Journal of Cleaner Production 321 (2021) 128890

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Creating a harmonized time series of environmentally-extended input-output tables to assess the evolution of the US bioeconomy - A retrospective analysis of corn ethanol and soybean biodiesel

Andre F.T. Avelino *, Patrick Lamers, Yimin Zhang, Helena Chum

National Renewable Energy Laboratory, 15013 Denver West Parkway, Golden, CO, 80401, USA

A R T I C L E I N F O

Handling editor: Yutao Wang

Keywords:
Environmentally-extended input-output
Input-output life cycle assessment
Bioeconomy
Biofuels
Corn ethanol
Soybean biodiesel

A B S T R A C T

Expanding the domestic bioeconomy can help diversify the use of national resources and reduce emissions. Evaluating the sustainability of a growing bioeconomy, however, is inherently complex since it spans several sectors and supply chains. It requires a comprehensive, integrated analysis framework to assess the developments across the traditional sustainability dimensions. Further, the assessment of bioeconomy developments requires a robust baseline of historic data and trends. In this paper, we analyze the evolution of the biofuel portion of the US bioeconomy, focusing on two fuels that had an exponential growth in the last two decades: corn ethanol and soybean biodiesel. For this purpose, we created a novel time series of harmonized environmentally-extended input-output (EEIO) tables based on a publicly available model from the US Environmental Protection Agency and expanded its disaggregation to reflect the main supply chains of the biofuels sectors. The EEIO time series provides the historical evolution of these biofuels relative to the rest of the economy as well as on an energy-unit basis. We find that, except for energy use, the broader US economy declined in both resource intensity and most environmental impacts when normalized per one million dollars of gross domestic product. Deviating from this trend are freshwater ecotoxicity and human toxicity, mainly attributable to the expansion of commodity crops and the increase of domestic oil and gas extraction respectively. We also find that the biofuel industry's total socioeconomic, resource use and environmental impacts grew with their production increases over time. However, the industry's maturation and scale-up, combined with higher feedstock yields, contributed to a reduction of most impacts on an energy-unit basis over time.

1. Introduction

The bioeconomy can be defined as a set of economic activities related to the invention, development, production, and use of biological products and/or processes for the production of renewable energy, materials, and chemicals (Biofuture Platform, 2018). Many governments, including the United States (US), encourage the expansion of a domestic bioeconomy, among others to enable the use of local, abundant biomass and waste resources for advanced biofuels, bioproducts, and biopower (U.S. Department of Energy, 2019). Whereas the expansion of a US bioeconomy is desired, the US Biomass Research and Development Board has recently stressed the need for macroeconomic analyses of the entire bioeconomy to allow adequate evaluation of its benefits and tradeoffs (Biomass R&D Board, 2019). Evaluating the bioeconomy is inherently complex since it spans economic sectors and industries. It requires a comprehensive, integrated analysis framework to assess its development across the traditional sustainability dimensions of social, environmental, and economic metrics. Here, we describe a framework that integrates environmental and socioeconomic metrics via a life cycle based environmentally-extended input-output (EEIO) model to quantify the effects of an expanding US bioeconomy from a macro-level perspective.

EEIO models have been used to evaluate the relationship between economic activities and downstream environmental impacts since Leontief (1970) (Malik et al., 2019). Multiple EEIO models exist for the US (Tables SI–1), however their industrial classification, accounting structure, and environmental indicators remain inconsistent, limiting the possibility of intertemporal comparisons. In 2016, the US

* Corresponding author.
E-mail addresses: Andre.FernandesTomonAvelino@nrel.gov (A.F.T. Avelino), Patrick.Lamers@nrel.gov (P. Lamers), Yimin.Zhang@nrel.gov (Y. Zhang), Helena.Chum@nrel.gov (H. Chum).

https://doi.org/10.1016/j.jclepro.2021.128890
Received 22 October 2020; Received in revised form 9 August 2021; Accepted 30 August 2021
Available online 3 September 2021

Environmental Protection Agency (EPA) developed the open source coded, publicly available US Environmentally-Extended Input-Output (USEEIO) model (Yang et al., 2017). The USEEIO is based on national datasets including the 2007 benchmark Input-Output (IO) tables and 1873 environmental indicators encompassing air, water and soil pollutants, energy use, mineral production, water withdrawals and release, and land use. While it is the most comprehensive public EEIO model available for the US, its economic and environmental datasets are not temporally aligned and not available for multiple time steps. Thus, it is rather unsuited for historical trend analysis. Building upon the public USEEIO version, we temporally aligned the economic and environmental accounts and created a novel time series of harmonized EEIO datasets for the US. This consistent time series allows for an evolutionary perspective of specific technologies, technology portfolios, and related impacts. It also provides a comprehensive picture of economic and environmental conditions at the most disaggregated, i.e., detailed level for publicly available sectors and commodities.

We apply the framework to a historical impact analysis of the expanding US bioeconomy, in the form of a retrospective case study for first generation biofuel technologies including corn ethanol from dry-milling and biodiesel from soybean oil. Both fuels play an integral role within the current US bioeconomy, its exponential capacity expansion during 2002–2017, and are well documented with publicly available data on production volumes, technology evolution, practices, facilities, and consumption patterns.[1] The case study also showcases and specifies the methodological basis and data requirements to detail specific sectors of the economy for a historical trend analysis, i.e., the disaggregation and compilation of socioeconomic and environmental data related to the bioeconomy, and can be used as a blueprint for other sectoral impact analyses. Few integrated hybrid EEIO-LCAs have been conducted for biofuel pathways, and none has yet described their evolution of impacts for the US. Harto et al. (2010) evaluated the effects of US produced corn ethanol and soybean biodiesel in a hybrid framework, but only related to the water consumption profile per passenger vehicle mile traveled. Strogen and Arpad (2013) compared environmental releases from the construction, manufacturing, operation, and maintenance of the US distribution infrastructure (and thus only a portion of the supply chain) for petroleum and lignocellulosic ethanol. Liu et al. (2018) used a similar approach as the one presented here, but evaluated fast pyrolysis and hydro-processing biofuel pathways for a single timestep.

Hence, this paper's contributions are twofold: (1) a novel time-series of harmonized EEIO-LCA datasets for the US for 2002–2017 at five years intervals, and (2) an integrated hybrid EEIO-LCA analysis for first generation biofuels (corn ethanol and soybean biodiesel) in terms of economic, environmental and resource use contributions to the US in a consistent framework. In the next section we summarize the methodology used to create the EEIO time series for the US, and the data sources for the dry-mill corn ethanol and soybean biodiesel supply chains. Full details are presented in the Methodological Appendix. The evolution of the impacts for both biofuels in the US context is presented in section 3, followed by discussion and conclusions.

2. Material and methods

2.1. EEIO time series

We developed a time series of national EEIO tables, composed of the benchmark IO tables published by the US Bureau of Economic Analysis (BEA), and fully harmonized them to 2012 North American Industry Classification System (NAICS) codes. Then, we constructed a comprehensive set of temporally aligned physical accounts covering employment, energy, water, mineral extraction, land occupation, and emissions to air, water, and soil. In contrast to the public USEEIO dataset, our physical accounts were constructed to match, or align closely, to the BEA economic data vintages, providing an integrated picture of production and environmental burdens for 2002, 2007, and 2012. Finally, we also expanded these physical accounts for 2017 and linked them to the latest economic accounts of 2012. Once BEA releases the 2017 IO accounts, this temporal misalignment can easily be adjusted.

The economic accounts for each year include the Make, Use, and Imports tables in current producer's values before redefinitions (i.e., without adjustments to secondary commodities, see Horowitz and Planting (2009) for specific details). To allow intertemporal comparisons, we created a common schema based on the 2012 NAICS denoted Harmonized BEA (HBEA) that has 345 commodities and 346 industries. This is the maximum level of detail that does not require further disaggregation of commodities and sectors in the 2002 tables. In developing the physical accounts, we used the HBEA disaggregation for 2002, and the original BEA disaggregation for 2007 and 2012; hence all tables are harmonized to 2012 NAICS and offer the finest level of detail publicly available.

In addition to the original tables in current prices, we also created fully deflated tables in constant 2012 prices, which are essential when comparing the economic structure across years as nominal price effects can distort the observed change in technological relationships (Dietzenbacher and Los, 1998; Tukker et al., 2018). The deflation was performed using the SUT-RAS algorithm (Temurshoev and Timmer, 2011) based on price indexes for gross output by industry, value added by industry, intermediate purchases by industry, final demand by component, total exports and total imports from the National Product and Income Accounts.[2]

Most of the physical accounts were constructed following the same methodologies used in the original USEEIO (Yang et al., 2017) and encompass the same range of physical indicators. The USEEIO is freely available as a dataset, requiring the use of a separate open-source code to compile and transform the datasets.[3] Full details of our methodology to create the time series EEIO datasets are detailed in the Methodological Appendix. A summary of our data sources is provided in the Supplementary Information to this paper (Tables SI–2).

The life cycle impact assessment (LCIA) characterization factors were expanded to include additional chemicals from the physical accounts that were not present in the original USEEIO model. These factors were derived from the Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts (TRACI) (Bare, 2011) and reflect average impact potentials for the entire US for each chemical. They are assumed constant for the four years. The same number of impact categories were maintained (Tables SI–3). The relationships between physical accounts and impact categories are shown in Fig. 1.

2.2. Bioeconomy disaggregation

A key issue in analyzing biofuels, and more broadly bioeconomy sectors, is the absence of specific classifications for most of them in publicly available databases (Haggerty, 2012). This implies that several bioeconomy sectors are usually aggregated into broader activities which do not properly reflect their production/consumption structure. In our case, both biofuel sectors and their feedstocks (corn and soybean

[1] See e.g. datasets from the Renewable Fuels Association (https://ethanolrfa.org/statistics/), National Biodiesel Board (https://www.biodiesel.org/production/production-statistics), EIA Monthly Energy Review (https://www.eia.gov/totalenergy/data/monthly/).

