whether a specific flow is an input or an output, geospatially defined, et cetera).

Table 1 - Corn Grain Ethanol Process Model Amounts and Model Independent Variables. Cells in light green (from "Land Cost" to "N2O Emissions" correspond to the cultivation step, and cells in light blue (from "Sodium Hydroxide" to "Corn Grain") correspond to the grain fermentation step.

Corn Process Model Amount MIVs		
Name	**Base Value**	**Units**
Land Cost	0	dollars/ha
Capital Cost	5977.4	dollars/ha
Labor	81.4853	dollars/ha/yr
Corn Seed	17.6946	kg/ha/yr
Nitrogen in Fertilizer	220	kg/ha/yr
Phosphorus in Fertilizer	0.207390649	kg/kg Nitrogen
Potassium in Fertilizer	0.597285068	kg/kg Nitrogen
Ag Lime	528.82	kg/ha/yr
Herbicide	1.213	kg/ha/yr
Insecticide	0	kg/ha/yr
CO2, Atmospheric	2.286166667	kg/kg Corn Grain
Rain Water (Blue Water)	6480500	kg/ha/yr
Diesel on Farm	130	kg/ha/yr
Gasoline	10.70441989	kg/ha/yr
LPG	11.34	kg/ha/yr
Irrigation Water	0	kg/ha/yr
Natural Gas	8.56	kg/ha/yr
Electricity, Grid	145.4	MJ/ha/yr
Water	589.3417417	kg/kg Corn Grain
Corn Stover, Collected	0	kg/kg Corn Grain
Corn Stover, Left	0.90	kg/kg Corn Grain
Oxygen Emissions	1.662666667	kg/kg Corn Grain
LUC Emissions	0	kg/ha/yr
Corn Grain	10974	kg/ha/yr
N2O Emissions	0.01	kg/kg Nitrogen
Sodium Hydroxide	0.00498636	kg/kg Corn Grain
Lime, Hydrated	0.00118529	kg/kg Corn Grain
Urea	0.00198378	kg/kg Corn Grain
Alpha-Amylase	0.00069557	kg/kg Corn Grain
Glucoamylase	0.00100467	kg/kg Corn Grain
Sulfuric Acid	0.001983778	kg/kg Corn Grain
Yeast	0.000187438	kg/kg Corn Grain
Gasoline	0.014532693	kg/kg Corn Grain
Steam	0.92018	kg/kg Corn Grain
Water	11.33753422	kg/kg Corn Grain
Natural Gas	0.072331038	kg/kg Corn Grain
Electricity, Grid	0.307556766	MJ/kg Corn Grain
Capital Cost	0.284774923	dollars/kg Corn Grain
Land Cost	0	dollars/kg Corn Grain
Labor	0.02565	dollars/kg Corn Grain
Ethanol	0.331573026	kg/kg Corn Grain
DDGS	0.344532693	kg/kg Corn Grain
CO2 Emissions	0.338426974	kg/kg Corn Grain
Water	12.26974111	kg/kg Corn Grain
Corn Grain	10974	kg/yr

Table 2 - Soybean Biodiesel Process Model Amounts and Model Independent Variables. Cells in light green (from the first instance of "Land Cost" to the first instance of "Electricity, Grid") correspond to the cultivation step. Cells in light blue (from the second instance of "Land Cost" to "Soybean Meal") correspond to the hexane extraction step. Finally, cells in light yellow (from "Methanol" to "Glycerin") correspond to the transesterification process

Soybean Process Model Amount MIVs		
Name	**Base Value**	**Units**
Land Cost	0	dollars/ha
Capital Cost	6817	dollars/ha
Labor	61.75	dollars/ha/yr
Soybean Seed	293,333	#/ha/yr
Carbon Content	46	%
Nitrogen in Fertilizer	0.002	kg/kg Feedstock
Phosphorus in Fertilizer	1.78028169	kg/kg Nitrogen
Potassium in Fertilizer	5.60106383	kg/kg Nitrogen
Ag Lime	0	kg/ha/yr
Herbicide	0.0008	kg/kg Feedstock
Insecticide	0.00002	kg/kg Feedstock
Soybeans	3017.13296	kg/ha/yr
N2O Emissions	0.01	kg N2O/kg N Applied
Rain Water (Blue Water)	5750	m3/ha/yr
Diesel	0.0155	kg/kg Feedstock
Gasoline	0.0035	kg/kg Feedstock
LPG	0.000682	kg/kg Feedstock
Natural Gas	0.000878	kg/kg Feedstock
Electricity, Grid	0.0356	MJ/kg Feedstock
Land Cost	0	dollars/kg Feedstock
Capital Cost	0.357131479	dollars/kg Feedstock
Labor	0.008339832	dollars/kg Feedstock
Water	0.257777778	kg/kg Feedstock
Hexane Loss	0.000886548	kg/kg Feedstock
Natural Gas	0.863818158	MJ/kg Feedstock
Electricity, Grid	0.079856019	MJ/kg Feedstock
Soybean Oil	0.222222222	kg/kg Feedstock
Soybean Meal	0.777777778	kg/kg Feedstock
Methanol	0.098450319	kg/kg Feedstock
Natural Gas	1.075660893	MJ/kg Feedstock
Electricity, Grid	0.134001823	MJ/kg Feedstock
Water	0.455788514	kg/kg Feedstock
Capital Cost	0.662369484	dollars/kg Feedstock
Labor	0.0048483	dollars/kg Feedstock
Land Cost	0	dollars/kg Feedstock
Biodiesel, Produced	0.911577028	kg/kg Feedstock
Glycerin	0.088422972	kg/kg Feedstock

Table 3 - Life Cycle Inventory values, including the Higher Heating Value of selected outputs, in MJ/kg, the $/kg cost of selected inputs, and the gCO2eq/kg greenhouse gas impact ("GHG Impact") of selected inputs.

