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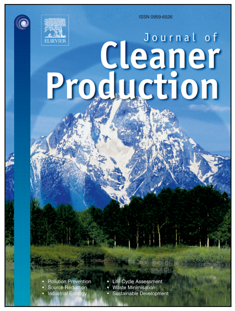

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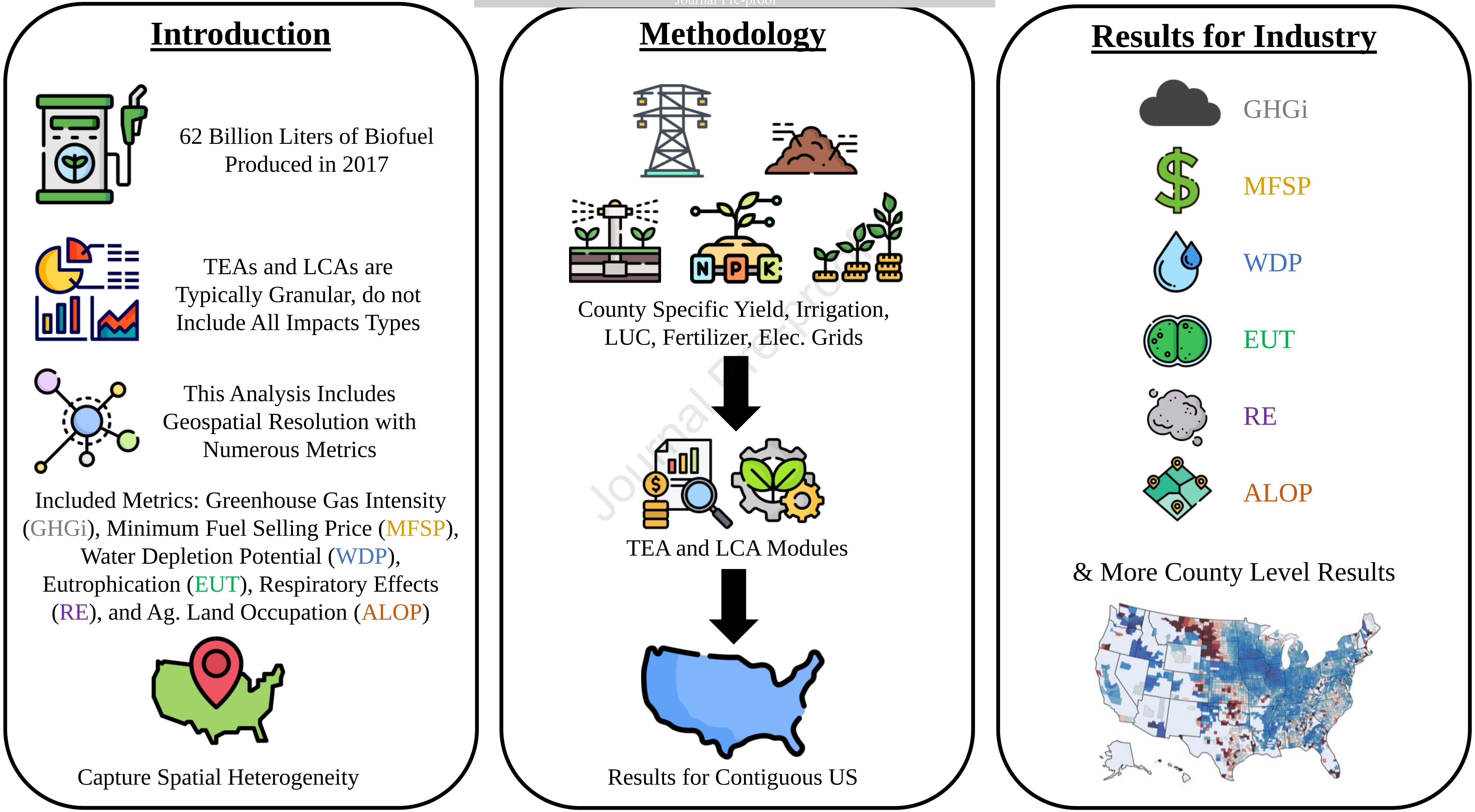

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ABSTRACT

The United States produced more than 66.2 billion Liters of biofuel, primarily in the form of corn ethanol (61 billion Liters) and soybean biodiesel (6 billion Liters), for the transportation industry in 2017. No work currently exists that evaluates both the economic and environmental outcomes of this industry with adequate geospatial resolution and national scope. In this study, a model framework is constructed to perform Techno-Economic Analysis and Life Cycle Assessment using high-resolution input datasets to provide a granular estimation of corn ethanol and soybean biodiesel sustainability performance in most counties in the United States in 2017 (the most recent year for which data is available). Results show a total life cycle, greenhouse gas emission volume of 99.5 million Mg $CO_{2\text{-eq}}$ produced in 2017 by these two biofuels (94.8 million Mg from corn ethanol, and 4.7 million Mg from soybean biodiesel), excluding indirect land use change emissions. This volume corresponds to a combined carbon intensity of 65.3 $gCO_{2\text{-eq}}$/MJ, which is a greenhouse gas improvement compared to petroleum-based gasoline (the carbon intensity of conventional gasoline is 93.0 $gCO_{2\text{-eq}}$/MJ). However, these biofuels are produced at an additional economic cost ($1.8 billion over the displaced gas/diesel). Additionally, these biofuels generate unfavorable impacts in other environmental categories when compared to petroleum-based fuels, particularly in areas of water, land, and nitrogen intensity. This work enables stakeholders to assess the specific value of biofuels as a means of emission reduction and determine if the attained improvements are worth the associated opportunity costs.

Keywords: Biofuel; Life Cycle Assessment; Techno-Economic Analysis; Land Use Change; Marginal Land; Renewable Fuel Standard

LIST OF ABBREVIATIONS

AGC	Avoided Greenhouse Gas Cost
ALOP	Agricultural Land Occupation
BUF	Biofuel Use Fraction
CAPEX	Capital Expenses
DDGS	Dried Distillers Grains with Solubles
DLUC	Direct Land Use Change
EIA	Energy Information Administration
EPA	Environmental Protection Agency
EUT	Eutrophication
GGE	Gasoline Gallon Equivalent
GHG	Greenhouse Gas
GHGi	Greenhouse Gas Impact
I/O	Input/Output
ILUC	Indirect Land Use Change
LCA	Life Cycle Assessment
LCI	Life Cycle Inventory
LUC	Land Use Change
MFSP	Minimum Fuel Selling Price
MIV	Model Independent Variable
MMT	Million Metric Tonnes
OPEX	Operating Expenses
RE	Respiratory Effects
TEA	Techno-Economic Analysis
WDP	Water Depletion Potential

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 (Energy Information Administration, 2022a). Domestic biofuel output more than doubled between 2005 and 2008 and the US industry production capacity reached 79.5 billion L (21 billion gallons) of biofuel per year in 2022 (Energy Information Administration, 2022b). Corn ethanol constitutes the majority of annual production, with nearly 61 billion L (16 billion gallons, or 89% of total biofuel volume) being produced in 2017 (Energy Information Administration, 2022a, 2022b). Biodiesel made up most of the remaining quantity with annual production reaching 6.1 billion L (1.6 billion gallons, or 9% of total biofuel volume) in 2017 (Energy Information Administration, 2022b, 2022a). The primary feedstock used for biodiesel production in 2017 was soybeans, and about 3.4 billion L (0.9 billion gallons, or 5% of total biofuel volume) can be attributed to this crop/fuel combination (Energy Information Administration, 2017). Numerous other niche producers constituted about 6% of biofuel production in the US (Energy Information Administration, 2022a). 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 (United States Environmental Protection Agency, 2010). It is important to note that the biofuel industry has changed since 2017. Notably, renewable diesel—a biofuel that is chemically indistinguishable from conventional diesel—has shown substantial growth in the last five years, with production volumes increasing more than four-fold since 2017 (US Energy Information Administration, 2023). Renewable diesel production nearly matched biodiesel production in 2022 (US Energy Information Administration, 2023). However, corn ethanol production has remained relatively constant over the past decade, and it continues to be the most prolific biofuel type by a wide margin (US Energy Information Administration, 2023).

Both of these biofuels represent greenhouse gas (GHG) emission-reducing systems with development supporting a reduction in the environmental consequences that are associated with the transportation industry (United States Environmental Protection Agency, 2010). These pathways are categorized as first-generation biofuels because the biomass that is used to produce the fuel is a food product. First-generation biofuels have been the subject of contention for many years (Babcock et al., 2011), and researchers have raised concerns about the use of a food resource for transportation fuel (the Food-vs-Fuel debate). Specifically, concerns regarding the dedication of a food resource for the transportation industry (the Food-vs-Fuel debate) and the variability associated with the quantification of life cycle emissions has called into question the sustainability of the industry. Lark et al. (Lark et al., 2022) recently evaluated the emissions impact of the corn ethanol industry to be worse than that of conventional gasoline, and other studies have identified the conversion of unused land for the purpose of feedstock production (Land Use Change, or LUC) as being generally detrimental to the emission profile of biofuels (Lark et al., 2022; Searchinger et al., 2008) and having negative impacts on ecosystems converted into row cropping (Schulte et al., 2017). The Lark et al. 2022 publication has received rebuttals and comments from numerous institutions that suggest the results presented are based on worst-case assumptions or are erroneously high (Falconi et al., 2022; Renewable Fuels Association, 2022; Taheripour et al., 2022), and the Searching et al. 2008 publication is no longer commonly used for quantitative reference. However, such concerns indicate a need for circumspect, thorough sustainability assessment of the corn ethanol and soybean biodiesel industries. The biofuel industry is constituted of numerous diverse farms, distribution centers, and processing facilities, each possessing unique characteristics and complex interactions with one another. This complexity makes accurate, granular assessment of a biofuel's environmental performance difficult.