[2] Data are from the National Income and Product Accounts (Bureau of Economic Analysis, 2019) underlying tables of real gross output, real value added and real intermediate inputs, and tables2.4.4, 3.9.4, 4.2.4 and 5.3.4.

[3] USEEIO dataset: https://edg.epa.gov/metadata/catalog/main/home.page; code repository to compile and transform the datasets: https://github.com/USEPA/USEEIO.

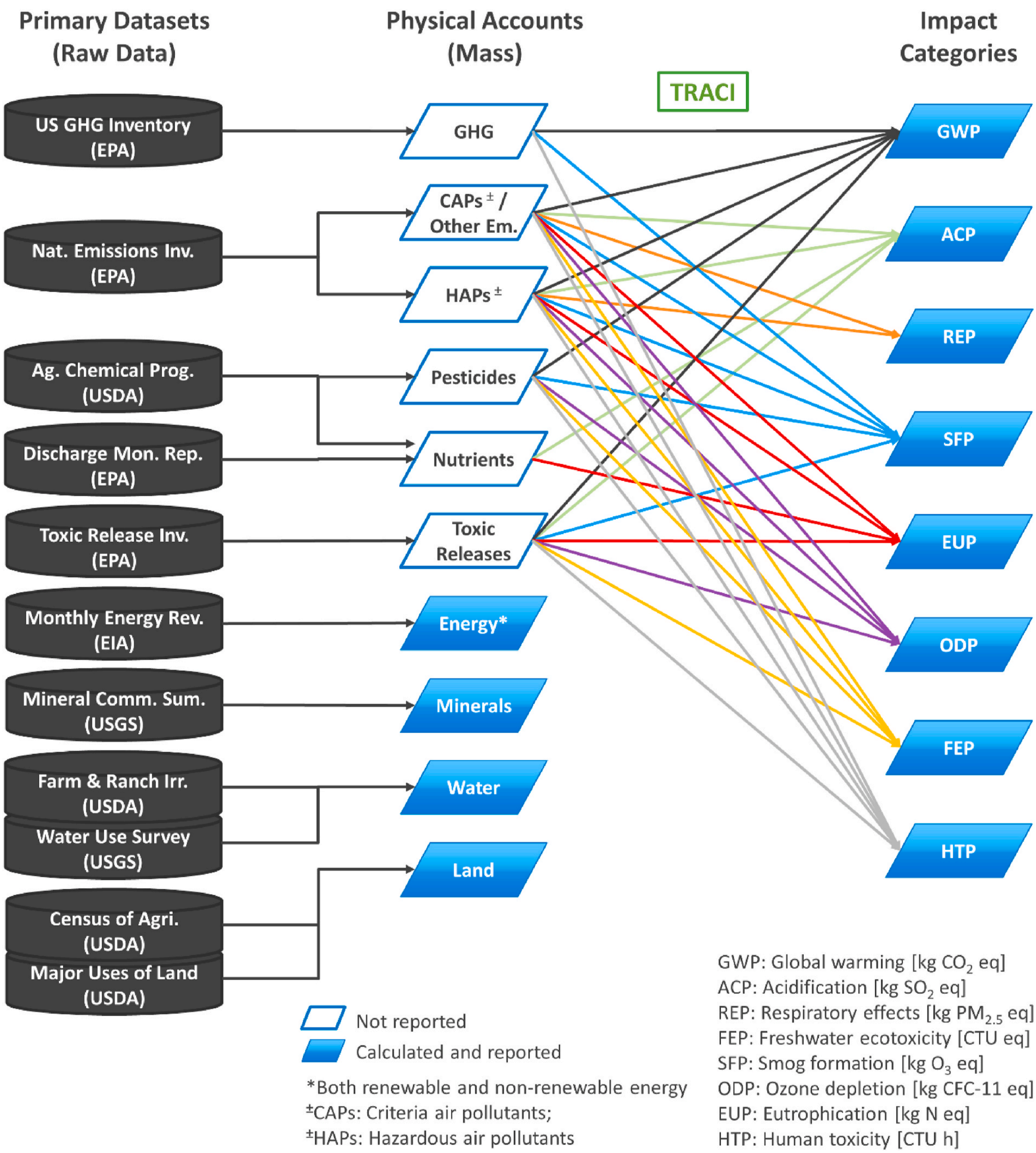

Fig. 1. Flows between environmental data sources, physical accounts and impact categories.

farming) are aggregated, requiring a disaggregation step.

Corn ethanol production (NAICS 325193) is included in the original BEA tables as part of the Other Basic Organic Chemical Manufacturing sector (NAICS 325190). However, simply using the latter sector to represent the corn ethanol industry would generate incorrect results, because the inputs, sales and environmental profiles of the aggregated sector are significantly distinct[4] (Steen-Olsen et al., 2014). Therefore, we disaggregated the main inputs to and outputs from the ethanol manufacturing process across all time-steps, including, among others, corn (farming) and co-products from dry-mill ethanol production, i.e., distiller's dried grains with solubles (DDGS), corn oil, and fermentation CO_2. Similarly, soybean biodiesel (32519A) was disaggregated from sector 325190, and its main supply chain (soybean farming, crude soybean oil processing, and soybean oil refining) and co-products (glycerin) were disaggregated from other sectors. The disaggregation procedure followed balancing constraints from the national accounting framework, as well as aggregation constraints from the original industries. Tables SI–4 shows the original and disaggregated sectors and commodities and Figure SI-1 shows the relationships among them. The description of unit conventions used in this paper is available in Tables SI–5.

Corn and soybean farming input uses were based on USDA's Cost of Production Surveys for 2002, 2007 and 2012 (U.S. Department of

[4] This sector includes the manufacturing of biofuels, calcium and carbon organic compounds, enzymes, fatty acids, plasticizers, silicone, synthetic sweeteners, etc.

Agriculture, 2020a). Fuel and energy consumption for corn and soybean was further disaggregated using physical breakdown from Foreman (2014) and Pradhan et al. (2009), respectively, and prices from the US Energy Information Administration. Purchasing prices were converted to producer prices using BEA's Margins Tables for each year. These sectors were assumed to produce a single commodity each: corn and soybean, and their sales structures (i.e., how much corn/soybean each sector in the economy consumed in the year) followed the structure of the aggregated commodity (1111B0 and 1111A0 respectively).

The dry-mill corn ethanol industry's inputs were based on Shapouri and Gallagher (2005), Hofstrand (2019) and Urbanchuk (2013), adjusted for trade and transportation margins according to the Margins Tables. The amount of fuel ethanol manufactured was based on the dry-mill share of total fuel ethanol production in the year as shown in Figure SI-2 (Chum et al., 2014; U.S. Energy Information Administration, 2019b). DDGS production and prices were obtained from USDA's US Bioenergy Statistics (U.S. Department of Agriculture, 2018), and corn oil production was based on Hoffman and Baker (2010), U.S. Department of Agriculture (2009), and Renewable Fuels Association (2013). Ethanol sales structure followed the same structure as gasoline, maintaining the existing economic flow constraints from the aggregated commodity 325190. DDGS consumption was allocated to cattle farming and animal food manufacturing only, and corn oil sales were allocated according to their respective aggregated commodities. Main parameters for the industry are shown in Table 1.

The soybean biodiesel industry production costs were based on several studies (Table 2) covering the 2002–2007 period. The main inputs (soy oil and methanol) were assumed fixed at 12.89 kg/L and 0.82 kg/L as no significant variation was found between studies. Average annual prices for methanol were obtained from Methanex (2020). The amount of biodiesel from soybean oil manufactured was based on the soy oil share of total biodiesel production in the respective year, as shown in Figure SI-3 (International Grains Council, 2008; Korbitz et al., 2003; U.S. Energy Information Administration, 2019a). Biodiesel sales structure followed the same structure as diesel, maintaining the existing economic flow constraints from the aggregated commodity 325190.

Soybean oil processing and refined soybean oil manufacturing yields were estimated as 174.8 kg crude oil/tonne soybean and 0.98 L refined oil/L crude oil, respectively, based on U.S. Department of Agriculture (2020b). Production volumes were estimated based on soybean oil supply data from U.S. Department of Agriculture (2018). Their production structures were based on sectors 311224 (Soybean and other oilseed processing) and 311225 (Fats and oils refining and blending) respectively by replacing their main feedstocks with the estimated data. Main parameters for the industry are shown in Table 2.

Table 1
Main parameters for ethanol manufacturing (dry-mill only).

	Unit	2002	2007	2012	Sources
Ethanol Production	MM L	4,861	21,250	46,607	Chum et al. (2014)
Outputs					
Ethanol Yield	L/kg	0.40	0.41	0.42	Shapouri and Gallagher (2005), Gallagher et al. (2016)
DDGS Yield	kg/kg	0.32	0.29	0.21	Shapouri and Gallagher (2005), Wu (2008), Gallagher et al. (2016)
Corn Oil Yield	kg/kg	0.002	0.002	0.009	Mueller and Kwik (2013)
Inputs					
Corn	kg/L	2.50	2.43	2.38	Shapouri and Gallagher (2005), Gallagher et al. (2016)
Total Energy Use	MJ/L	9.70	8.42	7.36	Shapouri and Gallagher (2005), Wu (2008), Mueller and Kwik (2013), Graboski (2002)
Electricity	kWh/L	0.31	0.18	0.20	
Natural Gas	MJ/L	7.45	6.61	5.67	
Coal	MJ/L	1.11	1.14	0.98	
Water	L/L	4.70	3.00	2.90	Shapouri and Gallagher (2005), Wu et al. (2009), Wu (2019)

Table 2
Main parameters for biodiesel manufacturing (soybean oil only).