Life Cycle Inventory Values			
Name and Units	**HHV (MJ/X)**	**Cost_($/X)**	**GHG_Impact_(g CO2e/X)**
Land Cost ($)		1	0
Capital Cost ($)		1	0
Labor ($/yr)		1	0
Alpha-Amylase (kg/yr)		4.50631263	1200
CO2, Atmospheric (kg/yr)		0	-1000
Corn Grain (kg/yr)		0.14	570.2
Corn Seed (kg/yr)		7.47	1462.15
Corn Stover (kg/yr)		0.082025	166.83
Glucoamylase (kg/yr)		4.50631263	7700
Herbicide (kg/yr)		6.340148994	8580.22
Insecticide (kg/yr)		30.11093502	1863
Irrigation Water (kg/yr)		0	0.348867
Lime, Ag (kg/yr)		0.03141555	43.87
Lime, Hydrated (kg/yr)		0.15	979.54
Nitrogen in Fertilizer (kg/yr)		0.5676	5205
Phosphorus in Fertilizer (kg/yr)		0.66236129	3097.81
Potassium in Fertilizer (kg/yr)		0.271876923	3237.99
Sodium Hydroxide (kg/yr)		0.4512	1314.85
Steam (kg/yr)		0.017	0
Sulfuric Acid (kg/yr)		0.15	186.29
Urea (kg/yr)		0.300420842	1728.38
Water, Process (kg/yr)		0.000552	0.087445
Water, Rain, Blue? (m3/yr)		0	0
Yeast (kg/yr)		5.5	4306.59
Diesel (kg/yr)	42.975	0.48	3715.084246
Diesel on Farm (kg/yr)	42.975	0.48	8235
Electricity, Grid (MJ/yr)	1	0.018722222	176
Gasoline (kg/yr)	43.44	0.48	3167.821065
Natural Gas (kg/yr)	50	0.25	2507.45781
CO2 Emissions (kg/yr)	0	0	1000
LUC Emissions (kg CO2e/yr)	0	0	1000
N2O Emissions (kg/yr)	0	0	298000
Oxygen Emissions (kg/yr)	0		
Corn Grain (kg/yr)	16	0.2	-2000
Corn Stover (kg/yr)	21.51	0.083	-2000
DDGS (kg/yr)	22.75	0.132276	-2000
Water, Output (kg/yr)	0	0	0
Ethanol (kg/yr)	29.7	0.42	-100
LPG, Produced (kg/yr)	49.3	0.644	-100

SELECTED MAPS

Maps which were referenced in the primary text above are supplied, here. Specifically, the total corn grain and soybean production of the nation, the total input LUC emissions quantities, the areal yield of both crop types, and the counties which are assessed to be cleaner or more expensive than their conventional, petroleum-based counterparts.

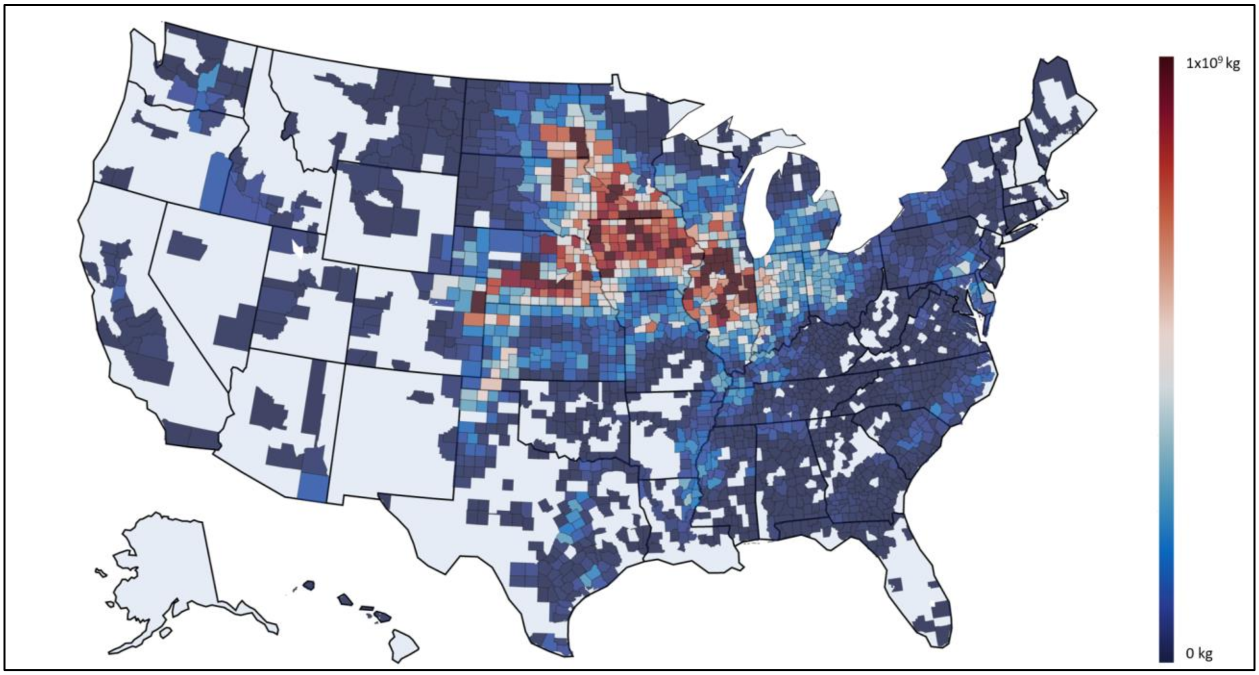

Figure 31 - Total Corn Grain production by county for the United States. Color scale ranges from 0 kg to 1 billion kg corn grain produced.