Stakeholders have assessed the environmental performance of corn ethanol and soybean biodiesel to determine if the intended emission improvements are being achieved (Greer et al., 2020; Kim et al., 2009; Kim & Dale, 2008; Kraatz, 2013; Li et al., 2021; Mekonnen et al., 2018; Mignone et al., 2022; Pereira et al., 2019; Rajaeifar et al., 2014; Scully et al., 2021; Tabatabaie et al., 2018; United States Environmental Protection Agency, 2010). However, only a few of these publications incorporate economic evaluation into their analysis (Li et al., 2021; Tabatabaie et al., 2018; United States Environmental Protection Agency, 2010). It is critical to include economic outcomes in biofuel sustainability assessment (Mahmud et al., 2021); doing so enables the quantification of tradeoffs in a tangible and consistently evaluated way. Beyond economic considerations, only a handful of publications characterize geospatial heterogeneity within their assessment (Li et al., 2021; Pelton et al., 2021; Tabatabaie et al., 2018). Geographic variation in pathway behavior causes regional tradeoffs that may not be identified in aggregated analysis (Li et al., 2021; Pelton, 2019; Pelton et al., 2021).

The overarching goal of this study is to quantify the economic and environmental performance of the 2017 US biofuel industry to evaluate performance tradeoffs and identify hot-spots with county-level results. To our knowledge, there are no prior studies that include economic and environmental performance analysis with nation-wide geospatial resolution for both corn ethanol and soybean biodiesel (the US Environmental Protection Agency, or EPA, has a current draft in production that provides thorough analysis of the industry but is not currently available for citation). To address this research need, this work involves the construction of a model that 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 to calculate the Minimum Fuel Selling Price (MFSP, \$/MJ), GHG impact (GHGi, $gCO_{2\text{-eq}}$/MJ), water depletion potential (WDP, m^3/MJ), eutrophication (EUT, kg N_{eq}/MJ), respiratory effects (RE, kg $PM_{2.5\text{-eq}}$/MJ), and agricultural land ~~use~~ occupation (ALOP, m^2a/MJ) of both fuel types. In addition to the result types above, other environmental impact results are generated and discussed and include acidification potential, ecotoxicity, human health – carcinogens, human health –

non-carcinogens, ozone depletion, tropospheric ozone formation, fossil resource depletion, and cumulative energy demand. Country-wide and county-scale input datasets are incorporated in order to deliver a solution set that characterizes the sustainability performance of both biofuel types in all counties across the US with adequate geospatial resolution. This work produces results that describe the economic and environmental performance of corn ethanol and soybean biodiesel production for each county in the continuous United States. The analysis presented here is conducted for the 2017 year as this is the most recent year for which Census of Agriculture data is available (Perdue & Hamer, 2019). Based on the current state of the field there is a need for such quantification, and this work is aimed at addressing this gap. No work thus far delivers this array of performance results for the contiguous United States with this level of resolution.

2. METHODS

The methods are broken down into six subsections representing the components necessary for the completion of this analysis. The first two subsections detail the model structure and the process modeling techniques used. The third and fourth subsections discuss the assumptions used for the TEA and the LCA calculations. The fifth section details the specific geographic input data used in this study and the sixth section provides the methods used to calculate the effective economic cost of avoided emissions.

2.1 MODEL STRUCTURE

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 2.2). The process models quantified material, energy, and economic flows for the production systems (defined the Input/Output, or I/O, array). The TEA and LCA modules then imported these I/O lists and ran economic and environmental performance analysis on the specific flow amounts described. The TEA module calculated MFSP (Section 2.3) and the LCA module quantified environmental impacts (Section 2.4). The process models were constructed with default values for substance and energy requirements (e.g., the amounts of corn seed, irrigation water, or capital costs used in fuel production) that were retrieved from the literature. These default (or baseline) values represent generic corn ethanol and soybean biodiesel production systems. The results of the process models with these default flow amounts constitute the baseline pathway results, and these results were used for validation and comparison to other corn ethanol and soybean biodiesel TEA/LCAs. For nationwide analysis, county-specific flows (e.g., the amount of irrigation water used in Cherry County, Nebraska) replaced the default flows in order to provide a characterization of the specific production pathway present in some given county. Constructing the model in this way enabled thousands of geographically unique counties to be assessed in a consistent manner. A comparison of the baseline results to published literature sources is presented in the Supplementary Information: Appendix B. Section 2.5 provides a more thorough description of how geospatial data is utilized.

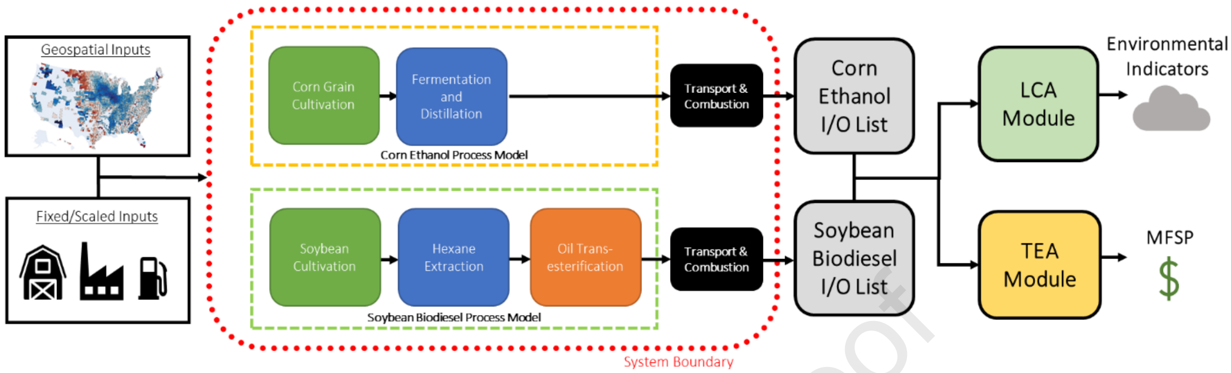

Figure 1—Process Flow Diagram of primary model components. Geospatial input datasets are integrated with fixed/scaled inputs to produce process models for corn ethanol and soybean biodiesel pathways. Process models characterize aggregated flows associated with fuel production (Input/Output or I/O list). The I/O list feeds into the Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) modules to quantify economic and environmental performance with county level resolution. (MFSP = Minimum Fuel Selling Price)

2.2 PROCESS MODELS

The process models quantified the flow amounts in the I/O arrays for each step in a fuel production process. For instance, the substance and energy requirements associated with corn production were defined by the corn cultivation process model. The particular quantity of every flow was specified with a Model Independent Variable (MIV). These values were retrieved from literature sources that have performed similar characterization of the corn ethanol and soybean biodiesel production pathways. MIVs fall into three categories: fixed, geospatial, or scaled. Fixed MIVs define flow amounts that are static and do not vary from county to county (e.g., herbicide application). Geospatial MIVs define flow amounts that are county specific (e.g., volume of irrigation water used). Scaled MIVs define flow amounts relative to another flow (e.g., nitrous oxide emission quantity scales off the nitrogen fertilizer application rate). Supplementary Information: Appendix A presents an exhaustive list of the MIVs used in both pathways. Supplementary Information: Appendix C presents a more thorough description of the process models and literature sources from which the MIVs were retrieved. Figure 2 provides a shortened list of key MIVs.