	Unit	2002	2007	2012	Sources
Production	MM L	36	1465	2033	EIA (2019b)
Outputs					
Biodiesel Yield	L/kg	1.08	1.08	1.08	VanWechel et al. (2003), Fortenbery (2005), Haas et al. (2006), Paulson and Ginder (2007), Hofstrand (2020)
Glycerin Yield	kg/kg	0.10	0.13	0.13	
Inputs					
Soy Oil	kg/L	0.90	0.90	0.90	VanWechel et al. (2003), Fortenbery (2005), Haas et al. (2006), Paulson and Ginder (2007), Van Gerpen (2008), Hofstrand (2020)
Methanol	kg/L	0.02	0.02	0.02	
Total Energy Use	MJ/L	2.49	2.49	2.49	
Electricity	kWh/L	1.81	1.81	1.81	
Natural Gas	MJ/L	0.16	0.16	0.16	
Water	L/L	2.00	2.00	2.00	Hofstrand (2020)

The estimation of physical accounts which do not have point-source data followed the same estimation procedure as for other sectors of the economy. For ethanol manufacturing, facility-level data from EPA's Toxic Release Inventory, National Emissions Inventory, Discharge Monitoring Report, and Greenhouse Gas Reporting Program Subpart C were used to estimate national-level releases. However, not all dry-mill ethanol plants report emissions and releases because several small facilities fall under the reporting requirement thresholds of these databases. Therefore, we complemented the reported information at state-level by assuming that the non-reporting ethanol dry-mills released chemicals at the same rate per gallon as the weighted average of ethanol facilities in the state. The states' weighted averages were calculated by chemical (kg emitted per million gallon of fuel ethanol), over the entire distribution except outliers (defined as 1.5 times above/below the third/second quartile). Because this is one possible estimation option, we report the uncertainty in impacts in the results. The range reflects the lower bound of using only the reported data, and the upper bound of using a homogenous weighted average for the US for all facilities (reporting or not). The largest uncertainty is found in ozone-related emissions, due to limited data points available for all years, with a variation of up to 6000% from the baseline emissions. However, due to its relatively low impact in the economy, this variation is not significant for the results. The most important uncertainty that can significantly affect the results is in human toxicity (HTP).

Due to its small industry size, the variety of feedstocks used (different vegetable oils, used cooking oils, and animal fats), and the limited number of facilities reporting, soybean biodiesel is fairly underrepresented in these databases (especially when compared to corn ethanol). We narrowed down our soybean biodiesel sample to five facilities that utilize soybean oil as feedstock and that consistently report across all the aforementioned databases[5]: AC&S (WV, 3 MPGY), Deerfield Energy (MO, 30 MGPY), Louis Dreyfus Agricultural Industries (IN, 90 MGPY), Owensboro Grain Biodiesel (KY, 45 MGPY) and Stepan Co. (IL, 21 MGPY). Emissions were weighted averaged for these facilities for each year and scaled up using the total national soybean biodiesel production. The uncertainty range reflects the lower bound of using the lowest plant emission factor, and the upper bound of using the highest plant

[5] Only three facilities appear in the Greenhouse Gas Reporting Program Subpart C (Louis Dreyfus Agricultural Industries, Owensboro Grain Biodiesel and Stepan Co.).

emission factor, both scaled up.

Combustion emissions of ethanol and biodiesel for use in vehicles were derived from GREET (Argonne National Laboratory, 2019) and represent releases from a theoretical (spark ignition) internal combustion engine vehicle burning E100 and B100, respectively. Impacts from fuel distribution, i.e., from plant gate to consumers' vehicles tanks, are calculated using the wholesale, retail and transportation margins from the margins table for final demand based on consumption of petroleum refinery products.

The final expanded harmonized model has 352 sectors and 355 commodities. We applied this model to perform an impact analysis to quantify the contribution of fuel ethanol from dry-mills and soybean biodiesel production to selected resource use and environmental impacts from the whole US economy on a well-to-wheel (WTW) basis for 2002, 2007, 2012 and 2017. Given that the benchmark IO table for 2017 has not been released, 2017 uses the economic structure of 2012; hence any technology change in the period will not be captured in terms of interindustrial dependency. Nonetheless, changes in environmental emissions will reflect changes in technology for 2017. The model applied is a single-region domestic model: only economic impacts and emissions occurring in the US are accounted for. Foreign impacts and feedback effects from international trade are not captured.

Results are presented first as absolute effects, i.e., the contribution of the total dry-mill corn ethanol/soybean biodiesel sectors to each US socio-environmental impact category in the respective year, accounting for all co-products and thus providing a 'footprint' of the entire industries (which forms a central part of the US bioeconomy). Secondly, we illustrate the impacts of the commodities corn ethanol and soybean biodiesel on a unit basis, accounting for co-products via economic value.

3. Results

3.1. National trends

We find that the national level absolute resource uses and environmental releases by the US economy over the four years (Tables SI–6) follow specific patterns. Total US employment, gross domestic product and mineral extraction followed the overall economic trend of the period with the 2008 economic crisis separating the series into two distinct periods. The 2002, 2007 years reflect the economic expansion phase with low unemployment and high construction activity, driving domestic mining of sand, gravel, and stone. The 2008 financial crisis drove the sharp decline between 2007 and 2012, with the 2012 and 2017 years reflecting the recovery period following the recession.

The declining trend of total water withdrawals is particularly linked to significant structural changes in the energy sector and irrigation technology in agriculture. Economic growth between 2000 and 2005 increased water consumption for electricity generation, following the upward trend in the energy accounts (Table SI-2 in the Supplementary Materials), but overall water use declined, especially due to a reduction in irrigation withdrawals attributable to a continuous replacement of traditional surface irrigation systems with more efficient sprinkler systems (Dieter et al., 2018). In the later years, the reduction in water withdrawals was primarily driven by power generation, mainly due the shift from coal to natural gas fired power plants that cut onsite water use by more than 50% (Kondash et al., 2019).

Total land occupation increased over the period driven by all land types, with a slight reduction in 2017, due primarily to a drop in oil and gas non-competitive leases in Nevada. There is also an overall growth in nitrogen (N) and phosphorus (P) consumption and related environmental releases. These can largely be attributed to the increase in corn and soybean acreages over the time span. Although most N and P releases came from agricultural sectors, release from non-agricultural sectors also increased between 2007 and 2017.

Fossil fuel combustion was the primary driver of CO_2 releases, with emissions from the electricity sector consistently decreasing after the 2008 financial crisis, and those from transportation following the overall economic dynamics (sharp decline between 2007 and 2012 followed by a rebound in the later period). The reduction in releases of ozone depleting chemicals reflects the phaseout of class II Ozone-Depleting Substances during the period: the significant decline in HCFC-141b use from 2002 to 2012 was due to ceased production of this chemical in 2003, while the reduction in HCFC-142b between 2007 and 2012 was driven by its production ban in 2010 (U.S. Environmental Protection Agency, 2019).

The reduction in criteria air emissions was mainly driven by fuel switching (from coal to natural gas and from fossil to renewables, to a lesser extent) for electricity generation leading to a significant reduction in SO_2, NO_x and PM emissions. Also contributing to the overall reduction in air emissions were mobile sources due to a combination of improvements including the use of advanced emission controls to meet more stringent emission standards, switching to low and ultra-low sulfur diesel, and adoption of more efficient engines (U.S. Environmental Protection Agency, 2014; 2020a). Soil and water emissions were primarily driven by pesticide use in agriculture, and its evolution is partially attributed to recent changes in the type of pesticides applied (Hellerstein et al., 2019).

Normalizing the effects per one million US$$_{2012}$ of Gross Domestic Product (GDP) (Figure SI-4), we observe an increase in labor productivity with a decline in resource intensity (except for energy use). Moreover, for several environmental impact metrics, there is a reduction in negative environmental effects per dollar of GDP: acidification (ACP), global warming (GWP), ozone depletion (ODP), smog formation (SFP), and respiratory effects (REP). Ecotoxicity (FEP) and human toxicity (HTP) appear to exhibit an upward trend apart from a slight drop in 2007. While the former has been driven by crop farming, particularly due to the expansion of soybeans, the latter has been driven by the expansion of domestic oil and gas production (especially releases of acrolein and formaldehyde). Eutrophication (EUP) displays a decreasing trend despite a peak in 2012. Such peak was driven by a relative increase (to GDP) in water releases of nitrogen and phosphorus in both sewage systems and crops due to the slower economic growth from 2007 to 2012 and the 2012 drought that affected the agricultural sector.

3.2. Bioeconomy trends – absolute effects

Analyzing the contributions of the corn ethanol and soybean biodiesel industries to the US national totals for the years and metrics evaluated (Figs. 2–4), we can determine total direct and indirect impacts due to the production of ethanol/biodiesel and related co-products in the respective years, as well as the combustion of fuel ethanol/biodiesel consumed domestically. The national absolute trends are included in each figure for comparison. Note that the 2017 results (highlighted in a non-solid pattern) should be interpreted as the economy in 2012, producing and emitting as in 2017 due to the temporal misalignment between environmental and economic datasets in that year.

The value added (GDP) and job contributions from dry-mill ethanol production to the total US economy grew more than fivefold between 2002 and 2017 (Fig. 2). The upstream supply chains were a major contributor accounting for more than 65% of GDP and 74% of jobs while the ethanol conversion industry itself only accounted for 20% and 6% respectively of the total sector contribution per year on average.