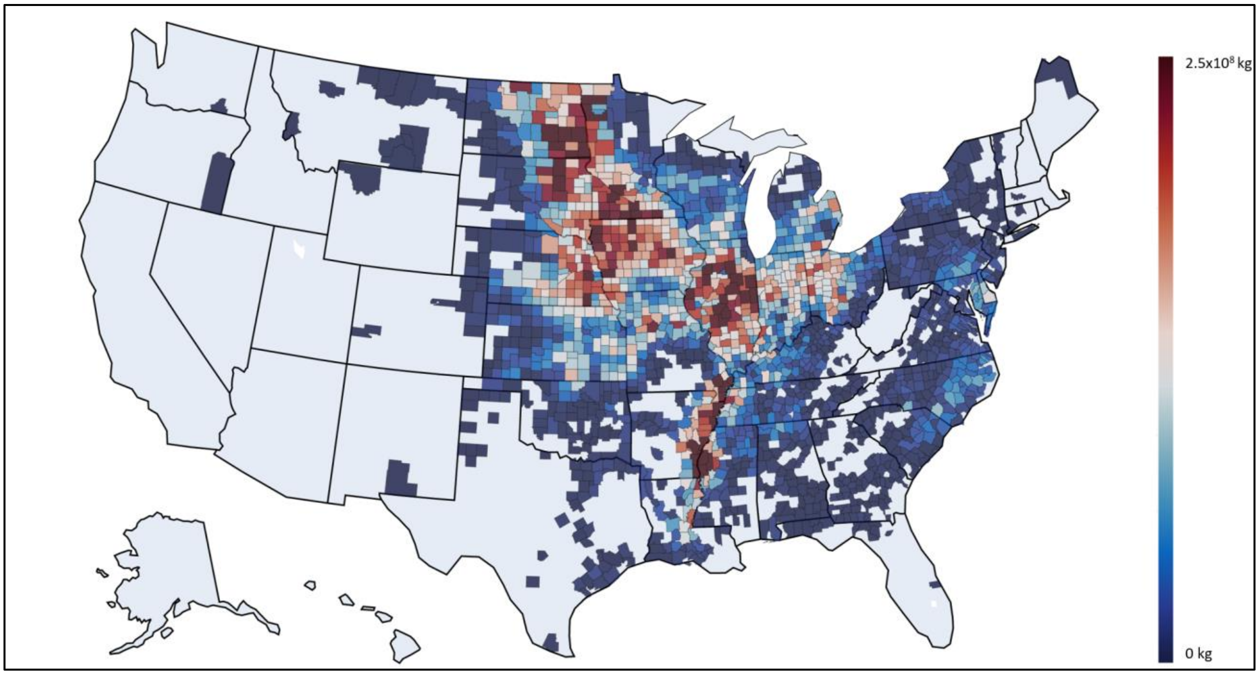

Figure 32 - Total Soybean production by county for the United States. Color scale ranges from 0 kg to 250 million kg soybean produced.

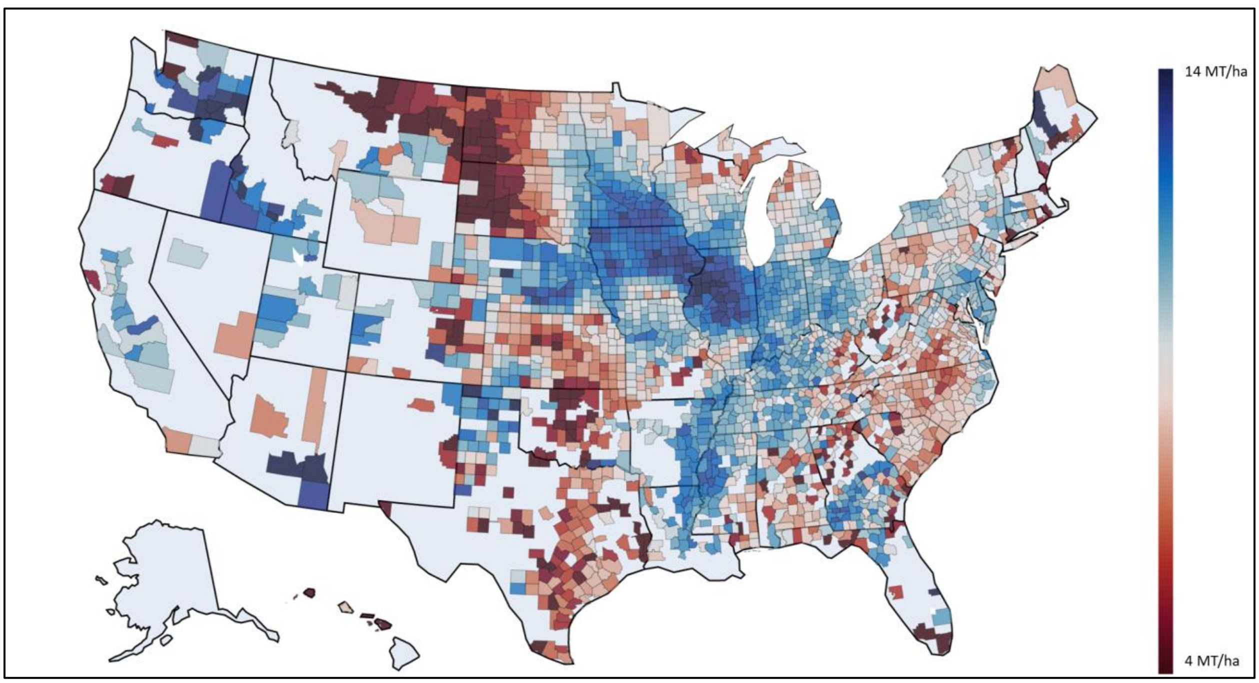

Figure 33 - Corn Grain areal yield, in Metric Tonnes per hectare.