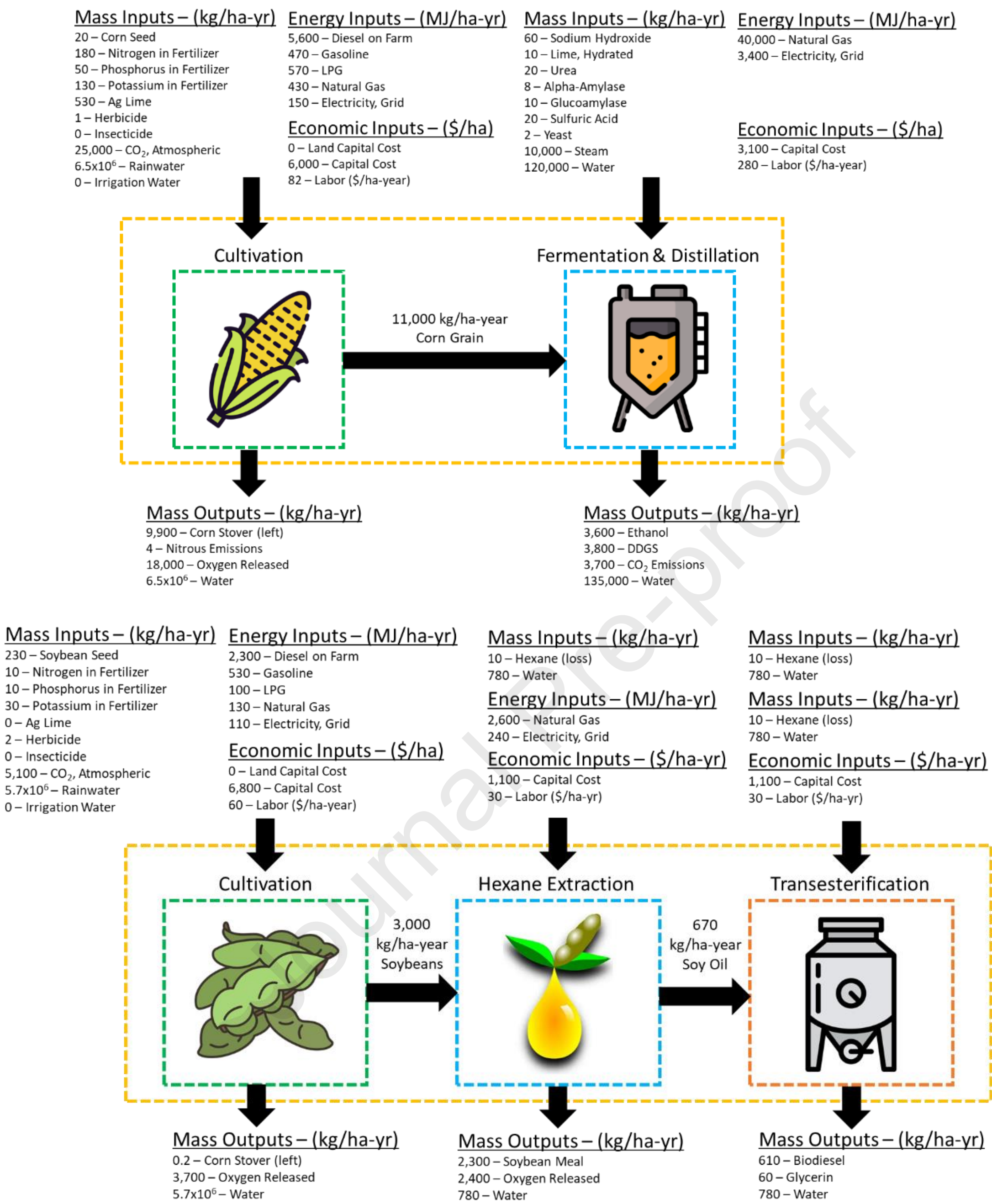

Figure 2—Process Flow Diagrams for the corn ethanol and soybean biodiesel pathways. Primary Model Independent Variables (MIVs) for the baseline scenarios are presented.

2.3 TECHNO-ECONOMIC ANALYSIS

A TEA was performed with a 30-year Discounted Cash Flow Rate-of-Return analysis 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 the MFSP. Specific parameters used for the TEA include a discount rate of 10%, a federal tax rate of 21%, a state tax rate of 6.1%, an investor equity share of 40%, an interest rate of 8%, a loan term of 10 years, a maintenance rate of 3%, an insurance rate of 1%, no construction period, no tax credit, and a 7-year Modified Accelerated Cost Recovery System depreciation schedule. Financial incentives (e.g., Renewable Identification Numbers) exist for biofuels in the US and it is important to recognize that they can influence the economic balance in substantial ways. However, the analysis presented in this work is aimed at quantifying the cost of fuel production (rather than the retail price of the biofuel), so such incentives are not included here. Operating expenses (OPEX) for the fuel production processes were calculated from the I/O arrays using prices listed in Supplementary Information: Appendix A. Nth of a Kind capital cost assumptions were applied as defined by the National Renewable Energy Lab and the Department of Energy’s Bio-Energy Technologies Office for all process steps (Humbird et al., 2002). This is a reasonable assumption to make as both the corn ethanol and soybean biodiesel industries are well established: 192 corn ethanol and 69 soybean biodiesel plants were operating in 2017 (U.S. Energy Information Administration, 2018). This analysis assumes that cropland is not being purchased and paid off with substantial loans; a small percentage of total US agricultural land changes ownership through direct purchase at any given time (Bigelow et al., 2016). However, nearly 60% of all corn and soy farms make rent payments (Bigelow et al., 2016). Average rent payments were retrieved from the USDA’s 2017 Census of Agriculture and incorporated into the analysis (Perdue & Hamer, 2019).

2.4 LIFE CYCLE ASSESSMENT

The LCA applied a well-to-wheels system boundary to quantify environmental impacts for GHGi, WDP, EUT, RE, and ALOP. GHGi quantifies the total GHG emissions that are associated with the fuel production process, including all direct and upstream processes that contribute to the greenhouse effect, and is given in units of $gCO_{2\text{-}eq}$ (Bare et al., 2012). WDP quantifies water that is “evaporated, incorporated into products, transferred to other watersheds or disposed in the sea” (Huijbregts et al., 2017), and its units are m^3. EUT is defined by the US EPA as the “enrichment of an aquatic ecosystem with nutrients (nitrates, phosphates) that accelerate biological productivity (growth of algae and weeds) and an undesirable accumulation of algal biomass” (U.S. Environmental Protection Agency, 2008a) and its units are kg N_{eq}. RE quantify the total amount of “’fine particles’ which are smaller than or equal to 2.5 micrometers in diameter and are often products of combustion” (U.S. Environmental Protection Agency, 2008b) and its units are kg $PM2.5_{eq}$. ALOP assesses the “relative species loss due to local land use” (Huijbregts et al., 2017) and is quantified in square-meter years (m^2a). The functional unit was 1 MJ of liquid transport fuel. This functional unit is frequently selected when assessing the environmental outcomes of a liquid biofuel (Pereira et al., 2019; Scully et al., 2021). The model performed co-product burden attribution through economic (market-based) allocation methods (DeRose et al., 2019). Specific co-products included Dried Distillers Grains with Solubles (DDGS) for the corn ethanol production pathway, and soymeal and glycerol for the soybean biodiesel production pathway. Economic allocation factors were 0.81 for ethanol and 0.44 for biodiesel. Supplementary Information: Appendix A provides energy allocation results.

The model incorporates Life Cycle Inventory (LCI) data from the EcoInvent 3.8 Database accessed through the OpenLCA 1.11 platform. LCI values that corresponded to the United States region were selected where possible, and inventories of the market type were prioritized. LCI values of the market type were selected when available as this includes not only the embodied emissions of a substance but also relevant market shares and transportation emissions (Wernet et al., 2016a). Cutoff allocation, in the context of LCI values, refers to the specific way that environmental burdens from recycled flows are assessed. Due to the organization of this particular analysis, the distinction between cutoff and allocation at-point-of-substitution data is not critical; remaining consistent in the selected allocation type is relevant (Wernet et al., 2016a). These LCI values apply the TRACI v2.1 and ReCiPe impact assessment methodologies in order to provide flow specific metrics of environmental impact. The TRACI v2.1 assessment methodology evaluates the GHGi of emissions on a 100-year timeline (Bare et al., 2012). Because different gases possess different greenhouse behavior, GHGi results are presented in units of carbon dioxide equivalents ($CO_{2\text{-eq}}$), where the total global warming potential of other GHGs are normalized to the equivalent amount of carbon dioxide emissions which would produce the same effect. The gas specific equivalence factors are 1 $gCO_{2\text{-eq}}/gCO_2$, 27 $gCO_{2\text{-eq}}/gCH_4$, and 273 $gCO_{2\text{-eq}}/gN_2O$ as are specified by the Intergovernmental Panel on Climate Change Sixth Assessment Report methodology (Calvo Buendia; Peru et al., 2019).

The LCA module is constructed to accept data regarding LUC emissions. LUC impacts are separated into two categories: direct (DLUC) and indirect (ILUC) (Brandão et al., 2022; Searchinger et al., 2008). DLUC quantifies the soil organic carbon emissions that are physically released at the farm when previously unused land is converted to support agricultural cultivation (Brandão et al., 2022). ILUC quantifies the emissions that are associated with a nontrivial increase in a market's demand for a crop, and that crop's subsequent extensification. Specifically, previously unused land in a different geographic location is converted in order to accommodate the existing food/feed demand for a crop due to its diversion to fuel production. The LUC emissions that occur at this geographically separate location (due to the physical conversion of this land) are then attributed to the fuel production system, as it is this system that is deemed responsible for the change (Brandão et al., 2022). ILUC is very difficult to quantify, and a high level of uncertainty regarding its assessment has resulted in corn ethanol ILUC contributions ranging from 6 $gCO_{2\text{-}eq}$/MJ to 39 $gCO_{2\text{-}eq}$/MJ (Elliott et al., 2014; Lark et al., 2022) (for context, the EPA evaluates the GHGi of gasoline use at 93 $gCO_{2\text{-}eq}$/MJ (U.S. Environmental Protection Agency, 2022b)). 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 (Beal et al., 2021; Pelton et al., 2021). LUC, in the context of this analysis, refers to the DLUC emissions which results from the change in the soil organic carbon profile of a particular plot of land. Quantified DLUC emissions were brought into the model at a county scale for both corn and soybean, and a more thorough discussion of these data is provided in Section 2.5.