By comparison, due to the much smaller size of the industry, soybean biodiesel contributed much less to the total US economy and environmental impacts, with most metrics reporting below 1%. Nevertheless, in relative terms, biodiesel had a significant increase in impacts from 2002 to 2007 due to a vast expansion of its production volume (from 9 to 387 million gallons), despite a change in many plant operations from batch production to continuous (Paulson and Ginder, 2007). The relative GDP and job contributions from soybean biodiesel production to the US economy also grew significantly more than ethanol between 2002 and 2017 (Fig. 2). Similar to corn ethanol, the upstream supply chains were a

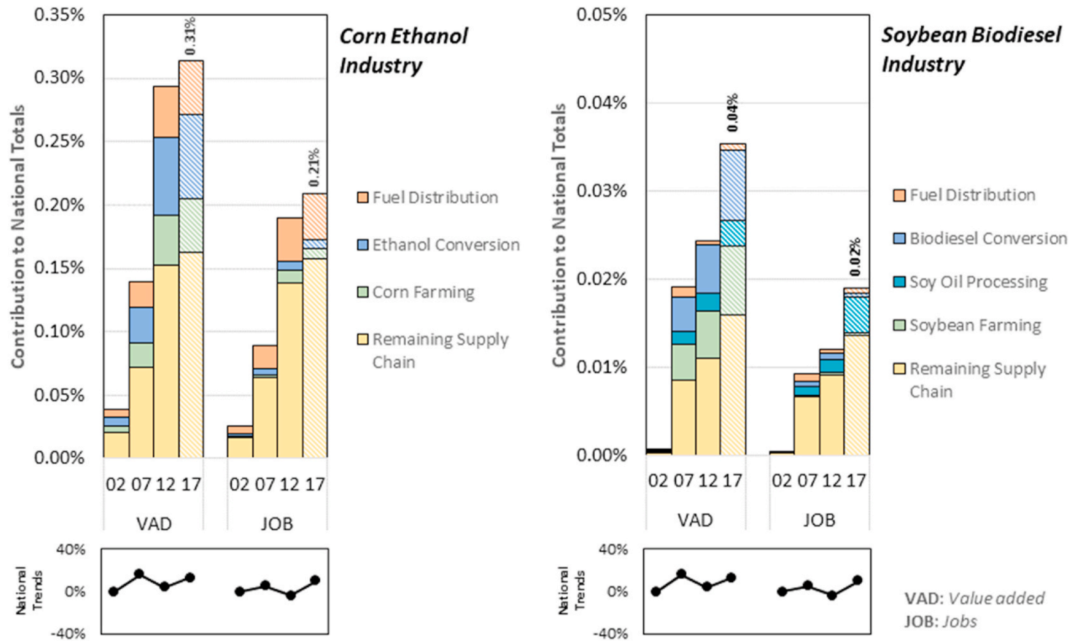

Fig. 2. Trend in the share of value added and jobs by biofuel industry in relation to the total US economy in the respective year.

major contributor accounting for more than 75% of GDP and 87% of jobs while the biodiesel conversion industry itself accounted for 22% of GDP and 8% of jobs on average.

It is worth noting that total employment from both biofuel industries grew despite the sharp drop in national employment levels between 2007 and 2012. The positive trend in these economic effects and in the following environmental metrics is a direct reflection of the exponential growth experienced by the sectors over the analysis period (Figures SI-2 and SI-3).

When evaluating resource use over the period, we can clearly discern the impacts of the 2012 drought, particularly on water use, including freshwater withdrawals (H2O) and land occupation (LOC), manifested in the increased irrigation and lower corn yields per acre planted (Fig. 3). While minerals use (MIN) is not directly related to corn farming, its impact stems from the production of fertilizer for corn farming (the corn supply chain). The drought-related reduction in soybean yields in 2012 (roughly −4%) was relatively smaller than that for corn (−18%) and dampened the impacts on crop-driven metrics. As expected, due to the industry's growth, resource use increased in the period (Fig. 3). While minerals use (MIN) is not directly related to soybean farming, its impact stems from the production of fertilizer for farming (the soybean supply chain).

Both sectors' releases to air, water, and soil, characterized via TRACI showed an overall increase in impacts, relative to the total impacts from the US economy (Fig. 4). This relative increase in eutrophication (EUP), freshwater ecotoxicity (FEP), and respiratory effects (REP) was driven by the exponential growth of both sectors, which increased at a faster pace than the rest of the US economy on average across the period evaluated. Except for ozone depletion (ODP) and human toxicity (HTP), the observed increases from ethanol production were mainly driven by environmental releases attributable to corn farming. Also, the peak in contribution observed in EUP, ACP (almost same contribution as 2017), FEP and REP in 2012 is directly related to lower corn yields due to the drought that year. For most air-related metrics, soybean farming represented a significant portion of the biodiesel industry impacts. For both fuels, most of the sharp decline in REP between 2012 and 2017 can be attributed to a change in assumption in the number of passes for conventional tilling in the 2017 NEI (reduced by two-thirds from the previous NEIs), which significantly reduced particulate matter emissions for corn and soybean farming (U.S. Environmental Protection Agency, 2020b). For comparison, the trends without tilling emissions for REP for ethanol and biodiesel are shown in Figure SI-5 and Figure SI-6, respectively.

3.3. Bioeconomy trends – relative effects

The relative trend analysis shows how the impacts resulting from producing one energy unit (1 MJ) of the respective fuel evolved over time. This result is obtained by dividing the total effects from producing the fuel (not considering other co-products) from each year by the total US dry-mill ethanol/biodiesel production in the respective year. In Figs. 5–7, for illustration purposes, the year with the higher impact per metric is used as the respective benchmark (100%) for that metric. The impacts of the other years are then shown as a relative comparison to that benchmark. The impacts are broken down into supply chain steps (stacked bars), including upstream supply chain activities, farming, conversion, fuel distribution, and end-use combustion.

Across socioeconomic effects, value added remained relatively constant, while jobs declined steeply per MJ of corn ethanol over the 2002–2017 period, primarily due to economies of scale and production efficiency gains such as yield increases (Fig. 5). The direct contribution of the ethanol industry for these impacts was relatively small, representing on average 19% of value added and 5% of jobs, with most of the effect being indirect. On average, upstream sectors (excluding corn farming) contributed 49% of value added and 57% of jobs, and downstream sectors (fuel distribution) contributed 16% and 19% respectively.

For biodiesel, the steep reduction in jobs per MJ between 2002 and 2007 can be traced to significant structural changes in the industry between these two years: initially plants were generally small and designed for batch fuel production, while later plants were designed to operate in continuous flow, reducing operating costs and job requirements (Paulson and Ginder, 2007). The direct contribution of the biodiesel industry for these impacts was relatively small (especially for jobs), representing on average 21% of value added and 7% of jobs, with most of the effect being indirect. On average, upstream sectors (excluding farming and oil processing) contributed 44% of value added and 54% of jobs, and downstream sectors (fuel distribution) contributed 3% and 4% respectively (this low contribution is because most biodiesel is consumed by industries instead of final demand, which is the opposite from corn

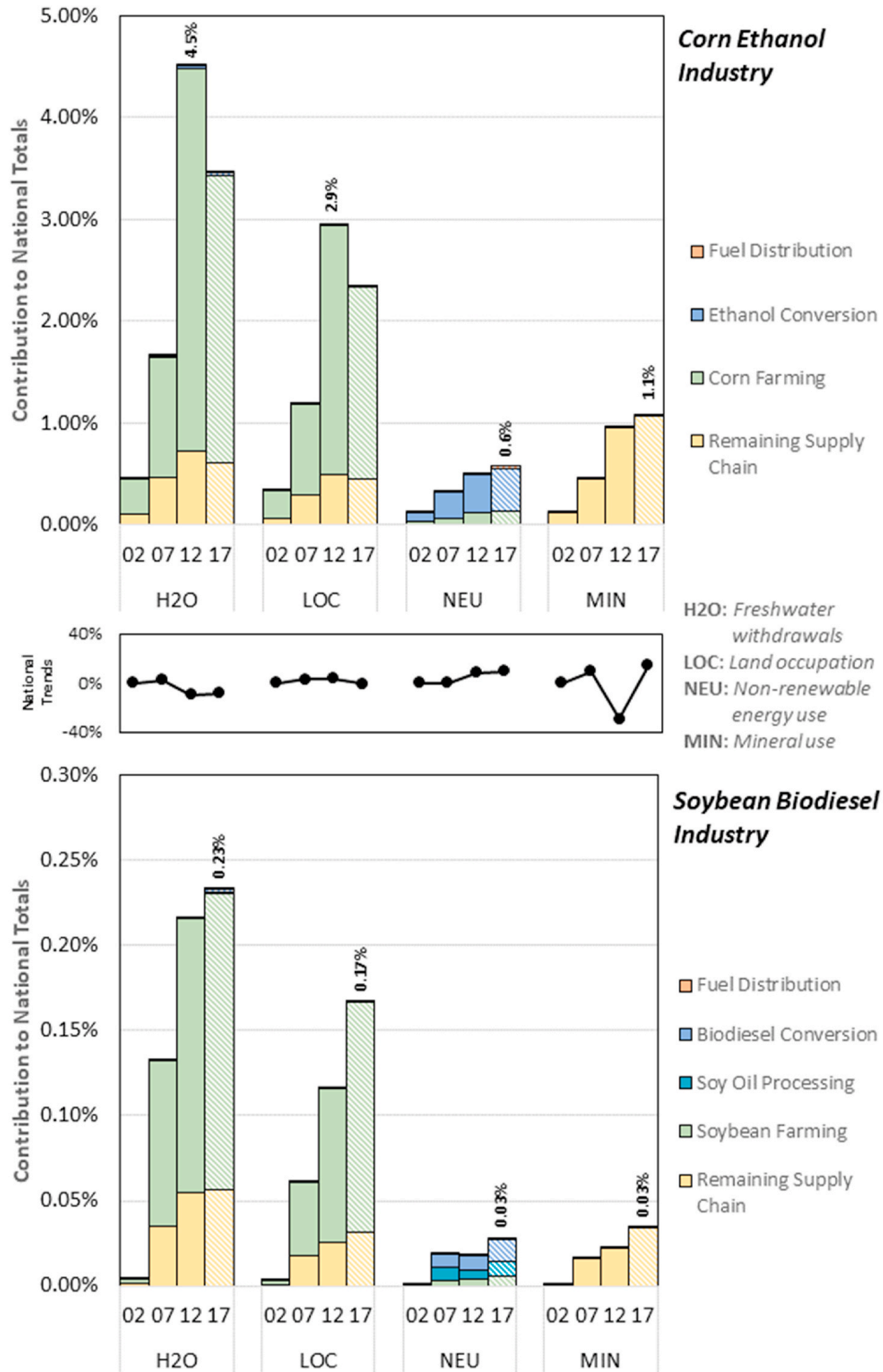

Fig. 3. Trend in the share of resources used by biofuel industry in relation to the total US economy in the respective year.

ethanol).