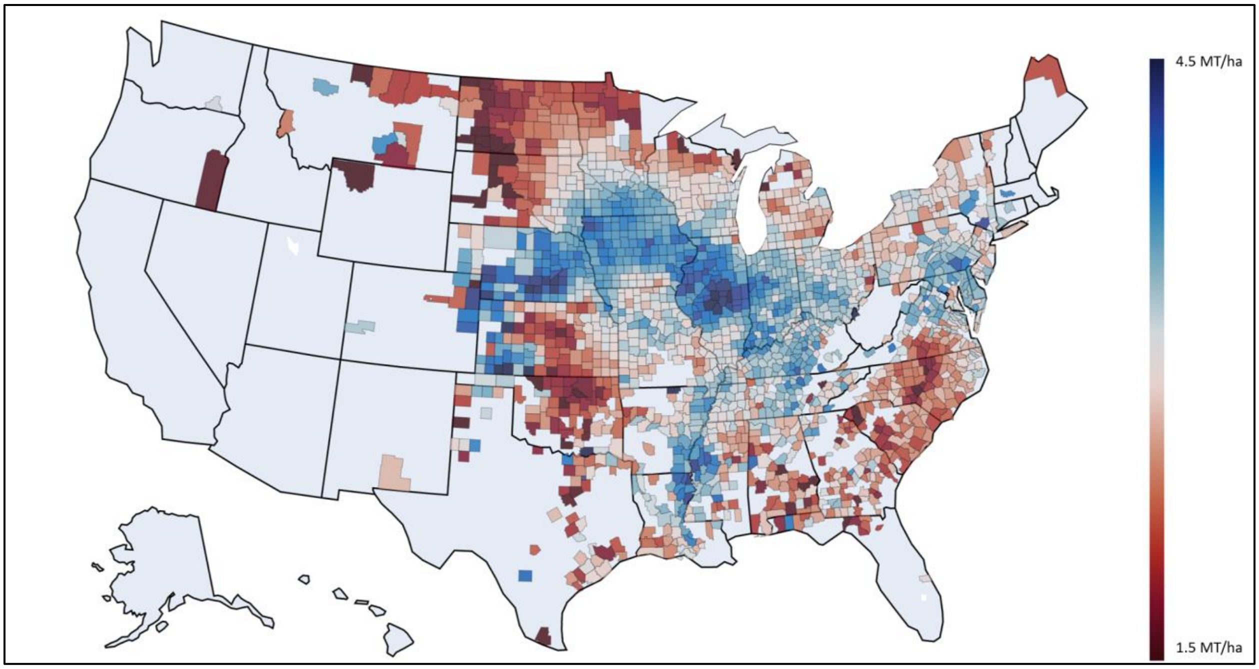

Figure 34 - Soybean areal yield, in Metric Tonnes per hectare.

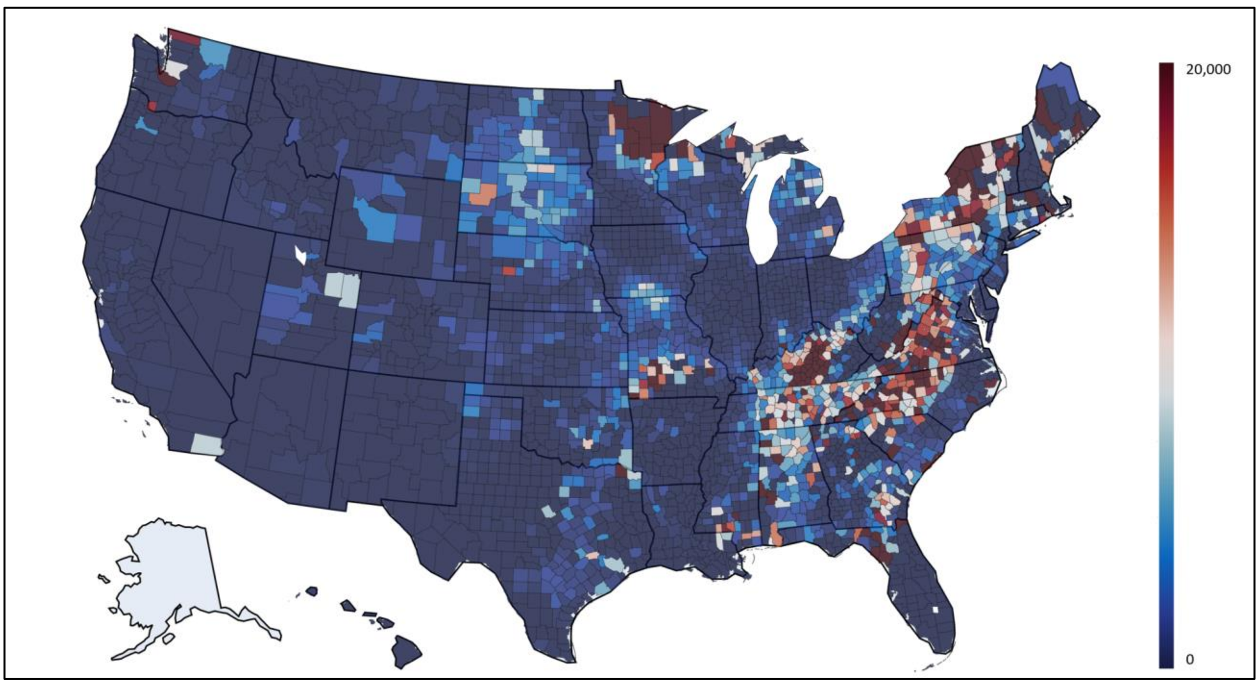

Figure 35 - Corn Grain Land Use Change emissions inputs by county. Units are kg $CO_{2\text{-}eq}$/hectare dedicated land.

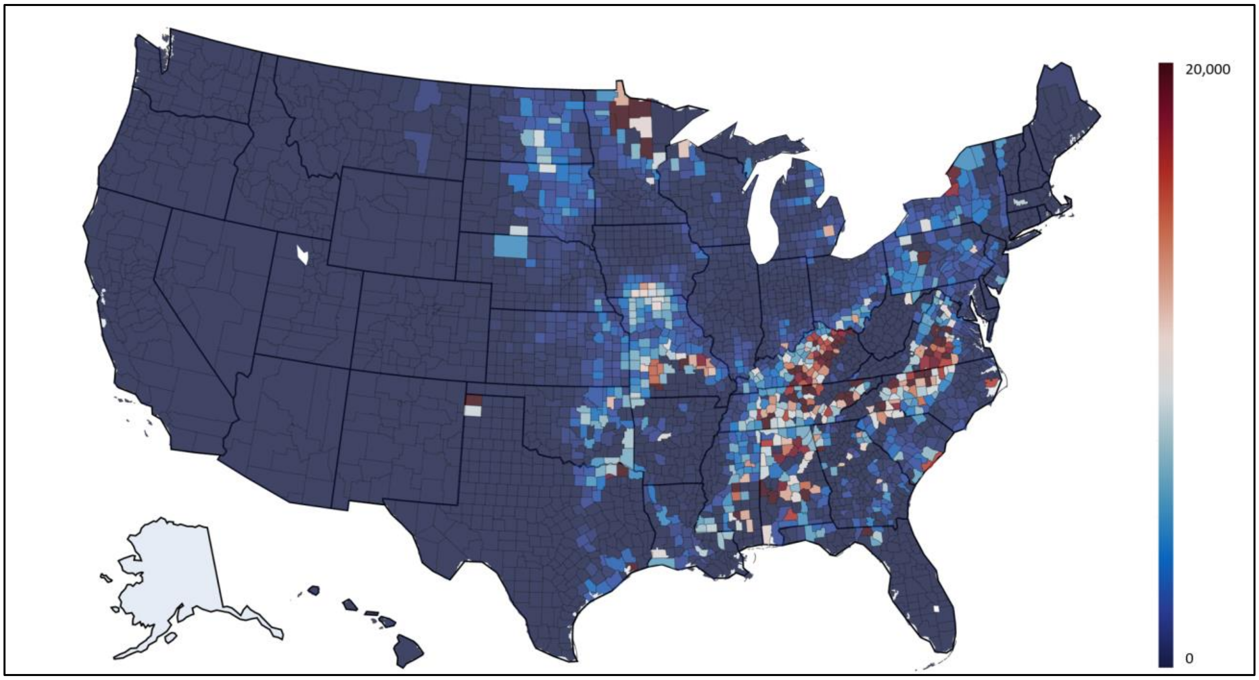

Figure 36 - Soybean Land Use Change emissions inputs by county. Units are kg $CO_{2\text{-}eq}$/hectare dedicated land.