2.5 GEOSPATIAL INPUT DATA

In order to accurately capture the geospatial variability that is present across the contiguous United States, county-level data was integrated as shown in Figure 1. Specific input sets include areal crop yield (kg/ha), cost of electricity ($/kWh), emissions from electricity ($gCO_{2\text{-}eq}$/kWh), nitrogen fertilizer application rates (kg N/ha), irrigation rates (kg water/ha), and DLUC emissions rates (kg $CO_{2\text{-}eq}$/ha). These data are available in Supplementary Information: Appendix A. The United States Department of Agriculture National Agricultural Statistics Service provides 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 census data was available (Perdue & Hamer, 2019). From these two sets, the model obtained a county average kg/ha areal crop yield. Electricity grid emissions and cost quantities were retrieved from the EPA's eGrid service and from the Energy Information Administration (EIA), respectively (Energy Information Administration, 2019; U.S. Environmental Protection Agency, 2022a). Only state level characterizations of this data were available. Secondary impact values of the electricity grid (e.g., EUT) were obtained from the EcoInvent 3.8 database, and were only available at a grid-level resolution. Finally, Pelton et al. 2021 (Pelton et al., 2021) offers county-level datasets which include nitrogen fertilizer application rates (kg/ha), emissions due to DLUC (kg/ha), and irrigation rates (kg/ha) at a county-level for most of the contiguous US. The DLUC values were calculated through the incorporation of land conversion data from (Lark et al., 2020) with the carbon emissions model of (Spawn et al., 2019). Pelton et al.'s 2021 analysis then approximated the carbon emissions for a specific parcel of land with the stock-difference method. Data from Pelton et al. 2021 was incorporated as it is the highest-resolution characterization of inputs for the corn and soybean production industries that is readily available to date. This approach was preferrable to attempting to replicate the same information through analysis of disparate sources that likely possess inconsistent footprints or methodologies. A more detailed explanation of how these values were obtained is available in (Pelton et al., 2021). By integrating these datasets, the model achieved a decoupled set of geospatial inputs that are independent of the county-specific biomass produced, which is critical to capturing geospatial heterogeneity and its impact on sustainability performance. This geospatial input data is primarily related to characterizing agricultural production rather than fuel conversion; only the electricity grid variations influenced fuel production behavior. This was done as the primary processes that dictate agricultural production are more sensitive to geographical location than those that govern fuel production. For instance, the required volume of water for ethanol fermentation changes much less than the total water requirements for agricultural production of corn grain does from location-to-location.

The process models quantified flows on an areal basis (e.g., kg soybeans produced per ha, kg nitrogen fertilizer applied per ha, etc.), for each county where input data was available. In order to characterize the aggregate outcomes of the biofuel sector, these county results were weighted based on their 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 difficult. Pelton et al. 2021 has previously addressed this behavior in the context of an LCA but did not publish estimates for biomass used for biofuel results on a county-by-county basis. As such, the biomass used for biofuel production was estimated for this work based on the geographic locations of biofuel plants provided by the EIA's US Energy Atlas (U.S. Energy Information Administration, n.d.-a, n.d.-b). County-level biomass was allocated to each biofuel plant based on distance to the plant assuming all biomass is located at each county's centroid. Each county's centroid was calculated using QGIS and Esri's USA Counties shapefile data (Esri, n.d.). If two plants were competing for the same county's biomass, priority was given to the biofuel plant with the highest production capacity. County-level biomass estimation was validated using reported state-level biomass to biofuel values. Reported values could only be found for 11 states, but the mean difference between reported and estimated biomass used for biofuel production was 1.4% for corn ethanol. Full details on the biomass to biofuel estimation methods used are provided in Supplementary Information: Appendix D. The resulting county-level biomass to biofuel quantities are termed the Biomass Use Fractions (BUF; kg biomass used for biofuels/kg fuel produced). Therefore, the total amount of biofuel produced in the US in 2017 (V_{BF}) can be characterized in gallons of gasoline equivalent (GGE) as:

$$V_{BF}\left[\frac{GGE}{yr}\right] = \sum_{i}^{n} V_{CE\,i} + \sum_{i}^{n} V_{SB\,i} \tag{1}$$

where V_{CE} is the amount of corn ethanol and V_{SB} is the amount of soy biodiesel that is produced in all contiguous US counties (n=3,082 counties). The amount of corn ethanol produced in 2017, V_{CE}, is calculated as

$$V_{CE} = \sum_{i}^{n} V_{CE\,i} = \sum_{i}^{n} A_{C\,i}\left[\frac{ha}{yr}\right] \cdot Y_{C\,i}\left[\frac{t}{ha}\right] \cdot BUF_i\left[\frac{t\ used}{t}\right] \cdot FY_{CE}\left[\frac{t\ fuel}{t\ used}\right] \tag{2}$$

where A_{C_i} is the county-specific area of land dedicated to corn growth in 2017, Y_{C_i} is the county-specific areal corn grain yield achieved, and FY_{CE} is the ratio of fuel (corn ethanol) produced per biomass (corn grain) input that is derived from the process model steps detailed above. V_{CE} and V_{SB} were calculated to be 60.1 billion L (15.9 billion gallons) and 3.3 billion L (.9 billion gallons), respectively. These values display reasonable parity with the reported production volumes of the associated biofuels (Energy Information Administration, 2022b) and this calculation is available in Supplementary Information: Appendix A. The model was executed for each county in the contiguous United States where input data was available. The USDA's 2017 Census data have varying footprints for the corn and soy crops (Perdue & Hamer, 2019). This is responsible for the different footprints present in the maps below as the analysis was not performed for counties where no yield data was available. Monte Carlo Analysis was performed (Supplementary Information: Appendix E) and the results presented constitute the mean outcome for each county over the stochastic analysis.

2.6 EFFECTIVE COST OF AVOIDED GREENHOUSE GAS EMISSIONS

Comparing the sustainability performance of conventional fuels (with relatively low economic cost and relatively high carbon emissions) to biofuels (with relatively high economic cost and relatively low carbon emissions) is a difficult task. The Avoided GHGs Cost (AGC) metric presents the economic cost per unit of avoided emissions in order to enable clear comparison to other negative emissions technologies. The AGC of a biofuel is calculated as in Equation 3.

$$\frac{MFSP_B\left(\frac{\$}{MJ}\right) - MFSP_{Petr}\left(\frac{\$}{MJ}\right)}{GHGi_{Petr}\left(\frac{g\ CO_{2-eq}}{MJ}\right) - GHGi_B\left(\frac{g\ CO_{2-eq}}{MJ}\right)} \times 10^6 \left(\frac{gCO_{2-eq}}{Mg\ CO_{2-eq}}\right) = AGC\left(\frac{\$}{Mg\ CO_{2-eq}}\right) \tag{3}$$

Where $MFSP_B$ is the calculated MFSP of a biofuel (i.e., of corn ethanol or soybean biodiesel) and $MFSP_{Petr}$ is the cost of petroleum-based, conventional fuels (i.e., of gasoline or diesel). $GHGi_{Petr}$

corresponds to the reported GHGi of the petroleum-based fuel and $GHGi_B$ corresponds to the calculated GHGi of the biofuel. The assumed cost of petroleum-based fuels presented for this analysis is \$0.0207/MJ (\$2.50/Gal gasoline or \$2.84/Gal diesel). It is important to note that this value is volatile and the retail price of gasoline ranges substantially. Moreover, the additional cost of biofuel is sensitive to this petroleum-based volatility. In order to provide an accurate characterization, a sensitivity analysis is presented in Supplementary Information: Appendix A that evaluates AGC for a number of petroleum-based fuel prices.

3. RESULTS AND DISCUSSION

Sustainability results are presented in three sections. First, results in Section 3.1 include sustainability outcomes that are not weighted by their relative share of national production. This section serves to highlight regional variations in fuel performance and to explain the mechanisms that are responsible for economic or environmental hot spotting. Second, results in Section 3.2 include sustainability outcomes that have been weighted by their relative share of national production. This section serves to quantify the total impacts of the biofuel industry by aggregating emissions and costs. Finally, results in Section 3.3 include AGC results for both pathways.