Across most of the environmental metrics, the effects related to biofuels production have, in general, improved over time with an almost linear trend across resource use and impacts (Figs. 6 and 7). The year 2012 deviated from this general trend for metrics driven by crop farming due to the 2012 drought. On the other hand, the yield increase in ethanol conversion and thus the reduction of corn feedstock per MJ of fuel produced has enabled the reduction in environmental and economic effects across most metrics. This effect is particularly noticeable for those metrics whose impacts are dominated by corn farming including water (H2O), land occupation (LOC), eutrophication (EUP), acidification (ACP) and ecotoxicity (FEP). For biodiesel, increasing yields in soybean farming drove most of these metrics.

Resource use in ethanol production was mainly driven by corn farming, which was the largest contributor to ethanol's lifecycle water consumption at national level (Fig. 6). In terms of non-renewable (primary) energy use (NEU), ethanol's requirements derived from the consumption of natural gas, electricity, and fuel for farm equipment. Moreover, fertilizer production was the main contributor to mineral use (MIN).

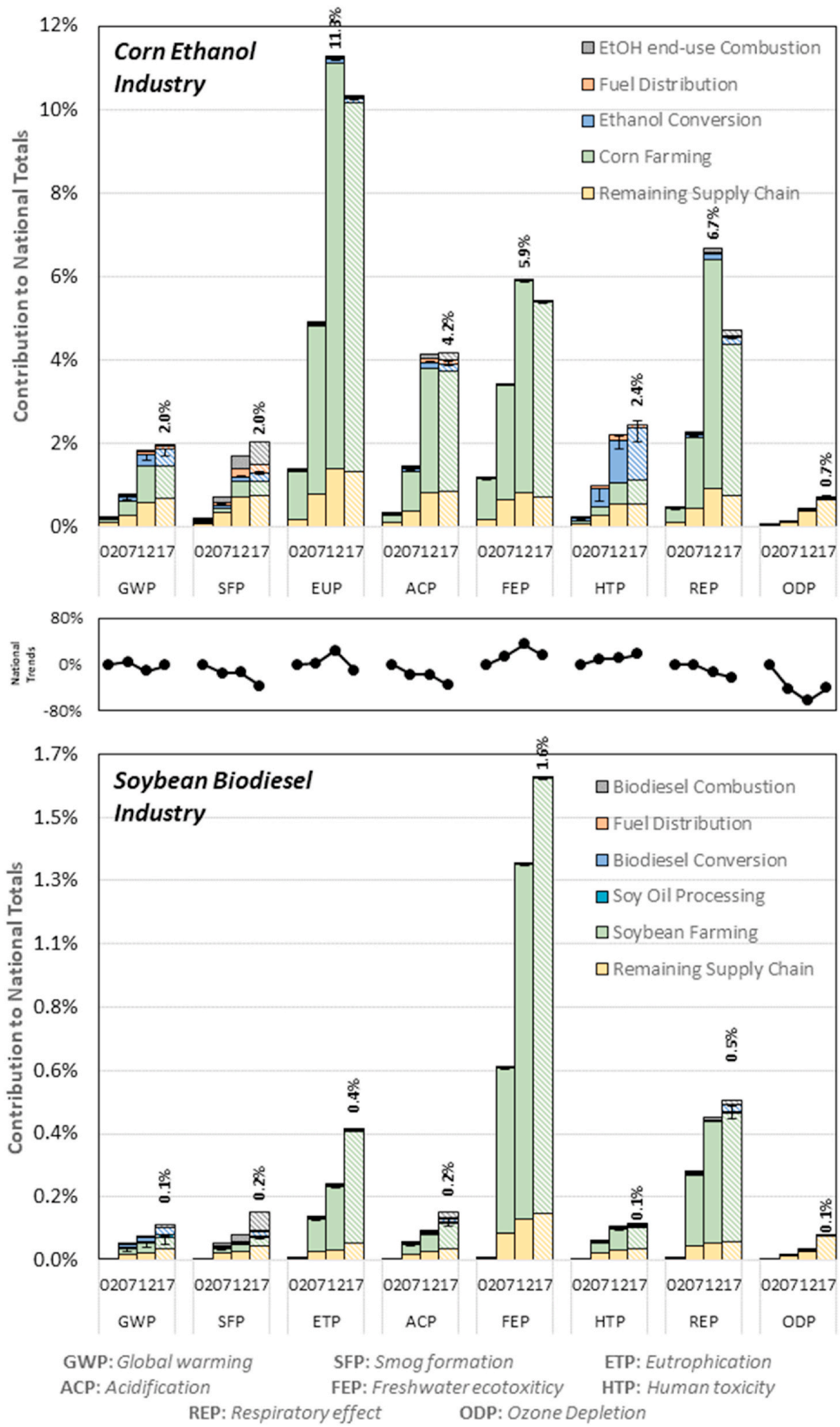

Fig. 4. Trend in the share of impacts by biofuel industry in relation to the total US economy in the respective year.

Regarding biodiesel, freshwater withdrawals (H2O) and land occupation (LOC) in 2017 have reduced 40% from their 2002 levels, mainly due to farming improvements (Fig. 6). The 2012 drought impact on water consumption is evident in the spike in H2O for that year. The lower soybean acreage in 2007 (down on average 12% from 2002) was driven by Midwest farmers favoring corn instead of soybeans due to a more favorable price ratio for the former (Ash and Dohlman, 2007). Despite lower production, soybean crushing expanded in 2007 with average oil production growing 10% between 2002 and 2007, driven by higher demand for soybean meal and oil (the cost of other oilseed oils increased faster than soybean's). This increased domestic consumption and higher soybean prices in the year also impacted exports (Ash and

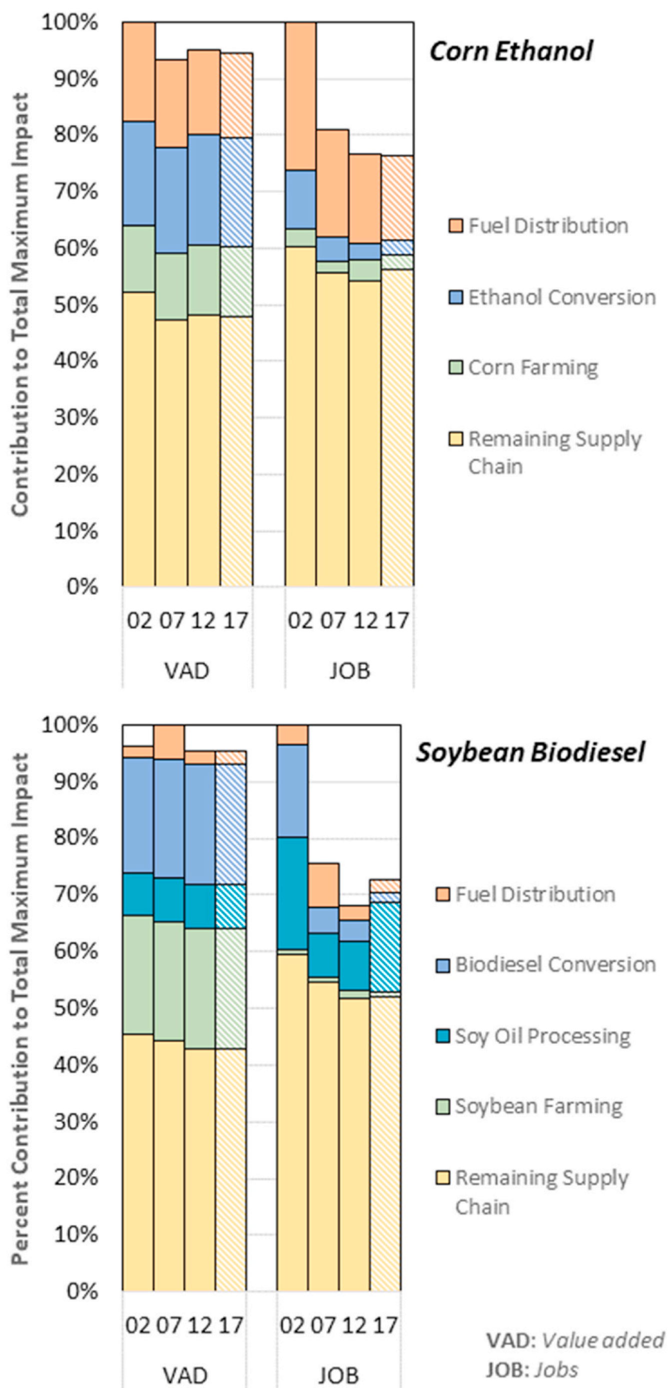

Fig. 5. Trend value added and jobs per MJ of biofuel.

Dohlman, 2008), which grew modestly (8%) in relation to 2002. The consumption of natural gas, electricity, and fuel for farm equipment contributed the most to the non-renewable (primary) energy use (NEU). The decline in non-renewable energy use was in part driven by the increasing share of renewables in energy generation (Figure SI-4). Moreover, like corn ethanol, fertilizer production was the main contributor to mineral use (MIN).

Corn and soybean farming also contributed the most to GWP totals (due to farm equipment use and nitrogen fertilizer application), although contributions were more evenly spread across the supply chain (Fig. 7). The smog formation potential (SFP) for both biofuels was related to end-use combustion and corn farming emissions of nitrogen oxides (from farm equipment) and volatile organic compounds (VOCs) from pesticide applications, transportation, and electricity generation. The reduction in emissions from transportation as well as the switch to natural gas in the electric grid drove the reduction in SFP from ethanol.