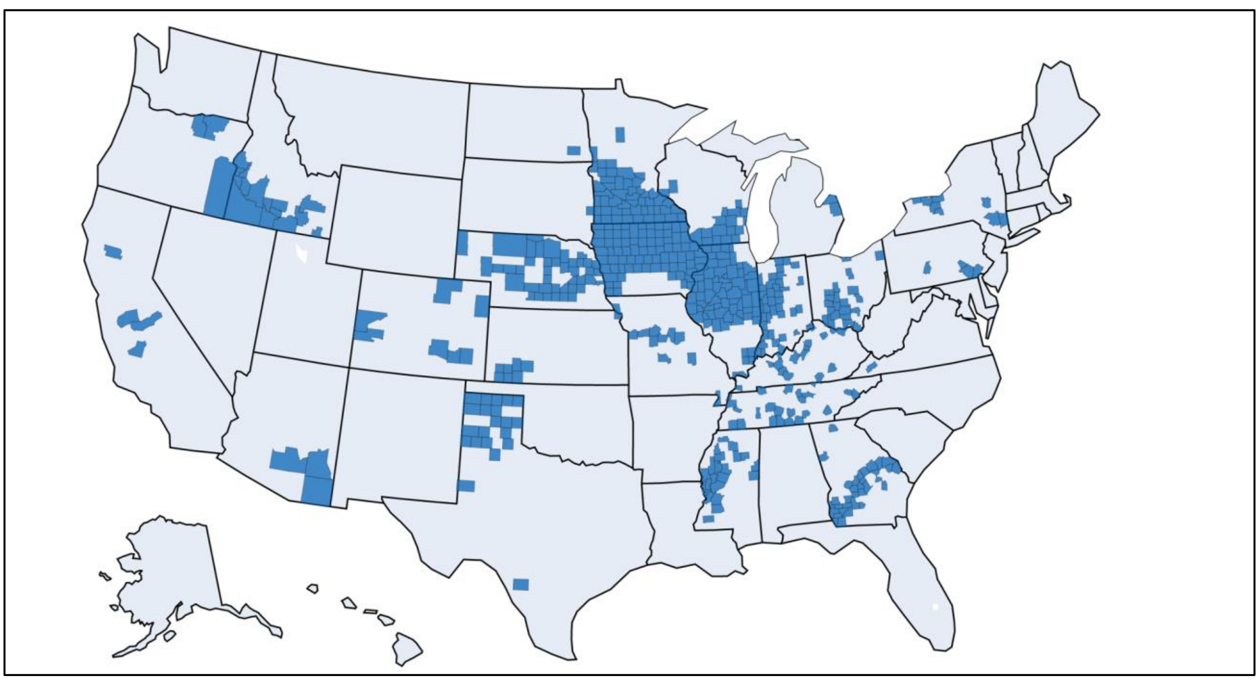
Figure 37 - Map of counties which are assessed to produce ethanol from corn grain with a MFSP of less than that of conventional gasoline ($2.50/GGE).

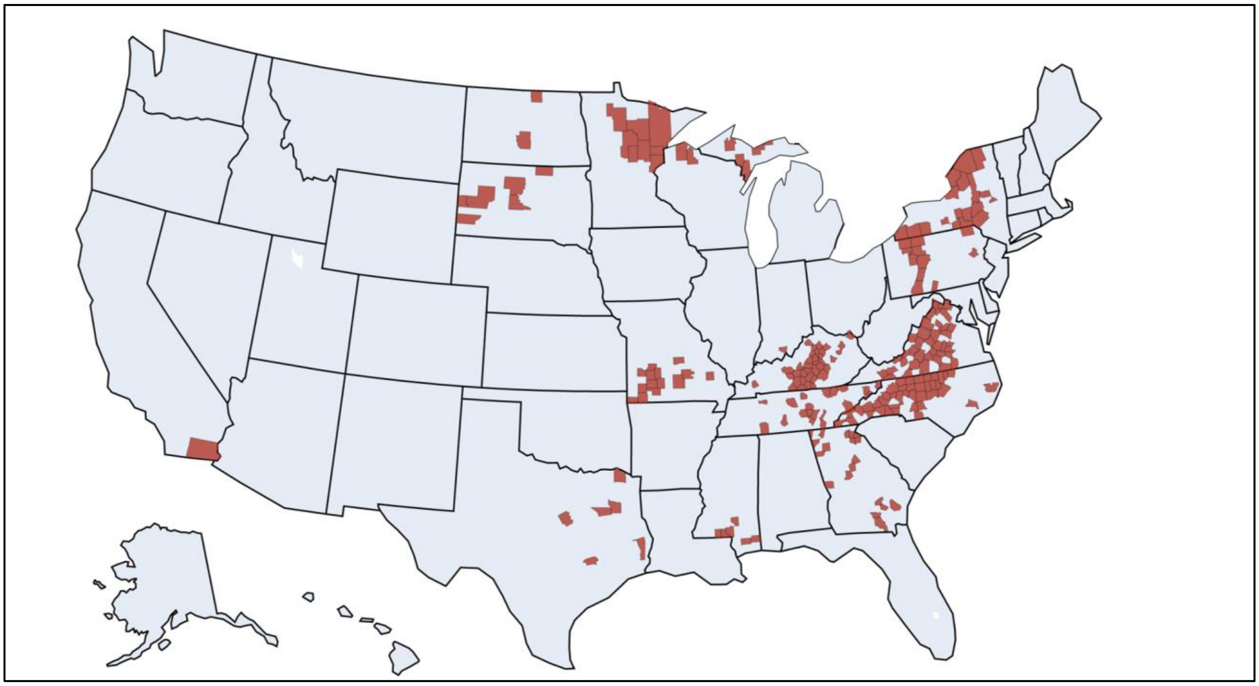

Figure 38 - Map of counties which are assessed to produce ethanol from corn grain with a GWP of greater than that of conventional gasoline (93 $gCO_{2\text{-}eq}$/MJ).