3.1 SUSTAINABILITY PERFORMANCE RESULTS

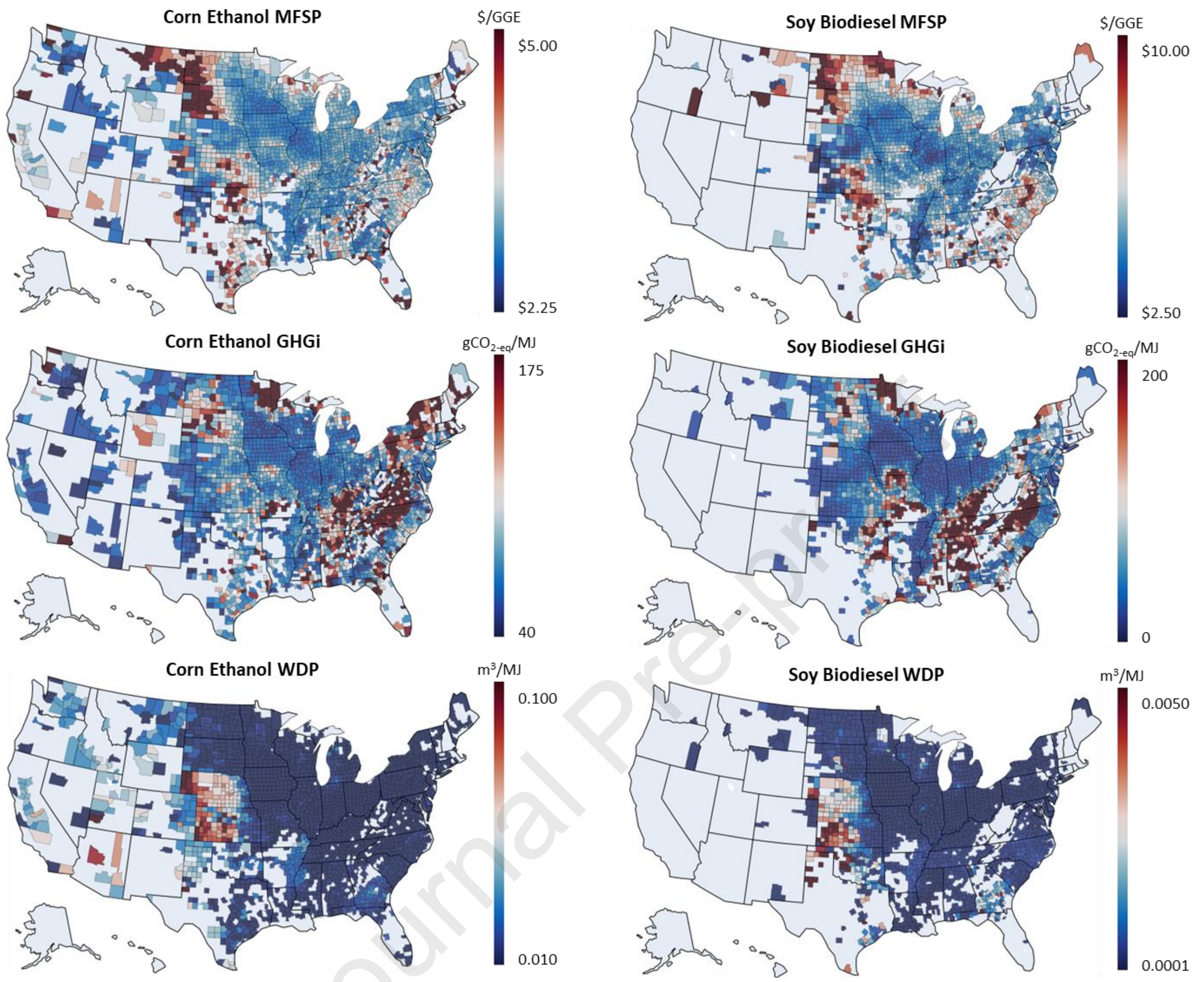

Figure 3a—Economic and Environmental results for the corn ethanol and soybean biodiesel pathways. Plotted metrics include Minimum Fuel Selling Price or MFSP (Top), Greenhouse Gas Impact or GHGi (Middle), and Water Depletion Potential or WDP (Bottom). Maps present results for regions where agricultural yield data was available and have grayed-out counties where yield data was unavailable.

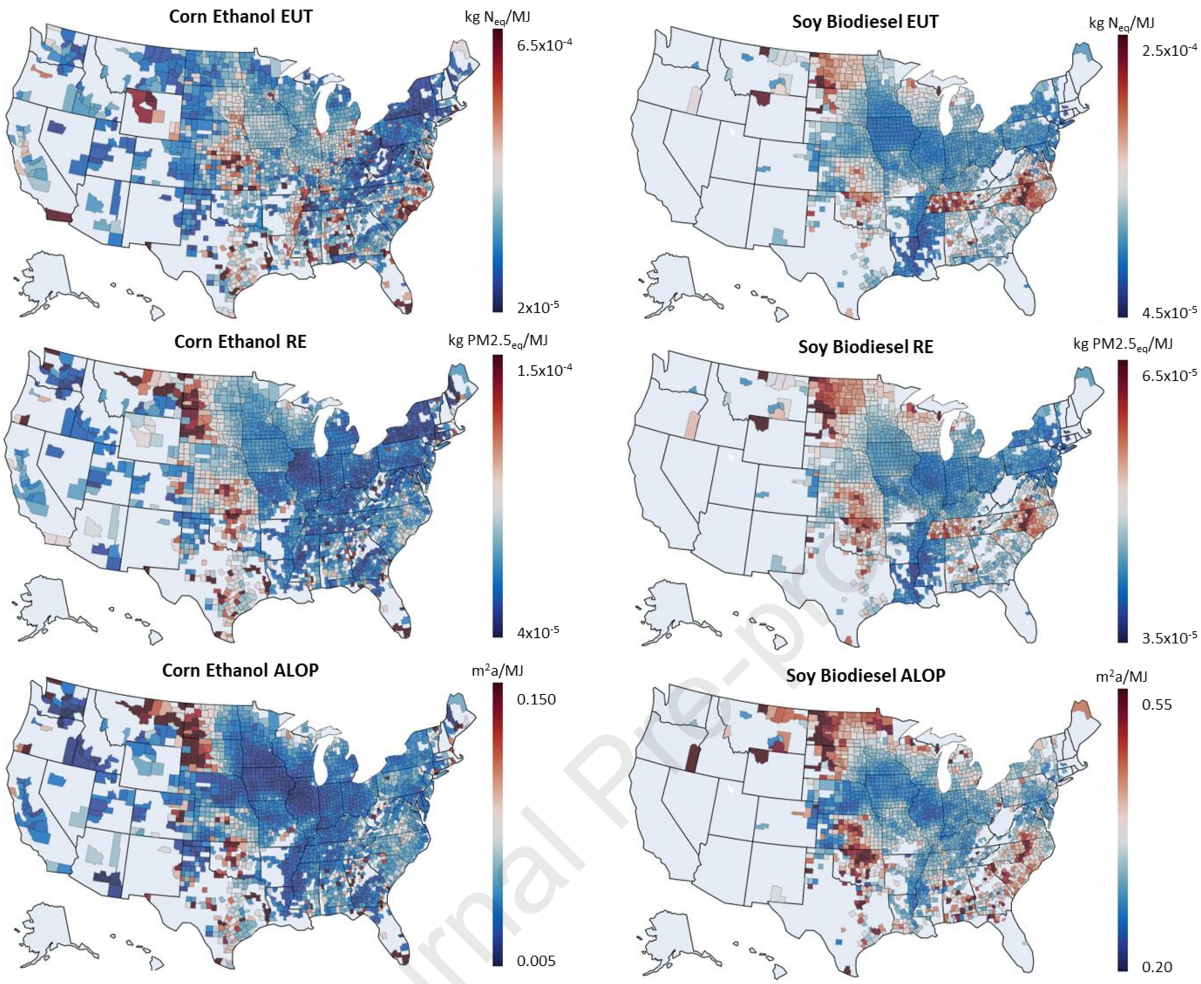

Figure 3b—Continued sustainability results for the corn ethanol and soybean biodiesel pathways. Plotted metrics include Eutrophication or EUT (Top), Respiratory Effects or RE (Middle), and Agricultural Land Occupation or ALOP (Bottom). Maps present results for regions where agricultural yield data was available and have grayed-out counties where yield data was unavailable.

Sustainability performance results for the corn ethanol and soybean biodiesel pathway are presented in Figure 3. Sustainability results are significantly sensitive to all geospatial inputs (yield, nitrogen fertilizer use, emissions from DLUC, and irrigation rate), and an exhaustive list of all correlation coefficients (and associated p-values) between each input and each output is available in Supplementary Information: Appendix A. The following section will explore relationships between geospatial inputs and results that have strong (>0.7) correlations. Scatter plots were generated for each I/O combination and a select few are available in Supplementary Information: Appendix E (the rest are available upon request).

MFSP results are highly sensitive to the yield that is associated with a particular county: the Spearman Correlation Coefficient between MFSP and areal yield is 0.960 for ethanol and 0.997 for biodiesel (p-values of zero in both cases). This correlation is strong as areal yields are decoupled from assumed capital expenses associated with the farm. Thus, any farm with low areal yield would need to charge more for its crop in order to break even on investment. Due to this dependence on areal yield, it is economically inadvisable to dedicate low productivity lands to producing first-generation biofuel feedstocks. Though this particular relationship is obvious, quantifying the specific strength of the relationship enables comparison of result sensitivity to other inputs.

GHGi is significantly sensitive to the DLUC effects associated with a county (Pearson's r: 0.911 for ethanol and 0.965 for biodiesel, p-value = 0 in both cases). This relationship is strong as GHG emissions due to DLUC effects are added to life-cycle emissions and do not improve the fuel yield in any way; DLUC emissions constitute a GHGi penalty for which there is no upside. DLUC effects are responsible for the particularly high GHGi counties (i.e., counties with a GHGi of 200 $gCO_{2\text{-}eq}$/MJ and above); all counties with this GHGi and above have a non-zero DLUC impact associated with them. Many of these counties also have moderate to low yields, which amplifies the effect. However, DLUC is the primary driver of the assessed GHGi in these cases. This sensitivity demonstrates that land conversion is a critical consideration for biofuel LCAs. Biofuels are an inherently land-intensive technology and production of substantial volumes in the future will not be possible without sizable conversion of land. Marginal and barren lands can be leveraged for future feedstock production, but there is a need for additional datasets with improved scope to accurately quantify DLUC impacts in future analyses.

WDP shows significant correlation with the associated irrigation amount (Pearson's r: 0.955 for ethanol and 0.940 for biodiesel, p-value = 0 in both cases). This correlation is due to the substantial volumes of water that are pulled from surface and sub-surface reservoirs and applied to the crop. These irrigation volumes dwarf the volumes of water depleted during other steps of (or upstream of) the biofuel production process. Due to the fragile state of the water resources (particularly the Ogallala Aquifer), future biomass solutions should leverage low water-intensity pathways where the resource is scarce. EUT effects show significant correlation with the applied nitrogen fertilizer quantities (Pearson's r: 0.830 for ethanol, p-value = 0). Corn is analyzed here as the nitrogen fertilizer demands for soy cultivation are relatively low. This correlation is strong because, in general, more nitrogen fertilizer applied in a given location will result in more nitrogen leaching and run-off. However, two additional factors exist. First, the crop yield is relevant to the EUT calculation as burden is distributed across the total product (corn) amount. Second, grid electricity EUT impacts vary substantially from region to region (Supplementary Information: Appendix A). These EUT impacts could be reduced in the future by leveraging algae pathways (which do not discharge substantial quantities of the valuable nutrient (Batan et al., 2013)) or by ensuring high nitrogen-efficiency application practices are pursued in biomass cultivation stages.