Pesticide use in corn farming grew over time, particularly the application of glyphosate herbicides (Osteen and Fernandez-Cornejo, 2016). The adoption of glyphosate in lieu of traditional herbicides (such as atrazine, acetochlor and s-metolachlor) nonetheless reduced the freshwater aquatic ecotoxicity (FEP) and human toxicity (HTP) due to its lower characterization factor compared with other herbicides, in-line with the finding from Yang and Suh (2015). Contributing to the reduction in FEP was also a decline in corn acreage treated with insecticides (particularly chlorpyrifos and tefluthrin) from 24% in 2002 to 13% in 2018 (U.S. Department of Agriculture, 2019). Fertilizers contributed the most for ACP (ammonia) and to EUP (due to nitrogen and phosphorus runoffs and leaching). For total human toxicity potential (HTP), the main chemicals driving the impact from corn ethanol were acrolein and formaldehyde (from farm equipment use, field burning and pesticide application), and atrazine (from herbicide application). Respiratory effects potentials (REP) were primarily driven by particulate matter emissions (PM_{10} and $PM_{2.5}$) from tilling (over 90%) and harvesting in corn farming fields. Excluding tilling emissions, REP decreased over the period, an effect attributable to increasing yields in both corn farming and ethanol conversion (Figure SI-5). Releases of acrolein to air at ethanol conversion facilities also contributed to HTP.

Despite a widespread adoption of herbicide resistant soybean and the resulting substitution of traditional herbicides with glyphosate compounds, freshwater ecotoxicity (FEP) has increased over time due to increasing use of insecticides (particularly lambda-cyhalothrin and cyfluthrin). This pest management choice was in response to the invasion of soybean aphid that appeared in Wisconsin in 2000 and rapidly spread in the Midwest (Yang and Suh, 2015). This FEP trend is the opposite to the evolution of corn ethanol impacts.

Similar to corn ethanol, total human toxicity (HTP) impacts for soybean biodiesel were driven by acrolein (from farm equipment use), but more significantly due to an increase use of acephate-based insecticides for pest management.

The changes in the NEI methodology for estimating crop field burning increased their uncertainty. Yet these represented less than 5% of HTP and did not impact the overall trend observed.

Eutrophication (EUP) was driven by fertilizer applications in soybean farming (nitrogen and phosphorous runoffs), following the evolution in the number of planted acres treated, which varied in a V-shaped fashion in the period. Differently from fuel ethanol (which improvement in EUP was due to growing ethanol yields), the almost V-shaped evolution for biodiesel was primarily due to an increased number of soybean fields treated with fertilizers. In relation to corn farming, soybean fertilizer applications were lower (8 times for nitrogen and 1.3 times for phosphorous) and less adopted than in corn farming (averaging 24% and 32% of planted acres treated with nitrogen and phosphorus respectively, against 97% and 79% for corn) (U.S. Department of Agriculture, 2019).

REP were primarily due to particulate matter emissions (PM10 and PM2.5) from tilling (over 90%) and harvesting in soybean farming fields. Without tilling emissions, REP is decreasing over the period (Figure SI-6). Ozone-related emissions were mainly indirect and the ODP trend reflected the national phaseout of class II Ozone-Depleting Substances during the period (U.S. Environmental Protection Agency, 2019).

Due to the uncertainty in ethanol conversion emissions, it is not possible to derive an overall trend for HTP. Without ethanol conversion, HTP remained mostly constant over the period. Previous LCA work from Yang (2013) indicated a decrease in this metric between 2001 and 2010, however that paper has a more limited scope (feedstock, conversion, transportation and combustion only) and therefore did not consider economy-wide indirect effects which in our analysis contributed in excess of 20% of the results. GWP emissions from ethanol manufacturing

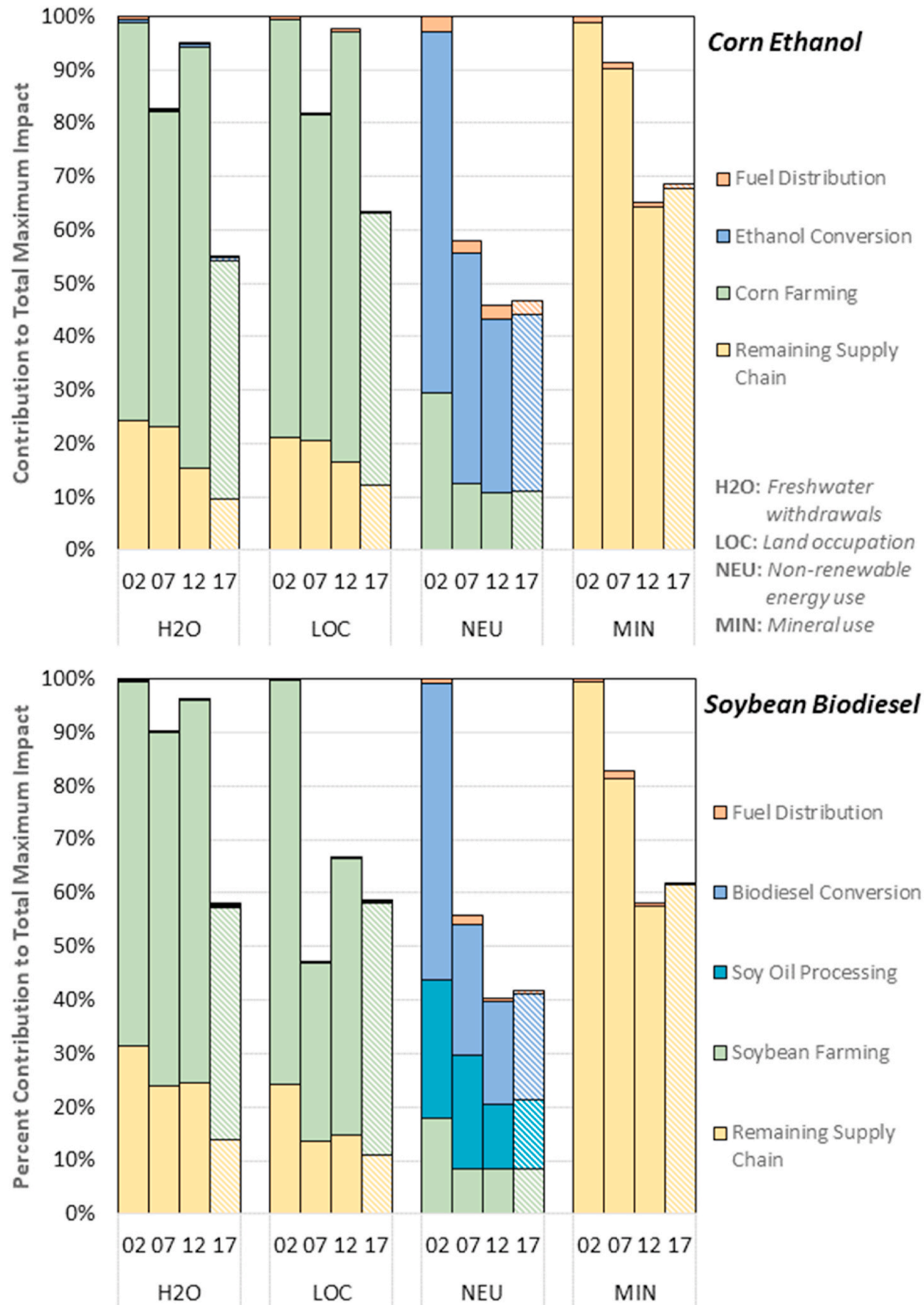

Fig. 6. Trend in resource use per MJ of biofuel.

were constant over time due to limited facility level data on greenhouse gases (2012 emission factors were used in all four years).

4. Discussion and conclusions

Apart from integrating socioeconomic and environmental sustainability dimensions across more than a dozen related metrics into one framework, an important contribution of this paper is that it builds a harmonized time series of EEIO tables for the US economy, in whose context the (retrospective) expansion of the US bioeconomy can be evaluated with geospatial and temporal details. The framework thus allows to trace and measure changes in the bioeconomy's effect on recognized economic indicators used by the US government, the public, businesses, and state governments (Office of Management and Budget, 2018), among others. The increasing need of a system approach to understand both economic and environmental impacts of an evolving complex society, e.g., changing trade patterns, introduction of new technologies, conservation policies, etc., has led to the development of several EEIO databases in the last decade that widened the timeliness and spatial extension of these analyses. However, these datasets have not been developed to same extent in the US as abroad. This paper tries to partially fill this gap by providing a harmonized time series of EEIO tables for the country, and a roadmap for future updates of the US EEIO databases, allowing US focused practitioners to expand EEIO and LCA works.

The EEIO-LCA approach accounts for inter-industry effects within the entire economy and does not require a subjective cutoff to define a system boundary as is the case for process-based LCA. Consequently, the broader scope typically leads to higher impacts. For example, a recent LCA study review indicated that the central best estimate for current US