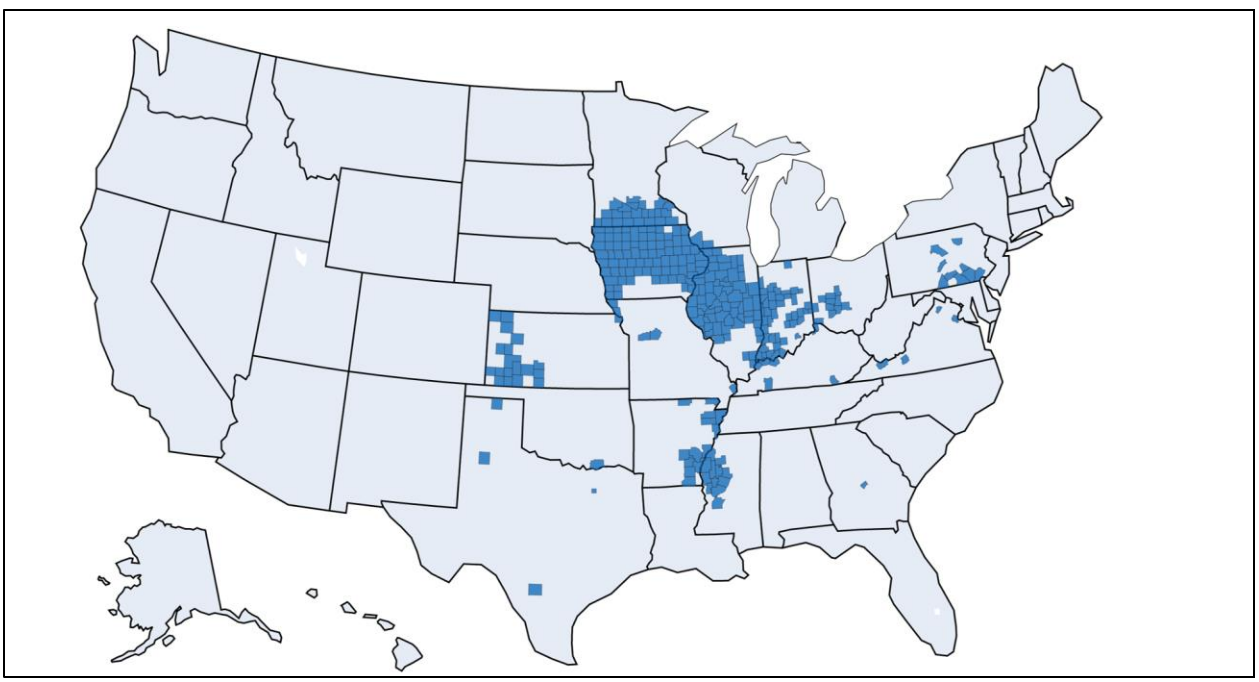

Figure 39 - Map of counties which are assessed to produce biodiesel from soybean with a MFSP of less than that of conventional diesel ($2.65/GGE).

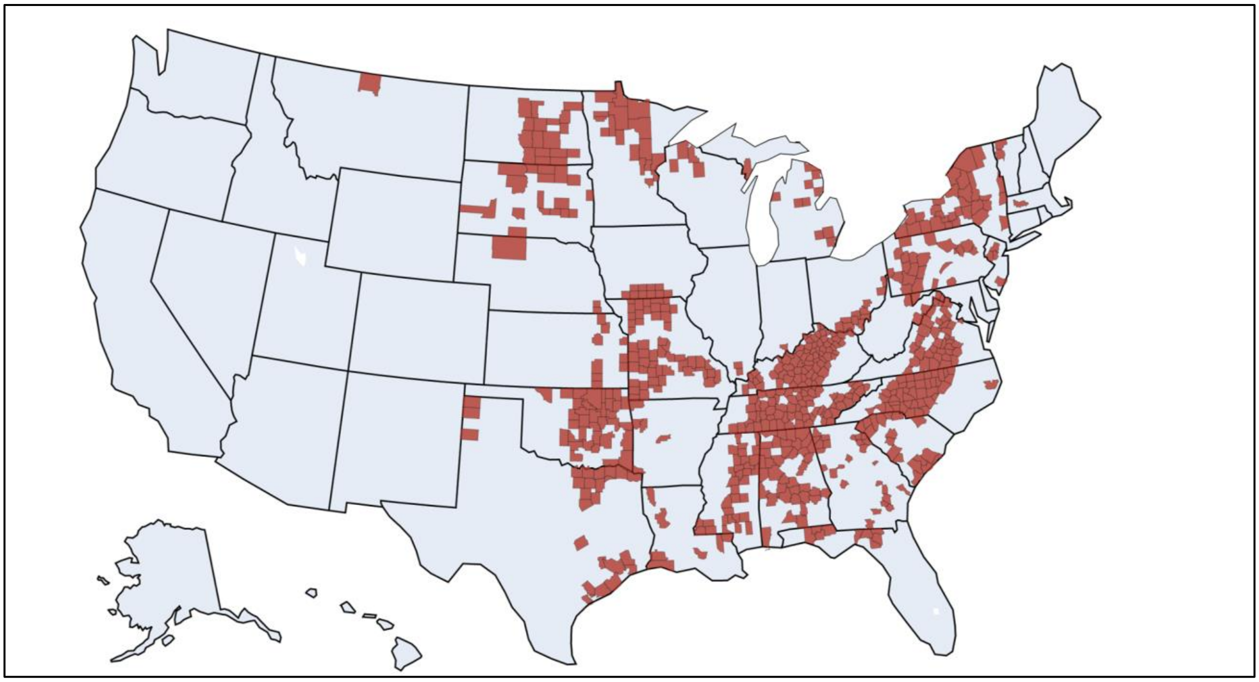

Figure 40 - Map of counties which are assessed to produce biodiesel from soybean with a GWP of greater than that of conventional diesel (92 $gCO_{2\text{-}eq}$/MJ).

CONTRIBUTION BREAKDOWNS

Contribution breakdown bar-charts are provided for the corn grain ethanol and soybean biodiesel pathways and for the total estimated expenditure and total estimated emissions results.