Finally, ALOP demonstrates a significant correlation with areal yield (Spearman's rho: 0.999 and p-value = 0 for both fuels). This relationship is almost deterministic (Figure E.1 in Supplementary Information: Appendix E) as the contribution to land occupation impact is dominated by the farmland that is dedicated to crop production. While upstream land occupation impacts are also tracked, they are dwarfed by the area of land that is required to produce the feedstock. As with the MFSP results, a lower yield causes a distribution of impact onto a smaller final product.

Many of these results are competing, in that making changes to improve one metric will simultaneously worsen another. For example, economic performance might be improved in some cases by applying additional nitrogen fertilizer to increase areal yield. However, this would also cause EUT impacts to increase. WDP performance could be improved by reducing the irrigation rates for a given farm, but the subsequent drop in areal yield would worsen performance in almost all other assessment categories. This interaction is at the heart of what makes sustainability assessment both challenging and important: the relative merits of different solutions must be compared in a consistent way to deliver potential solutions. Future analysis should leverage Multi-Objective Optimization techniques to formally address these tradeoffs.

3.2 AGGREGATED IMPACT RESULTS

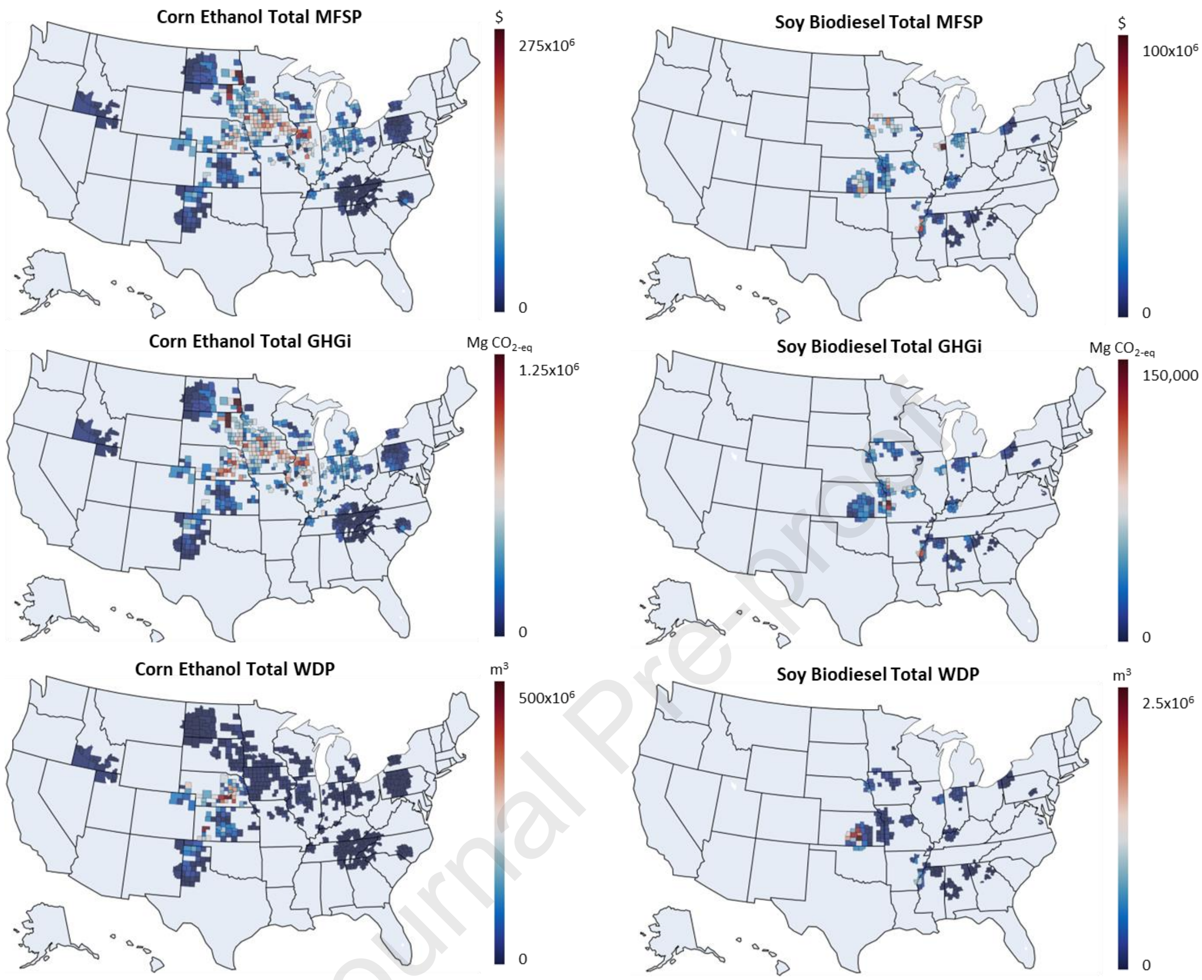

Figure 4a—Total impact amounts for corn ethanol and soybean biodiesel pathways. Plotted metrics include total Minimum Fuel Selling Price (Top), total Greenhouse Gas emissions (Middle), and total Water Depletion Potential (Bottom).

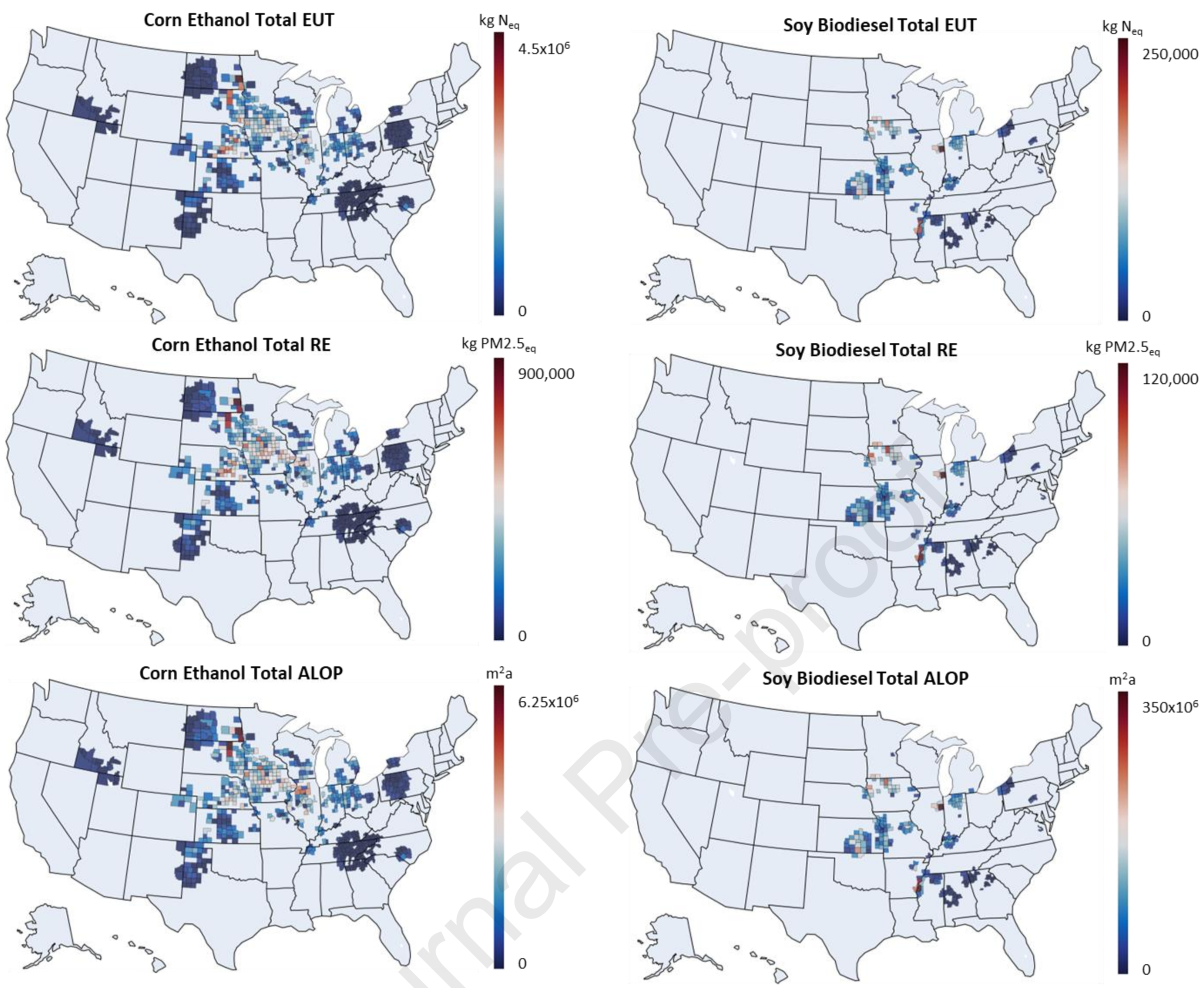

Figure 4b—Continued total impact results for corn ethanol and soybean biodiesel pathways. Plotted metrics include total Eutrophication impacts (Top), total Respiratory Effects (Middle), and Agricultural Land Occupation (Bottom).