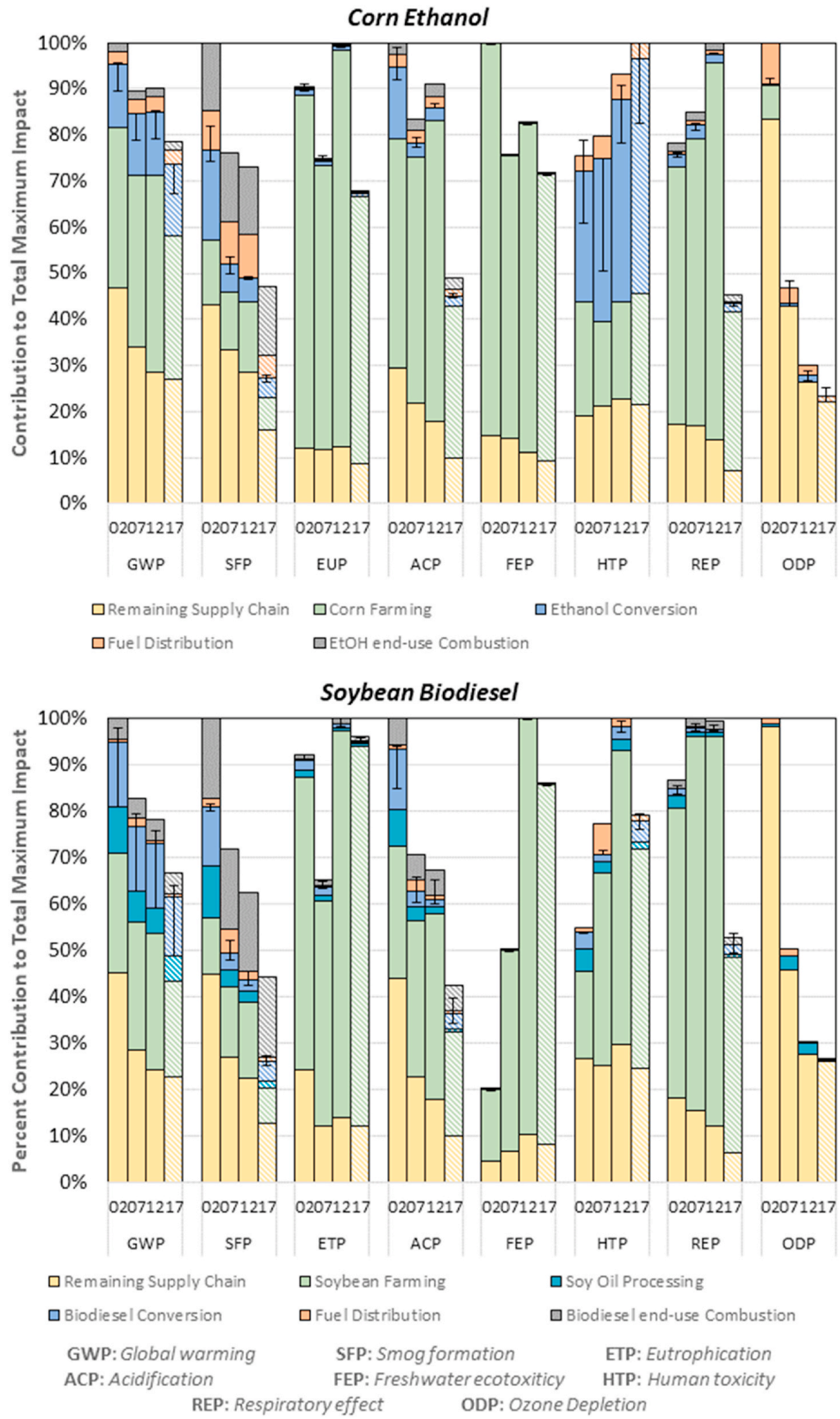

Fig. 7. Trend in impacts per MJ of biofuel.

corn ethanol is 47.5 g CO_{2eq}/MJ (range of 36.6–56.4 g CO_{2eq}/MJ) when land use change effect is not included (Scully et al., 2021). This is lower than our calculated corn ethanol carbon intensity of 69 g CO_{2eq}/MJ in 2017. The EEIO-LCA framework presented herein, relies on vetted, federal-level, public datasets (many of which are US Census related with 3–5 years publication intervals). It is less suitable to analyze plant-level technology changes or improvements and focuses more on the industry-level portfolio of technologies and the impact of this portfolio on the broader economic structure. Process-based LCA is designed to provide plant-specific process-level details. It can thus also capture latest industry technologies, best-in-class process-designs, and/or optimized systems (e.g., using waste heat from an adjoining process).

Due to the time range and detail level of our datasets, an important source of uncertainty is how the different environmental databases have evolved in terms of quality and comprehensiveness, data availability, and aggregation in the original sources. Although several steps were taken in this paper to mitigate some of these issues (such as eliminating sources and chemicals added between surveys), future work will continue to address this topic. Another limitation of the current work is the distinct scope of environmental and economic accounts: while publicly available physical data follow the territorial principle, i.e. account for all emissions inside the US geographical territory, the national accounts follow the residence principle, i.e., account for transactions from all "residents" (agents whose center of economic interest is the US, see Horowitz and Planting (2009)). For example, emissions from a truck owned by a Canadian company transporting freight in the US are recorded in the environmental data, but economic transactions are considered foreign trade for the national accounts. This is a known issue in constructing EEIO datasets (Usubiaga and Acosta-Fernandez, 2015) and was not addressed in this work to follow as closely as possible the construction methodology from USEEIO.

Future work will focus on adding more US bioeconomy products into the framework, including several near-commercial biofuel pathways. The framework will also be adapted for regionally-specific analyses, building on several spatially explicit environmental accounts such as Yang et al. (2018). We also plan to integrate this domestic model with existing global multiregional environmentally extended input-output databases such as EXIOBASE (Stadler et al., 2018) or Eora (Lenzen et al., 2012) to account for non-US impacts due to imports. Finally, we will expand the framework's capability to model emerging technologies and simulate cross-sectoral transitions for determining the impacts of potential future expansion scenarios of the US bioeconomy.

Disclaimer

This information was prepared as an account of work sponsored by an agency of the US Government. Neither the US Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. References herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the US Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the US Government or any agency thereof.

Financial & competing interests disclosure

This work was supported by the US Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. The US Government retains and the publisher, by accepting the article for publication, acknowledges that the US Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for US Government purposes. The authors have no other relevant affiliations or financial involvement with any organization or entity with a financial interest in or financial conflict with the subject matter or materials discussed in the manuscript apart from those disclosed. No writing assistance was utilized in the production of this manuscript.

NREL is managed by the Alliance for Sustainable Energy, LLC, for DOE under contract DE-AC36-08GO28308. The views expressed in the article do not necessarily represent the views of the DOE or the US Government.

CRediT authorship contribution statement

Andre F.T. Avelino: Methodology, Software, Data curation, Formal analysis, Validation, Writing – original draft. **Patrick Lamers:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Yimin Zhang:** Writing – review & editing. **Helena Chum:** Conceptualization.

Declaration of competing interest

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.

Acknowledgments

We thank Alicia Lindauer (DOE BETO) and Kristen Johnson (formerly DOE BETO) for supporting this analysis. We also thank Dr. Wesley Ingwersen and Dr. Christopher Clark (both US EPA) for constructive suggestions and discussions. We are grateful to Ben Young and Jorge Vendries (ERG, Franklin Associates), Dr. Troy Hawkins (Argonne National Laboratory), and Dr. Alberta Carpenter (NREL) for supporting the initial stages of the modeling effort.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2021.128890.

References

Biomass R&D Board, 2019. The Bioeconomy Initiative: Implementation Framework. https://biomassboard.gov/sites/default/files/pdfs/Bioeconomy_Initiative_Implementation_Framework_FINAL.pdf.

U.S. Energy Information Administration, 2019b. Monthly Energy Review [Data File]. https://www.eia.gov/totalenergy/data/monthly/.

U.S. Environmental Protection Agency, 2019. Phaseout Of Class II Ozone-Depleting Substances. Phaseout of Class II Ozone-Depleting Substances. https://www.epa.gov/ods-phaseout/phaseout-class-ii-ozone-depleting-substances.

U.S. Environmental Protection Agency, 2020a. Diesel Fuel Standards. Diesel Fuel Standards. https://www.epa.gov/diesel-fuel-standards.

U.S. Environmental Protection Agency, 2020b. 2017 *National Emissions Inventory Complete Release* [Technical Support Document]. Environmental Protection Agency.

Argonne National Laboratory, 2019. GREET Model [Data File], p. 2019. https://greet.es.anl.gov/.

Ash, M., Dohlman, E., 2007. *Oil Crops Outlook: 2007 Soybean Acreage Drops To 12-Year Low* (OCS-07f. U.S. Department of Agriculture, Economic Research Service, p. 17.

Ash, M., Dohlman, E., 2008. *Oil Crops Outlook: Oilseed Prices Reach Unprecedented Levels* (OCS-08a. U.S. Department of Agriculture, Economic Research Service, p. 18.

Bare, J.C., 2011. Traci 2.0—the Tool for the reduction and assessment of chemical and other environmental impacts. Clean Technol. Environ. Policy 13 (5), 687–696.

Biofuture Platform, 2018. Creating the Biofuture: A Report on the State of the Low Carbon Bioeconomy. http://www.biofutureplatform.org/post/new-biofuture-report-global-greenhouse-gas-goals-out-of-reach-without-biofuels-and-bioproducts.

Bureau of Economic Analysis, 2019. National Income and Product Accounts [Data File]. https://apps.bea.gov/iTable/index_nipa.cfm.

Chum, H., Zhang, Y., Hill, J., Tiffany, D.G., Morey, R.V., Eng, A.G., Haq, Z., 2014. Understanding the evolution of environmental and energy performance of the US corn ethanol industry: evaluation of selected metrics. Biofuels, Bioproducts and Biorefining 8, 224–240. https://doi.org/10.1002/bbb.1449.

Dieter, C.A., Maupin, M.A., Caldwell, R.R., Harris, M.A., Ivahnenko, T.I., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2018. *Estimated Use Of Water In the United States in 2015* (Circular 1441. U.S. Geological Survey, p. 65. https://doi.org/10.3133/cir1441.

Dietzenbacher, E., Los, B., 1998. Structural decomposition techniques: sense and sensitivity. Econ. Syst. Res. 10 (4), 307–324. https://doi.org/10.1080/09535319800000023.

Foreman, L., 2014. *Characteristics And Production Costs Of U.S. Corn Farms, Including Organic, 2010* (Economic Information Bulletin No. 128. U.S. Department of Agriculture, p. 43.

Fortenbery, T.R., 2005. *Biodiesel Feasibility Study: an Evaluation Of Biodiesel Feasibility In Wisconsin* (No. 481; Staff Paper Series. University of Wisconsin-Madison, p. 36.

Renewable Fuels Association, 2013. 2013 Ethanol Outlook. Renewable Fuels Association.

Gallagher, P.W., Yee, W.C., Baumes, H.S., 2016. 2015 Energy Balance for the Corn-Ethanol Industry. U.S. Department of Agriculture, p. 21.

Graboski, M.S., 2002. Fossil Energy Use in the Manufacture of Corn Ethanol. National Corn Growers Association, p. 122.