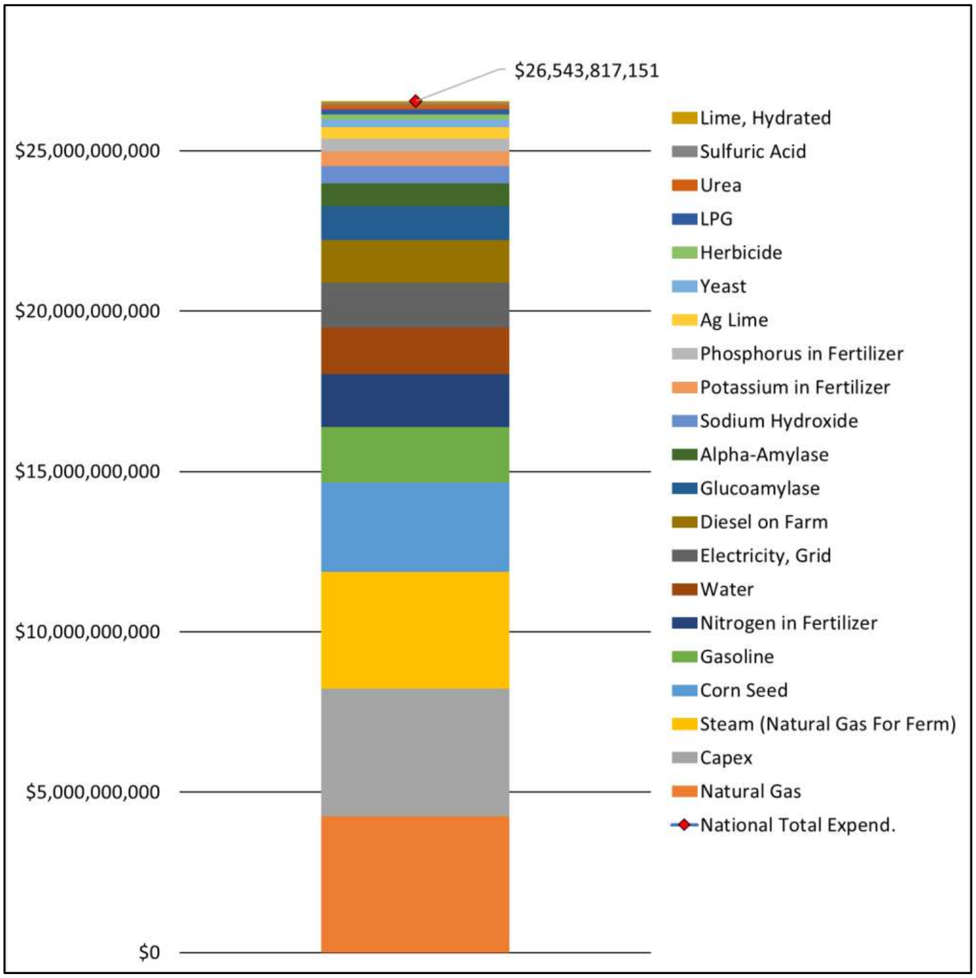

Figure 41 - Corn Ethanol total estimated expenditure contribution breakdown.

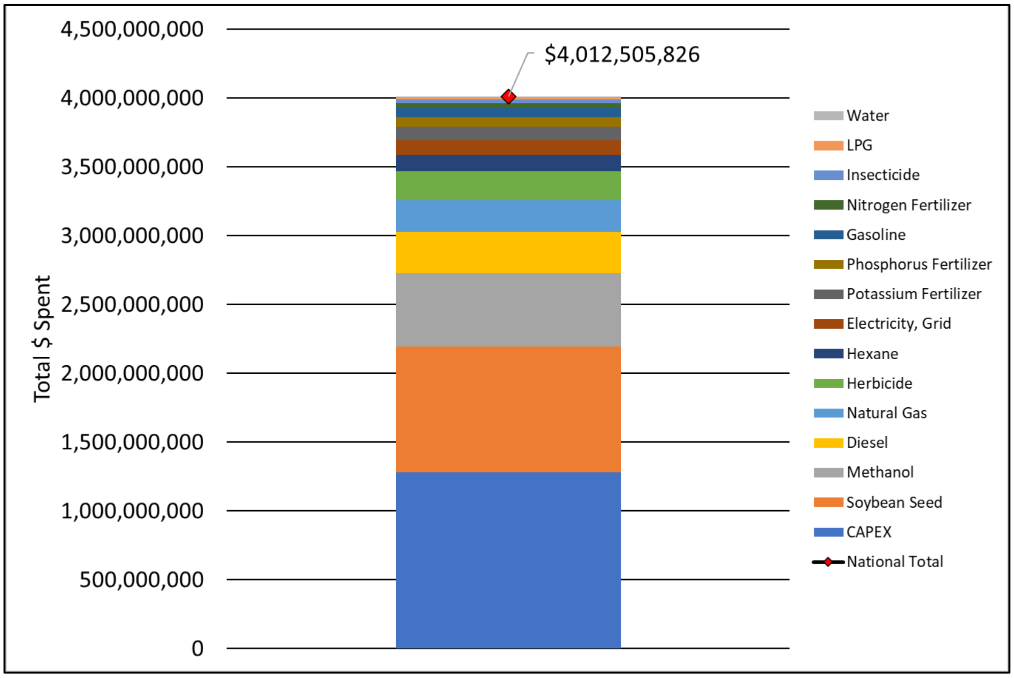

Figure 42 - Soybean biodiesel total estimated expenditure contribution breakdown.

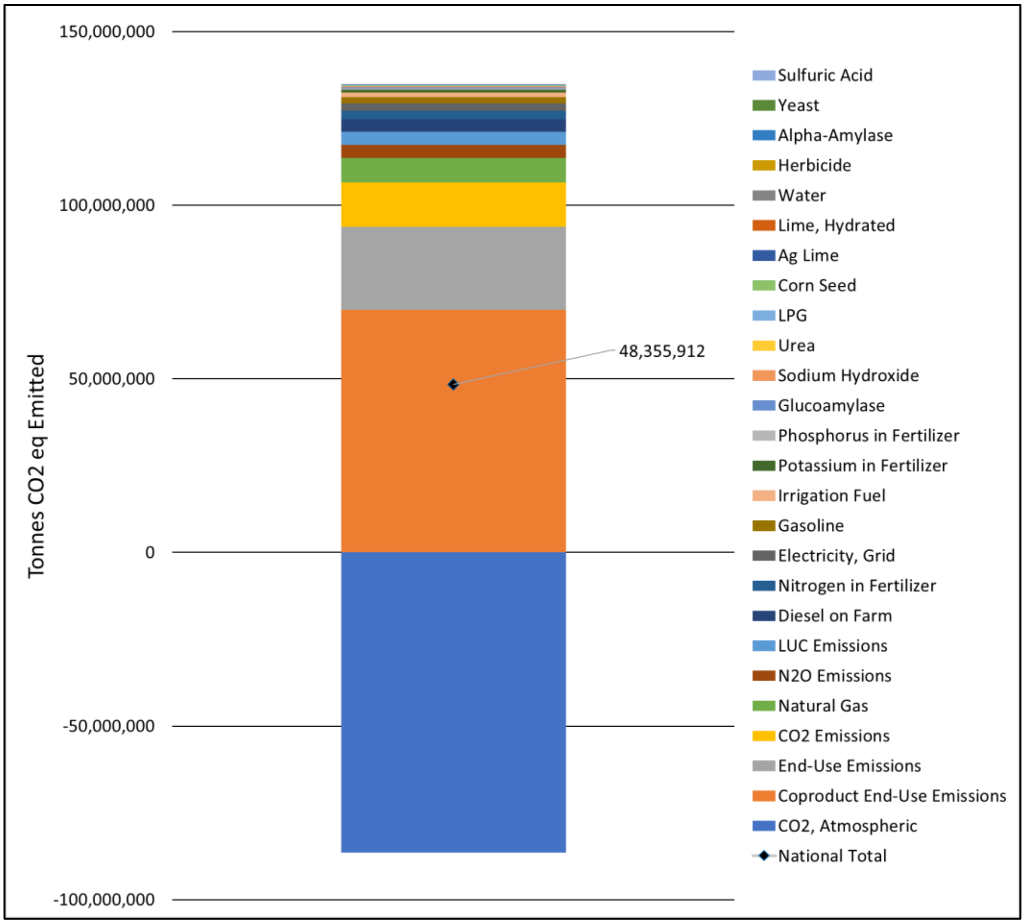

Figure 43 - Corn Ethanol total emissions contribution breakdown.

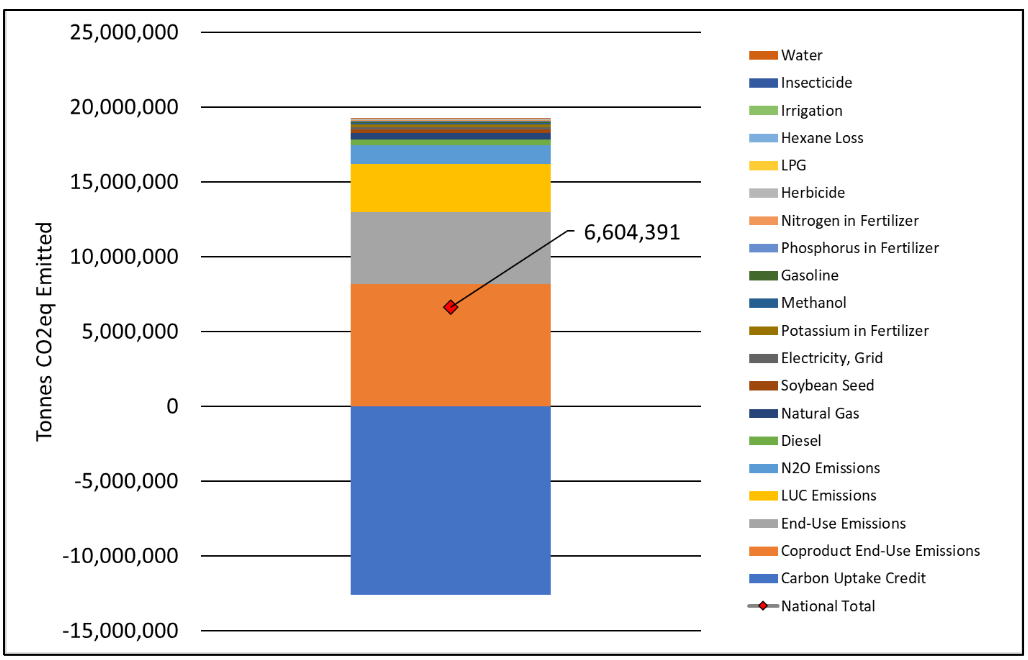

Figure 44 - Soybean Biodiesel total emissions contribution breakdown.

LIST OF ABBREVIATIONS

MMT	Million Metric Tonnes
MT	Metric Tonnes
EPA	Environmental Protection Agency
EIA	Energy Information Administration
RIA	Regulatory Impact Analysis (EPA's 2010 Report)
GGE	Gasoline Gallon Equivalent
TEA	Techno-Economic Analysis
LCA	Life Cycle Assessment
MFSP	Minimum Fuel Selling Price
GWP	Global Warming Potential
ZEC	Zero-Emissions Cost
DAC	Direct Air Capture
MIV	Model Independent Variable
PM	Process Model
DDGS	Dried Distiller's Grains with Solubles
OPEX	Operational Expenditure
CAPEX	Capital Expenditure
NOAK	N^{th} of a Kind
NREL	National Renewable Energy Lab
DOE	Department of Energy
DOE-BETO	Department of Energy's Bioenergy and Technologies Office
DCFROR	Discounted Cash-Flow Rate of Return
MACRS	Modified Accelerated Cost Recovery System
LCI	Life Cycle Inventory
TRACI	Tool for Reduction and Assessment of Chemicals and other environmental Impacts
$CO_{2\text{-eq}}$	Carbon Dioxide Equivalent
LUC	Land Use Change
DLUC	Direct Land Use Change
ILUC	Indirect Land Use Change
USDA	United States Department of Agriculture
USDA-NASS	United States Department of Agriculture National Agricultural Statistics Service
USDA-ERS	United States Department of Agriculture Economic Research Service
MCA	Monte-Carlo Analysis
PDF	Probability Density Function
MJ	Megajoule
BEC-DAC	Break-Even Cost of Direct Air Capture