National corn ethanol production totaled 14.1×10^{11} MJ (117×10^{8} GGEs) and soybean biodiesel production totaled 1.1×10^{11} MJ (9.1×10^{8} GGEs). Total estimated cost was $34 billion for corn ethanol and $4 billion for soybean biodiesel. Total emissions from corn ethanol were 94.8 Million Metric Tonnes (MMT) $CO_{2\text{-eq}}$ and from soybean biodiesel were 4.7 MMT $CO_{2\text{-eq}}$. Total WDP from corn ethanol was 147×10^{8} m^3 and from soybean biodiesel was 0.35×10^{8} m^3. National total EUT impacts were 447×10^{6} kg N_{eq} from corn ethanol and 10.8×10^{6} kg N_{eq} from soybean biodiesel. RE impacts totaled 94×10^{6} kg $PM_{2.5\text{-eq}}$ emitted due to corn ethanol production and 5×10^{6} kg $PM2.5_{eq}$ emitted due to soybean biodiesel. Finally, ALOP impacts of 70×10^{9} m^2a and 14×10^{9} m^2a were attributable to corn ethanol and soybean biodiesel, respectively.

Total economic and environmental outcome values can be normalized over national biofuel production to deliver the MFSP, GHGi, WDP, EUT, RE, and ALOP impacts of the US biofuels industry in 2017. These results constitute a core product of this work. National, weighted MFSP was $0.0239/MJ ($2.89/GGE) for ethanol and $0.0361/MJ ($4.37/GGE) for biodiesel. National, weighted GHGi was 67 $gCO_{2\text{-eq}}/MJ$ for ethanol and 42 $gCO_{2\text{-eq}}/MJ$ for biodiesel. National, weighted WDP was 0.0104 m^3/MJ for ethanol and 3.2×10^{-4} m^3/MJ for biodiesel. National, weighted EUT was 3.16×10^{-4} kg N_{eq}/MJ for ethanol and 9.8×10^{-5} kg N_{eq}/MJ for biodiesel. National, weighted RE was 6.69×10^{-5} kg $PM_{2.5\text{-eq}}/MJ$ for ethanol and 4.38×10^{-5} kg $PM_{2.5\text{-eq}}/MJ$ for biodiesel. Finally, national, weighted ALOP was 0.052 m^2a/MJ for ethanol and 0.089 m^2a/MJ for biodiesel. Conventional gasoline has a typical retail price of $0.0207/MJ ($2.50/GGE), GHGi of 93 $gCO_{2\text{-eq}}/MJ$ (U.S. Environmental Protection Agency, 2022b), WDP of 0.27×10^{-4} m^3/MJ, EUT of 0.57×10^{-4} kg N_{eq}/MJ, RE of 8.71×10^{-5} kg $PM_{2.5\text{-eq}}/MJ$, and ALOP of 1.3×10^{-4} m^2a/MJ (Wernet et al., 2016b).

Cost contribution breakdowns are depicted in Figure 5. Major contributions to the corn ethanol operating costs include natural gas used for distillation and fermentation (32.5% of OPEX), corn seed (11% of OPEX), agricultural land rent payments (10% of OPEX), grid electricity (8% of OPEX), nitrogen in fertilizer (7% of OPEX), water for fermentation (6% of OPEX), and diesel use on the farm (5% of OPEX). Major contributions to the soybean biodiesel pathway OPEX include agricultural land rent payments (26% of OPEX), methanol (19% of OPEX), soybean seed (16% of OPEX), diesel use on the farm (10% of OPEX), natural gas (8% of OPEX), and grid electricity (6% of OPEX). In making the same rent payments for the land, the soybean biodiesel pathway is disproportionately affected by the expense: because corn grain is roughly 3x as productive as soybean (in terms of average kg/ha yields), each dollar spent on land for soybean production has roughly 3x the impact on the economic balance than it does for corn.

GHGi contribution breakdowns are depicted in Figure 5. Major contributions to the corn ethanol pathway include GHG emissions due to natural gas use for distillation and fermentation (40% of GHGi or $gCO_{2\text{-}eq}$/MJ), N_2O emissions (11% of GHGi or $gCO_{2\text{-}eq}$/MJ), nitrogen in fertilizer (9% of GHGi or $gCO_{2\text{-}eq}$/MJ), diesel use on the farm (8% of GHGi or $gCO_{2\text{-}eq}$/MJ), and emissions due to DLUC effects (7% of GHGi or $gCO_{2\text{-}eq}$/MJ). Major contributions to the soybean biodiesel pathway include GHG emissions due to DLUC effects (33% of GHGi or $gCO_{2\text{-}eq}$/MJ), diesel use on the farm (16% of GHGi or $gCO_{2\text{-}eq}$/MJ), natural gas (16% of GHGi or $gCO_{2\text{-}eq}$/MJ), and potassium in fertilizer (9% of GHGi or $gCO_{2\text{-}eq}$/MJ). Transportation emissions of biomass to refinery and fuel to pump constituted 2% and 5% of GHGi for the corn ethanol and soybean biodiesel pathways, respectively. The corn ethanol production pathway produces a substantial quantity of high-concentration CO_2 as a by-product of fermentation. This flow is not depicted in Figure 5 as a GHGi contributor as the CO_2 emitted is biogenic and is thus burden-free. A substantial volume of this fermentation CO_2 is produced annually (45 MMT in 2017), and these emissions are typically high in concentration (90+%) (Emery & Informed Sustainability Consulting, 2022).

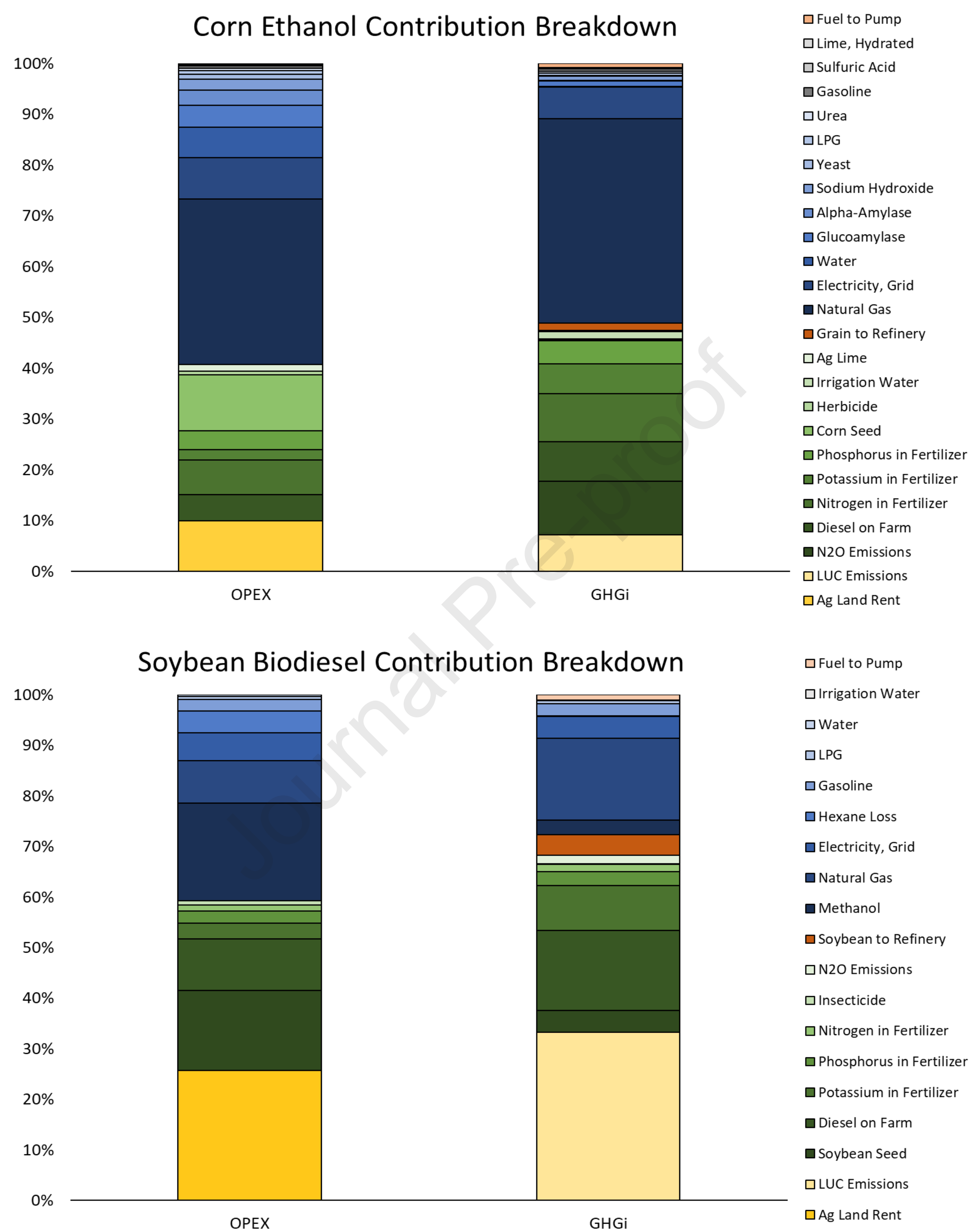

Figure 5—Contribution breakdowns for the operational expenditure (OPEX) and greenhouse gas intensity (GHGi) of both the corn ethanol and soybean biodiesel pathways.