Haas, M.J., McAloon, A.J., Yee, W.C., Foglia, T.A., 2006. A process model to estimate biodiesel production costs. Bioresour. Technol. 97, 671–678. https://doi.org/10.1016/j.biortech.2005.03.039.
Haggerty, J., 2012. Green Jobs Metrics: A Guide to Efforts to Quantify the Green Economy, p. 21. Headwaters Economics. http://headwaterseconomics.org/energy/clean/green-jobs-metrics.
Harto, C., Meyers, R., Williams, E., 2010. Life cycle water use of low-carbon transport fuels. Special Section on Carbon Emissions and Carbon Management in Cities with Regular Papers 38 (9), 4933–4944. https://doi.org/10.1016/j.enpol.2010.03.074.
Hellerstein, D., Vilorio, D., Ribaudo, M., 2019. *Agricultural Resources And Environmental Indicators, 2019* (EIB-208). U.S. Department of Agriculture, Economic Research Service.
Hoffman, L.A., Baker, A., 2010. Market Issues and Prospects for US Distillers' Grains. Supply, use, and price relationships. U.S. Department of Agriculture, Economic Research Service.
Hofstrand, D., 2019. *Ethanol Profitability* [Model]. Iowa State University. https://www.extension.iastate.edu/agdm/energy/xls/d1-10ethanolprofitability.xlsx.
Hofstrand, D., 2020. *Biodiesel Profitability* [Model]. Iowa State University. https://www.extension.iastate.edu/agdm/energy/xls/d1-15biodieselprofitability.xlsx.
Horowitz, K.J., Planting, M.A., 2009. Concepts and Methods of the U.S. Input-Output Accounts. U.S. Bureau of Economic Analysis. https://www.bea.gov/papers/pdf/IOmanual_092906.pdf.
International Grains Council, 2008. Marketing and finance: grain market trends in the stockfeed and biodiesel industries. Australian Grain 17 (6), 30–31.
Kondash, A.J., Patino-Echeverri, D., Vengosh, A., 2019. Quantification of the water-use reduction associated with the transition from coal to natural gas in the US electricity sector. Environ. Res. Lett. 14 (12), 124028 https://doi.org/10.1088/1748-9326/ab4d71.
Korbitz, W., Friedrich, St, Waginger, E., Worgetter, M., 2003. Worldwide Review on Biodiesel Production. Austrian Biofuels Institute, p. 121 [IEA Bioenergy Task 39].
Lenzen, M., Kanemoto, K., Moran, D., Geschke, A., 2012. Mapping the structure of the world economy. Environ. Sci. Technol. 46 (15), 8374–8381. https://doi.org/10.1021/es300171x.
Leontief, W., 1970. Environmental repercussions and the economic structure: an input-output approach. Rev. Econ. Stat. 52 (3), 262–271. https://doi.org/10.2307/1926294.
Liu, C., Huang, Y., Wang, X., Tai, Y., Liu, L., Liu, H., 2018. Total environmental impacts of biofuels from corn stover using a hybrid life cycle assessment model combining process life cycle assessment and economic input–output life cycle assessment. Integrated Environ. Assess. Manag. 14 (1), 139–149. https://doi.org/10.1002/ieam.1969.
Malik, A., McBain, D., Wiedmann, T.O., Lenzen, M., Murray, J., 2019. Advancements in input-output models and indicators for consumption-based accounting. J. Ind. Ecol. 23 (2), 300–312. https://doi.org/10.1111/jiec.12771.
Methanex, 2020. Methanex Methanol Monthly Average Regional Posted Contract Price History [Data File]. https://www.methanex.com/our-business/pricing.
Mueller, S., Kwik, J., 2013. 2012 Corn Ethanol: Merging Plant Energy and Environmental Technologies. University of Illinois at Chicago, Energy Resources Center, p. 31.
Office of Management and Budget, 2018. Statistical Programs of the United States Government—Fiscal Year 2018. https://www.whitehouse.gov/wp-content/uploads/2018/05/statistical-programs-2018.pdf.
Osteen, C.D., Fernandez-Cornejo, J., 2016. Herbicide use trends: a backgrounder. Choice 31 (4), 1–7.
Paulson, N.D., Ginder, R.G., 2007. *The Growth And Direction Of the Biodiesel Industry in the United States* (Working Paper No. 07-WP 448. Iowa State University, p. 29.
Pradhan, A., Shrestha, D.S., McAloon, A., Yee, W.C., Haas, M., Duffield, J.A., Shapouri, H., 2009. *Energy Life-Cycle Assessment Of Soybean Biodiesel* (No. 845; Agricultural Economic Report). U.S. Department of Agriculture.
Shapouri, H., Gallagher, P., 2005. *USDA's 2002 Ethanol Cost-Of-Production Survey* (Agricultural Economic Report No. 841. U.S. Department of Agriculture, p. 19.
Stadler, K., Wood, R., Bulavskaya, T., Södersten, C.-J., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernandez, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J.H., Theurl, M.C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K., Tukker, A., 2018. EXIOBASE 3: developing a time series of detailed environmentally extended multi-regional input-output tables. J. Ind. Ecol. 22 (3), 502–515. https://doi.org/10.1111/jiec.12715.
Steen-Olsen, K., Owen, A., Hertwich, E.G., Lenzen, M., 2014. Effects of sector aggregation on CO2 multipliers in multiregional input-output analyses. Econ. Syst. Res. 26 (3), 284–302. https://doi.org/10.1080/09535314.2014.934325.
Strogen, B., Arpad, H., 2013. Greenhouse gas emissions from the construction, manufacturing, operation, and maintenance of U.S. Distribution infrastructure for petroleum and biofuels. J. Infrastruct. Syst. 19 (4), 371–383. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000130.
Temurshoev, U., Timmer, M.P., 2011. Joint estimation of supply and use tables. Pap. Reg. Sci. 90 (4), 863–882. https://doi.org/10.1111/j.1435-5957.2010.00345.x.
Tukker, A., Giljum, S., Wood, R., 2018. Recent progress in assessment of resource efficiency and environmental impacts embodied in trade: an introduction to this special issue. J. Ind. Ecol. 22 (3), 489–501. https://doi.org/10.1111/jiec.12736.
Urbanchuk, J.M., 2013. Contribution of the Ethanol Industry to the Economy of the United States in 2013. Renewable Fuels Association, p. 10.
U.S. Department of Agriculture, 2009. *2007 Census Of Agriculture* [Data File]. https://www.nass.usda.gov/Publications/AgCensus/2007/.
U.S. Department of Agriculture, 2018. U.S. Bioenergy Statistics. United States Department of Agriculture, Economic Research Service. https://www.ers.usda.gov/data-products/us-bioenergy-statistics/.
U.S. Department of Agriculture, 2019. Agricultural Chemical Use Program [Data File]. https://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Chemical_Use/.
U.S. Department of Agriculture, 2020a. Commodity Costs and Returns: Corn [Data File]. https://www.ers.usda.gov/data-products/commodity-costs-and-returns/.
U.S. Department of Agriculture, 2020b. *Fats And Oils: Oilseed Crushings, Production, Consumption And Stocks* [Data File]. https://usda.library.cornell.edu/concern/publications/mp48sc77c?locale=en.
U.S. Department of Energy, 2019. *Multi-Year Plan* [Unpublished Draft]. U.S. Department of Energy, Energy Efficiency and Renewable Energy, Biotechnology Office.
U.S. Energy Information Administration, 2019a. Monthly Biodiesel Production Report [Data File]. https://www.eia.gov/biofuels/biodiesel/production/.
U.S. Environmental Protection Agency, 2014. *Regulations To Reduce Mobile Source Pollution*. Regulations to Reduce Mobile Source Pollution. https://www.epa.gov/mobile-source-pollution/regulations-reduce-mobile-source-pollution.
Usubiaga, A., Acosta-Fernandez, J., 2015. Carbon emission accounting in MRIO models: the territory vs. The residence principle. Econ. Syst. Res. 27 (4), 458–477. https://doi.org/10.1080/09535314.2015.1049126.
Van Gerpen, J.H., 2008, January 9. *Biodiesel Economics*. Oilseeds and Biodiesel Workshop. Billings, MT. https://deq.mt.gov/Portals/112/Energy/EnergizeMT/EnergySites/Documents/Biodiesel_Production_Educ_Presentations/11Montana_Economics_Billings_Jan2008_JVG.pdf.
VanWechel, T., Gustafson, C.R., Leistritz, F.L., 2003. Economic Feasibility of Biodiesel Production in North Dakota. In: [Paper Prepared for Presentation at the American Agricultural Economics Association Annual Meeting Montreal, Canada, July 27-30, 2003]. North Dakota State University, p. 42.
Wu, M., 2008. Analysis of the efficiency of the U.S. Ethanol industry 2007. ANL 7.
Wu, M., 2019. Energy and water sustainability in the U.S. Biofuel industry. ANL 56.
Wu, M., Mintz, M., Wang, M., Arora, S., 2009. Water consumption in the production of ethanol and petroleum gasoline. Environ. Manag. 44 (5), 981–997.
Yang, Y., 2013. Life cycle freshwater ecotoxicity, human health cancer, and noncancer impacts of corn ethanol and gasoline in the U.S. J. Clean. Prod. 53, 149–157. https://doi.org/10.1016/j.jclepro.2013.04.009.
Yang, Y., Suh, S., 2015. Changes in environmental impacts of major crops in the US. Environ. Res. Lett. 10, 1–9. https://doi.org/10.1088/1748-9326/10/9/094016, 94016.
Yang, Y., Ingwersen, W.W., Hawkins, T.R., Srocka, M., Meyer, D.E., 2017. USEEIO: a new and transparent United States environmentally-extended input-output model. J. Clean. Prod. 158, 308–318.
Yang, Y., Ingwersen, W.W., Meyer, D.E., 2018. Exploring the relevance of spatial scale to life cycle inventory results using environmentally-extended input-output models of the United States. Environ. Model. Software 99, 52–57. https://doi.org/10.1016/j.envsoft.2017.09.017.