The biofuel industry in 2017 was assessed to have emitted 99.5 MMT $CO_{2\text{-eq}}$, which constitutes a GHG emissions reduction of 42 MMT $CO_{2\text{-eq}}$ when compared to the GHG emissions associated with the equivalent energy of gasoline and diesel. In 2017, the transportation sector was responsible for 1,886 MMT $CO_{2\text{-eq}}$ or about 37% of total national emissions (US Energy Information Administration, 2023), meaning that the industry reduced sector-wide emissions by approximately 2% and national emissions by 0.8%. Energy-based allocation results report a lower GHGi than economic-based allocation results (GHGi of 45 $gCO_{2\text{-eq}}$/MJ for the industry overall) and would constitute sector-wide emissions reductions of approximately 4%. Of all US farmland, approximately 10% (36.4 million hectares) was dedicated to producing corn grain (Perdue & Hamer, 2019), and about 38% of the produced corn grain was dedicated to ethanol production. Approximately 10% of US farmland was dedicated to producing soybeans (Perdue & Hamer, 2019), and about 12% of the produced soybean was dedicated to production of biodiesel. In short, dedication of 5% of US farmland constituted a 2-4% reduction in transportation emissions (depending on the allocation method applied) and a 0.8-1.4% reduction in national emissions. In addition, production of biofuel resulted in WDP impacts of 14.7×10^9 m^3 and EUT impacts of 458×10^6 kg N_{eq} when weighted by relative production share. For perspective, the US consumed 2.8×10^{13} MJ of fossil-based transportation fuels (about 95% of total production) and 1.5×10^{12} MJ of corn ethanol and soybean biodiesel (about 5% of total production) (US Energy Information Administration, 2023). Fossil-based transport fuels constituted a total WDP of approximately 7.6×10^9 m^3 and a total EUT impact of 1.6×10^9 kg N_{eq} with the reported per-MJ intensities taken from EcoInvent 3.8 (Wernet et al., 2016b). Despite producing 18 times more energy for transportation, fossil fuels constituted half the WDP and only 3.5 times the EUT impacts of the 2017 biofuel industry. Emissions reductions are achieved through biofuel production but include a considerable opportunity cost in terms of water and nitrogen intensity.

The sustainability performance of the industry may be improved with some modification. For instance, the high-purity CO_2 vent that is produced during fermentation could be captured and stored.

Capture and successful storage of this volume would constitute an additional GHG reduction of 45 MMT $CO_{2\text{-}eq}$ and would reduce the GHGi of the biofuel industry by nearly 30 $gCO_{2\text{-}eq}/MJ$. However, this volume of high purity CO_2 is also available for industrial or consumptive use. A reduction of 30 $gCO_{2\text{-}eq}/MJ$ is only possible if the entirety of CO_2 from fermentation is captured and stored, so this result presents a best-case scenario. The ethanol produced from corn grain could also be diverted to production of jet fuel, which would help alleviate the emissions associated with an electrification-resistant industry (Beal et al., 2021), but relatively high GHGi associated with corn ethanol suggests that substantial GHG reductions would not be attained in this manner.

If the approximately 18 million hectares of land that were dedicated to biofuel production were not used to produce corn for ethanol and soybean for biodiesel, the same quantity of feed (DDGS and soymeal, specifically) that were produced as coproducts to the industry could likely be produced with less land; a dedicated crop would be more productive per square meter than corn grain and soybean used for biofuel production. This could essentially free-up a large portion of high-productivity agricultural land that could then be dedicated to an advanced biofuel pathway that possesses greater GHGi improvements than corn ethanol or soybean biodiesel. However, the considerable economic implications associated with these changes make it difficult to envision such a scenario without a low-cost advanced biofuel pathway and a much greater public emphasis on reducing environmental impacts. Future analysis should assess these—and other—potential scenarios with a similar geospatial resolution to the analysis presented here, as such work could better guide policymakers to potential improvements in national sustainability.

3.3 AVOIDED GREENHOUSE GAS EMISSIONS COST

The national AGC of the biofuel industry in 2017 was \$147/Mg avoided $CO_{2\text{-}eq}$ (\$126/Mg avoided $CO_{2\text{-}eq}$ for corn ethanol and \$287/Mg avoided $CO_{2\text{-}eq}$ for soybean biodiesel). This value is competitive with the majority of other reported costs of negative emission technologies, which range from \$50–\$500/Mg avoided $CO_{2\text{-}eq}$ (Fuss et al., 2018). As such, both corn ethanol and soybean biodiesel seem attractive means of reducing GHGs; both technologies are proven and commercially deployed. It is important to note that the AGC values presented here are predicated on actual displacement of petroleum fuels (i.e., every MJ of biofuel is assumed to prevent the production of a MJ of conventional fuel that would have been produced in the absence of biofuel production). It is not entirely clear that this is the case as the transportation industry is volatile and there was a nontrivial (10%) portion of corn ethanol exported in 2017 (US Energy Information Administration, 2023). These factors (along with numerous others) make it challenging to determine if biofuel production resulted in a one-to-one reduction in petroleum fuels. County-level AGC results are presented in Figure 6 and show low AGC results in areas where corn ethanol and soybean biodiesel production are concentrated. Corn ethanol and soybean biodiesel constitute a cost-competitive means of reducing GHG emissions in the transportation sector. However, the associated opportunity costs (particularly regarding water intensity) are frequently omitted from debates of the industries performance.

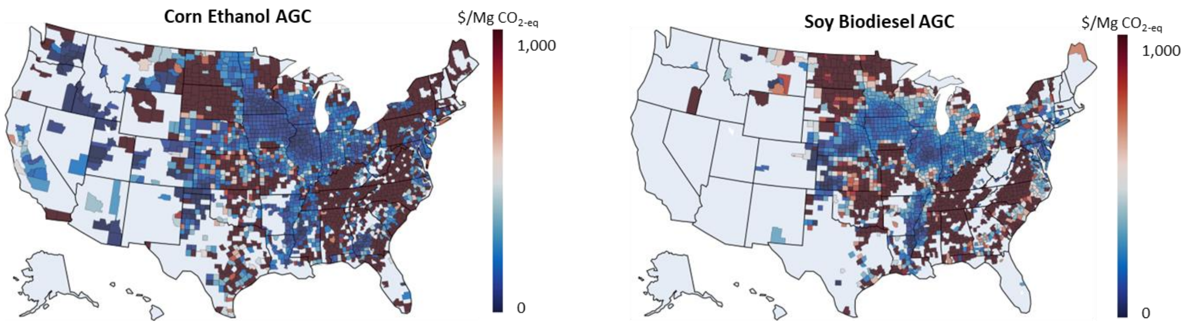

Figure 6—Avoided cost of greenhouse gas emissions for the corn ethanol and soybean biodiesel pathway. Results depict the effective cost of avoided greenhouse gas emissions when compared to conventional, petroleum-based fuels (i.e., gasoline) in $/Mg $CO_{2\text{-}eq}$ avoided.

4. CONCLUSION

This study evaluates the sustainability performance of the 2017 biofuel industry. Results in this work provide sustainability outcomes with high geospatial resolution. Economic (MFSP) and environmental (GHGi, WDP, EUT, RE, ALOP) results are presented at a county-level for the contiguous United States. Aggregate totals, and high-resolution, nation-wide sustainability results are delivered for the industry. These results highlight 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 99.5 MMT $CO_{2\text{-eq}}$ and total estimated expenditure is $37.8 billion. The weighted average GHGi for corn ethanol is 67 $gCO_{2\text{-eq}}$/MJ and 42 $gCO_{2\text{-eq}}$/MJ for soybean biodiesel when DLUC emissions are included. The weighted average MFSP results are $0.0239/MJ ($2.90/GGE) for corn ethanol and $0.0362/MJ ($4.37/GGE) for soybean biodiesel. Combined economic and environmental metrics show biofuel to be a strong performer when compared to conventional fuels and other negative emission technologies. Specifically, when compared to conventional diesel and gasoline, biofuels in 2017 reduced overall emissions by 42 MMT $CO_{2\text{-eq}}$ at an additional cost of $6.2 billion. The national AGC of the biofuel industry in 2017 was $147/Mg avoided $CO_{2\text{-eq}}$ ($126/Mg avoided $CO_{2\text{-eq}}$ for corn ethanol and $287/Mg avoided $CO_{2\text{-eq}}$ for soybean biodiesel), which is competitive when compared to other negative emission technologies. However, the land and water opportunity costs that are associated with biofuel production (and the total emissions reduction achieved) imply that the same portion of land dedicated to biofuels in 2017 could be better leveraged for sustainability. In the future, this model framework can be leveraged to evaluate potential future-state scenarios that include different biomass-to-biofuel pathways and can be sued to define the relative improvements and costs compared to existing technology. Such analysis would enable a holistic, consistent and high-resolution evaluation of different potential production options and support strategic investment to meet sustainability goals.

Data Availability: Associated data from all model executions is available in the appendices of this work or upon request.

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Author Contributions:

Jack P Smith: Conceptualization, Data curation, Formal analysis, Methodology, Software, Validation, Visualization, Writing – original draft. **Braden J Limb**: Investigation, Data curation, Formal analysis, Methodology, Writing – review & editing. **Colin M Beal**: Conceptualization, Funding acquisition, Investigation, Methodology, Supervision, Writing – review & editing. **Kelly R Banta**: Data curation, Investigation, Writing – review & editing. **John L Field**: Methodology, Funding acquisition, Writing – review & editing. **Steven J Simske**: Conceptualization, Funding acquisition, Supervision, Writing – review & editing. **Jason C Quinn**: Conceptualization, Funding acquisition, Methodology, Project administration, Resources, Supervision, Writing – review & editing.

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- Corn Ethanol and Soybean Biodiesel evaluated with multiple LCA metrics
- Country wide and county level results are provided for the 2017 biofuel industry
- Total life cycle, greenhouse gas emission volume of 99.5 million Mg CO2-eq produced in 2017
- Combined carbon intensity of 65.3 g$CO_{2\text{-eq}}$/MJ for corn and soy based biofuels in 2017
- Techno-economic results show biofuels result in $1.8 billion over the displaced gas/diesel cost

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: