Journal of Cleaner Production 158 (2017) 308–318

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

USEEIO: A new and transparent United States environmentally-extended input-output model

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ARTICLE INFO

Article history:
Received 15 December 2016
Received in revised form
13 April 2017
Accepted 26 April 2017
Available online 29 April 2017

Keywords:
Environmentally-extended input-output (EEIO)
Life cycle assessment
Sustainable materials management
Data quality assessment
Product hotspot analysis
Streamlined life cycle assessment

ABSTRACT

National-scope environmental life cycle models of goods and services may be used for many purposes, not limited to quantifying impacts of production and consumption of nations, assessing organization-wide impacts, identifying purchasing hotspots, analyzing environmental impacts of policies, and performing streamlined life cycle assessment. USEEIO is a new environmentally-extended input-output model of the United States fit for such purposes and other sustainable materials management applications. USEEIO melds data on economic transactions between 389 industry sectors with environmental data for these sectors covering land, water, energy and mineral usage and emissions of greenhouse gases, criteria air pollutants, nutrients and toxics, to build a life cycle model of 385 US goods and services. In comparison with existing US models, USEEIO is more current with most data representing year 2013, more extensive in its coverage of resources and emissions, more deliberate and detailed in its interpretation and combination of data sources, and includes formal data quality evaluation and description. USEEIO is assembled with a new Python module called the IO Model Builder capable of assembling and calculating results of user-defined input-output models and exporting the models into LCA software. The model and data quality evaluation capabilities are demonstrated with an analysis of the environmental performance of an average hospital in the US. All USEEIO files are publicly available bringing a new level of transparency for environmentally-extended input-output models.

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1. Introduction

In the report “Sustainable Materials Management: The Road Ahead”, the United States (US) Environmental Protection Agency (EPA) defined sustainable materials management (SMM) as “as fulfilling human needs and prospering while using less materials, reducing toxics and recovering more of the materials used” (USEPA, 2009a). This definition transcends historical material management lenses focused on single impacts (e.g., climate change), single life-stages (e.g., use, waste), political boundaries, or efficiency. To identify opportunities for reducing environmental impacts, material use and waste generation across the spectrum of goods and services consumed in the US, life cycle assessment was identified as the most appropriate framework. However, the methods typically used for LCA of single products are not scalable or practical to do a full economy analysis that includes product-level detail, given the lack of life cycle inventory data for all products or services consumed in the US (Huppes et al., 2006). Another method of generating life cycle inventory data that uses readily-available economic input-output data to model a network of goods and services is environmentally-extended input-output (EEIO) analysis (Tukker, 2006). The “Road Ahead” report used an EEIO model to perform an initial analysis of US goods and services for 2002.

EEIO analysis has become widely used in broad-scope studies of the environmental impacts of production and consumption by societies, such as total consumption in the US (Kucukvar et al., 2014), dietary consumption in Italy (Pairotti et al., 2015), and general

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http://dx.doi.org/10.1016/j.jclepro.2017.04.150
0959-6526/Published by Elsevier Ltd.

world consumption patterns (Pascual-González et al., 2015). It incorporates environmental data into the Input-Output (IO) framework (Leontief, 1941), and enables calculation of direct and indirect environmental impacts of economic activities or products (Hendrickson et al., 2006). EEIO models have been developed for many countries, including the US, such as CEDA (Suh, 2005), EIO-LCA (Hendrickson et al., 2006), Eco-LCA (Zhang et al., 2010), and openIO (Cox and Norris, 2011); China, such as Yang and Suh's model (2011) and CEEIO (Liang et al., 2016); Japan (Nansai, 2009); Australia (Lenzen, 1998); and the Netherlands (Kerkhof et al., 2009). There are also global EEIO models that include multiple countries or regions of the world, including Eora (Lenzen et al., 2013) and EXIOBASE (Tukker et al., 2013).

In addition to being able to provide a national level overview/hotspot analysis to inform SMM, the EPA SMM program has needs including (1) providing meaningful analyses of states or communities to identify more localized opportunities for SMM and (2) helping organizations identify their own environmental hotspots.

Numerous methods have been described for organization and institutional analyses using EEIO, related to topics such as GHG Protocol Scope 3 emissions (Huang et al., 2009), supply chain hotspot analysis (Pelton and Smith, 2015), and corporate sustainability benchmarking (Wiedmann et al., 2009). EEIO models have been used for subnational scale analyses in the US (Brown et al., 2009) and for purchasing analysis for US government procurement (SRA International and IERS, 2014). These precedents suggest that these additional SMM-related needs for providing quantitative detail on subnational and organizational scales can be at least partially addressed with an EEIO model. Along with multiple types of applications, using an EEIO model to support SMM decision making is anticipated to be an interactive process that a static model application described by a report would be insufficient to address. SMM-related policy development brings together decision makers and stakeholders from industry, communities, and various levels of government, all of which have their own motivations and objectives.

An EEIO model that can meet the multiple applications and interactive uses envisioned by EPA's SMM program must meet the following criteria.

1. *Transparent.* The underlying data must be transparent to support examination in close detail and the quality of these data should be clearly described.
2. *Reproducible.* The generation of the model must be reproducible to allow for efficient modification and customization.
3. *Open.* The model and data need to be open and freely-shareable to enable widespread adoption and customization for more specific applications.
4. *Up-to-date.* Models must reflect current conditions to the extent possible for the results to be relevant to decision making.

Meeting these criteria poses a challenge for EEIO models. In general, EEIO models suffer from a lack of data transparency (Lutter and Giljum, 2014). For any decision, it is important to understand the quality of the data. Unfortunately, this is another issue with EEIO models because the satellite tables assembled are often from assorted data sources, such as surveys and model simulations, with varying degrees of quality and uncertainty. Data quality in most EEIO models has thus far been limited to qualitative description. Although the process of data compilation may be documented, details on how some of the values have been exactly estimated are often missing. As a result, EEIO model estimates are generally hard to reproduce, with some exceptions for simpler EEIO models with fewer industries and emissions represented (Peters et al., 2006). Another requirement for an EEIO model to support SMM is adequate temporal representation. It is difficult to have meaningful conversations about the impacts of production and consumption if the underlying data significantly misrepresent the status quo, especially for industries that experience rapid changes. EEIO models are generally not up-to-date, mainly because it takes government agencies several years to update the IO tables and partly because some environmental data may be unavailable for more recent years.

Perhaps the three most used EEIO models of the US are the Comprehensive Environmental Data Archive (CEDA®) (Suh, 2010), The Economic Input-Output Life Cycle Assessment tool (EIO-LCA) (Weber et al., 2009), and Open IO (Cox and Norris, 2011). Although each of these models fulfills some of the requirements for an EPA SMM EEIO model, none completely satisfies all the needs. CEDA is a comprehensive EEIO model representing the year 2007 after its latest update, although versions that are more recent are in preparation. The CEDA data and model are proprietary and not conducive to open sharing and modification. EIO-LCA utilizes open-source data, but has not been updated beyond 2002 and covers only a small number of emissions. Open IO is a unique model that relies on publicly available data and adds consideration of the use phase based on 2002 data. However, the model is no longer supported or actively updated. In all three cases, formal description of data quality is lacking, and some recently available data sources have yet to be incorporated to make the models more complete.

Given the limitations with existing EEIO models of the US, successful creation of an EEIO model for EPA SMM-related needs requires the development of a new EEIO model that satisfies all of the specified requirements. Within the spirit of other recent efforts to achieve more transparency in industrial ecology (Pauliuk et al., 2015) and in keeping with the US federal governmental Open Data Directive (Orszag, 2009), the objectives of this research are to: (i) develop and document a transparent EEIO model of the US that reflects current conditions; (ii) analyze the quality of data in the resulting model; (iii) demonstrate the utility of the new model for an example SMM decision application; and (iv) distribute the model in ways that it can be easily used and reproduced. The resulting model will be referred to as USEEIO. This name was chosen to signify that this is a United States EEIO (US-EEIO) model and that it is intended to be as transparent (U-SEE-IO) and useable (USE-EIO) as possible. The details described in this article, the supporting information (SI) files, and the data files themselves will enable users to examine how the economic, environmental and life cycle impact assessment data from the different sources were collected, processed, and harmonized, how its data quality was evaluated, and how the model was then assembled. A summary of the resulting model and an example application to good & service hotspot analysis are then given.

2. Materials and methods

Given its potential role in informing policy decisions, USEEIO seeks to reflect, to the extent possible, the current life cycle environmental impacts of products and services. The process of building USEEIO first involved an examination of existing models, assembly and preparation of the best available data, evaluation of its quality, determination of impact methods, and development of a program for model assembly and calculation.

2.1. Evaluation of other EEIO models of the US

In effort to learn and build upon prior work, existing EEIO models of the US were evaluated. The team compared both documentation and the models themselves for two models, openIO and CEDA, in formats that could be evaluated both qualitatively and quantitatively. Both the documentation and the model sources were used to identify the sources used for calculations. The models were harmonized with the reference flow list for openLCA 1.4 (GreenDelta, 2014), and then transferred into a format (openLCA JSON-LD) for import into openLCA software to enable quantitative comparison between the models. For the quantitative comparison, life cycle impact assessment (LCIA) results were calculated with the same impact assessment method and for the same final demand. The original files for openIO (one version) and two versions of CEDA 4.6 were available ('a' and 'b') and for this analysis, CEDA v4.6a was used.

2.2. Data compilation for USEEIO

An EEIO model consists of two types of data. One is economic data in the form of IO tables, which record monetary transactions between industries and reflect their interdependency. The transactions between industries become the technosphere flows in the life cycle inventory data. The other is environmental data compiled into what are referred to as satellite tables (Rebitzer et al., 2002), the name of which comes from national environmental accounting systems and in which the amounts of resource use and emissions by industries are recorded. These become the elementary flows in the life cycle inventory. IO tables are often provided by the economic agencies of a country. Thus, developing an EEIO model is mostly a process of compiling environmental satellite tables in accordance with sectoral definition in IO tables. This process can be strenuous as it may involve collecting, processing, and harmonizing a large number of datasets from various sources (Suh, 2005). In some cases, data may be unavailable and need to be estimated from non-statistical sources, such as models (Yang and Suh, 2011). In other words, compilation of environmental satellite tables for an EEIO model may be filled with detailed modeling, assumptions, and expert judgments. For USEEIO, the most current economic and environmental data available were identified and combined in as transparent a fashion as possible.

2.2.1. Economic data

Detailed input-output data describing transactions between sectors at a fine level of detail are needed for an IO model that can distinguish between the different commodities to create unique sector and commodity profiles. The most recent IO tables at the detailed level (389 commodities by 389 industries), compiled by the Bureau of Economic Analysis (BEA), are for year 2007 in the form of "Make" and "Use" tables. Use and Make tables are a slight variant of the standard IO tables and were developed to account for secondary products (Miller and Blair, 2009; Stone, 1961). In this case, input-output coefficients derived from the detailed level BEA 2007 IO tables were used.

The 2007 Make and Use tables were available "before redefinition" and "after redefinition." "After redefinition" tables reflect adjustments made by the BEA to reallocate output of particular industries that should reflect output in another industry (Horowitz and Planting, 2006). For USEEIO, the determination was made that the majority of environmental data, as reported in environmental data sources, most likely reflect the original industries where an activity occurs, more in line with the before redefinitions approach. Therefore, USEEIO used the "before redefinitions" tables.

Four models for the direct requirement coefficients matrix, or technology matrix (A), can be derived from the Use and Make framework (Miller and Blair, 2009), i.e., the industry-by-commodity model, the commodity-by-commodity model, the industry-by-industry model, and the commodity-by-industry model. The most relevant for SMM-related analysis is the commodity-by-commodity model given that SMM is concerned mostly with products and services and their associated materials (USEPA, 2009a). The commodity-by-commodity model delivers different results depending on assumptions regarding how secondary products are produced. Two major assumptions pertain to the industry and commodity technologies. The former assumes that all commodities produced by an industry have the same input structure, while the latter assumes that a given commodity has the same input structure wherever it is produced (Suh et al., 2010). The current version of USEEIO is based on the industry technology assumption that all commodities produced by an industry have the same input structure. The IO tables contain a sector called "Scrap" which captures industrial by-products created by an industry. No sector produces scrap for its own sake, so the scrap commodity is removed from the table using the BEA "scrap adjustment" procedure (Horowitz and Planting, 2006). Detailed equations for constructing the model with this assumption from the Make and Use tables are presented in SI 1. The result is an economic model of total requirements to make 385 commodities,[2] or goods and services.

2.2.2. Environmental data

Environmental data for USEEIO include greenhouse gas emissions, criteria air pollutants, toxic chemical releases to water, air, and soil, nutrient releases to water, and use of land, water, energy, and mineral resources. The sources for all these datasets are summarized in Table 1. All primary data sources are regularly compiled by US federal government agencies to summarize national economic use, resource use, and emissions.

Details of how each of these sources was used to derive the respective satellite tables are provided in SI 1. In the case the source reported the amount of a chemical or resource applied and not emitted (primarily for agriculture), the modeling approach used to estimate emissions is described. Because some of the data sources can include reporting of the same environmental flows, additional procedures were put in place to avoid duplication by consulting with stewards of the sources and selecting the preferred data. A standard template was developed for collecting and processing the satellite table data, and it is a variant of the Federal LCA Commons unit process template (Cooper et al., 2015). The templates are generally structured with the final tables being in the form of a list of exchanges with an environmental flow, its amount, and the industry sector to which it is attributed, along with data quality information, sources, and comments. Often the same environmental flow will be listed with the same sector in multiple exchanges if other information regarding the flow differentiates it, such as location (e.g., state), data quality, or data source. The number of exchanges in a given satellite table can vary from 100s to >100,000, depending on the level of detail used to compile the original data. All exchange amounts are normalized to one 2013 USD industry output, thus in the form of a physical unit/$. The year 2013 was chosen because it was the most recent year that most of the environmental data were available when the team began preparing the satellite tables. The template allows the satellite tables to be exported into a standard csv format. The templates for each satellite table and supplementary files are available through the EPA Environmental Dataset Gateway (USEPA, 2016c).

2.2.3. Life cycle impact assessment data

USEEIO is provided with matching LCIA characterization factors based on the full suite of impact categories in the TRACI 2.1 LCIA

[2] Four commodities from the 389 in the BEA make and use tables cannot be modeled because they exist largely as accounting measures: non-comparable imports, used and secondhand goods, rest of world adjustment and scrap (removed in scrap-adjustment procedure).

methods (Bare, 2012) along with additional methods that sum up resource use for land, water, and energy use. More details on matching the model flows with impact assessment methods are available in SI 1. The version of the LCIA methods used is available along with the model datasets on the EPA Environmental Dataset Gateway (USEPA, 2016c).

2.3. Data quality assessment

Data quality assessment is important for understanding the limitations of models, where they can be improved, and how they can be interpreted (USEPA, 2009b). EPA has recently developed a guidance document on data quality assessment for life cycle inventory data (Edelen and Ingwersen, 2016). Use of the data quality assessment procedure described in this guidance document was demonstrated in a case study of acetic acid production (Cashman et al., 2016). For USEEIO, this same method was followed, where data quality scores are assigned at the level of the individual flow (>224,000) as well as at the level of the process (389). Following this procedure, flow level data quality was scored for each flow in the satellite tables as well as the inputs of commodities for each of the five criteria: flow reliability, temporal correlation; geographic correlation; technological correlation; and data collection methods. The criteria require the establishment of data quality goals. The goals for the development of each of the models for the 389 sectors were to capture complete inputs and outputs for each sector representing average US facilities and technologies. The approach to flow-level data quality scoring of each of the primary data sources can be found in SI 1.

Process completeness is a process level indicator that reveals the extent to which each of the processes contains a complete set of inputs and outputs including all resources, purchased products and services, products and co-products, emissions and other wastes that are necessary to connect a process to others to complete the life cycle and to enable calculation of impacts across all the impact categories. To determine process completeness, a standard process completeness evaluation form based on the EPA LCI data quality guidance was prepared for broad sector classes - agriculture, energy, mining, and others. Each of the 389 final sectors was evaluated for process completeness using the corresponding form. As part of this analysis, presence or absence of emissions captured in the satellite tables was determined for each sector (e.g., were water use or criteria pollutants present in the sector?). The process completeness scoring chart used can be found in SI 1.

2.4. Model assembly and calculation

Assembling the various data components of EEIO models and performing model calculations is computationally-intense. There is a need for capabilities to quickly build individual datasets, to build alternate versions of the model, and to validate that all the datasets used correspond to create a harmonized model. These procedures need to be easily repeatable. A decision was made to develop a software program to enable advanced users to construct this and other EEIO models. Program requirements included free and open-source availability, acceptance of user-created CSV files with predefined formats, operating system independence, inclusion of matrix math libraries, a stable development environment and active community, permitted use of natural syntax for easily shared coding, the option for a graphical user interface, and the ability to export processes in a standard LCA exchange format. In the end, Python was selected as the language/platform that best satisfied all the requirements. A Python module called the Input-Output Model Builder (iomb) was created to assemble the model and perform model calculations. LCI and LCIA results were calculated with the IO model builder using two perspectives, a direct perspective that associates all inventory/impacts in the sectors in which they occur, and a final perspective that embeds all inventory/impacts in the final goods and services that are consumed (the typical life cycle approach). The iomb functions are summarized in SI 1. A Python Jupyter notebook was used as a graphical interface to build and analyze USEEIO using the iomb. Results were exported into csv files for further analysis. The source code and documentation for the iomb are available at https://github.com/USEPA/IO-Model-Builder/.

3. Results and discussion

3.1. USEEIO model summary and data quality results

The total number of data points processed to build USEEIO was approximately 9,000,000 (see source summaries in SI 1). The majority of these data points are individual facility reports compiled in the National Emissions Inventory, Toxic Release Inventory, and Discharge Monitoring Report. The environmental data points were processed to create exchanges of resources or emissions by sector, of which the satellite tables have approximately 223,000.

Fig. 1 describes the environmental data coverage of each of the 385 commodities grouped by type of resources or emission. Land, water, energy, criteria pollutants, and GHG emissions occur in production of nearly all commodities. Minerals are only extracted directly to make mining commodities but are associated with some other manufacturing commodities that the mining industry produces as co-products. The release of toxics and, to a smaller extent, nutrients is not associated with many of the services. The small gaps in the release of toxics to water and soil for agriculture commodities are for beef and dairy cattle production.

Aggregate flow level data quality scores depend on the life cycle inventory. Assuming the independent output of $1 in all sectors, aggregated data quality scores were calculated for all flows (see SI 1). Scores for selected flows are provided in Table 2. The same flow is typically present in many sectors, sometimes with unique data quality, and therefore average and standard deviations of the data quality scores are calculated for these flows. A complete table along with all other results presented in this manuscript is available in SI 3.

The flow level scores for intermediate, or technosphere level flows, reflect the data quality of the direct requirements derived from the IO tables. All scores were evaluated of the highest quality (1) because of the reliability, high geographical (all of US) and technological correlation (by NAICS sector) and completeness of the economic census data on which they are based, except for the temporal correlation score, which was assigned a '3', due to the age of the data.

Reliability varies within each source based on how values were determined. The data reliability scores reflect that the mineral and fossil fuel energy flows are solely based on verified measurement (the best score of 1). The selected flows from TRI and for pesticides may be documented estimates, suggesting lesser reliability. N&P flows, criteria air pollutants, land occupation, GHG emissions and water use generally have average reliability. Temporally, nearly all of the selected flows with the exception of the land flows are within 6 years of the target year (2016) of the model. All sources have high geographical representativeness because they are either based on discrete sources reporting across the US or they are based on average US conditions. A number of the sources, including the GHGs, land and water, have emissions factors for some sectors that are based on mixed technologies, with assumptions that a particular emission data point applies equally across technologies in different sectors. In this case, this weakens the ability to truly distinguish between sectors where additional technology-specific

Table 1
Primary data sources for USEEIO environmental data.

Environmental data type	Emission and compartment released to[a]			Resource	Primary sources	Year	Secondary sources
	A	W	S				
Greenhouse gas emissions and sinks[b]	X				US GHG Inventory (USEPA, 2016a)	2013	DOE EIA MECS survey (EIA, 2013a) USGS Mineral Commodity Survey (USGS, 2015) USDA Ag Census (USDA, 2009a), USDA QuickStats (USDA, 2016a), 2007 Make and Use Tables (BEA, 2015)
Criteria air pollutants & precursors	X				National Emissions Inventory (USEPA, 2015c)	2011	Agricultural Chemical Use Program (USDA, 2016a), Literature[c] (Goebes et al., 2003; Krauter et al., 2002; Yienger and Levy, 1995)
Hazardous air pollutants	X				National Emissions Inventory (USEPA, 2015c)	2011	
Toxic releases	X	X	X		Toxic Release Inventory (USEPA, 2015b)	2013	
Pesticides	X	X	X		Agricultural Chemical Use Program (USDA, 2016a)	2009–2014	Modeled emissions using the PestLCI model (Vineyard et al., under review)
Nutrients	X	X			Agricultural Chemical Use Program (USDA, 2016a)	2009–2014	USDA QuickStats (USDA, 2016a) Field crop nutrient losses (USDA, 2006b)
		X			Discharge Monitoring Report (USEPA, 2016b)		Literature (Kim et al., 2013)
Land Occupation				X	Major Uses of Land in the United States (Nickerson et al., 2011)	2007	Public Land Statistics (BLM, 2008), Commercial Building Energy Consumption Survey (EIA, 2015), Manufacturing Energy Consumption Survey (EIA, 2013a); 2007 Make and Use Tables (BEA, 2015)
				X	Census of Agriculture (USDA, 2009a,b)	2007	
Water Withdrawal and Release				X	Farm and Ranch Irrigation Survey (USDA, 2009b)	2008	Canadian Industrial Water Survey (Statistics Canada, 2010), National Renewable Energy Lab Electricity Sector Water Use Reports for (Torcellini et al., 2003; Macknick et al., 2011); USGS Livestock Water Use Estimates (Lovelace, 2009) Literature (Blackhurst et al., 2010)
				X	Water Use in the United States (Maupin et al., 2014)	2010	
Mineral Use				X	Minerals Commodity Survey (USGS, 2016)	2014	
Energy use				X	Monthly Energy Review (EIA, 2016a)	2014	Commercial Building Energy Consumption Survey (EIA, 2015), Manufacturing Energy Consumption Survey (EIA, 2013a)

[a] A = air; W = water; S = soil.
[b] Carbon uptake included.
[c] Only for NH_3 and NO_x from fertilizers used in agriculture, which are not included in NEI.

data were unavailable. The extent that the data are based upon complete coverage of a sector is reflected in the data collection score. Resource uses are generally based on more complete data. The method used for the data collection score for the source where individual entities reported and were aggregated (NEI, TRI, DMR for N&P) was to compare the number of entities reporting with the total number of establishments for that sector as reported by the US Census. Using this method it appears that the flows from these sources represent 70% or less of the establishments in those sectors (see supporting satellite table data files for details). What these selected values do not show is the variation in data quality scores within a source across sectors. In general, there is more estimation, poorer technological correlation and less data collected across the service sectors than primary sectors such as electricity.

3.2. Comparison with existing models

Table 3 provides a summary of environmental data types included in openIO, CEDA v4.6, and USEEIO. In some cases, documentation of openIO and CEDA v4.6 were not sufficient to determine the year of the data sources. The environmental sources used by openIO and CEDA were largely the same for GHG emissions, criterial and hazardous air pollutants (CAPs and HAPs), water use, primary energy use, and agricultural and land use. USEEIO incorporates a number of the same primary data sources, but for a more recent year. USEEIO includes environmental data not included by the other models, notably nutrient releases from industrial sources, quantifications of water returns, renewable energy, minerals use, and land use for non-primary sectors. CEDA contains some other flows for harvested goods and waste not included in other models, but which do not correspond to known impact methods.

Quantitative comparison results of CEDA and openIO are included in SI 2. USEEIO was not quantitatively compared to the other models because it is based on a different reference year. Although it is not possible to ascertain which model is more accurate, it is clear that despite using the same environmental data sources for creating the satellite tables like those for the GHG and the criteria and hazardous air pollutants, there are significant differences in the results between openIO and CEDA (SI 2). These differences could be due to allocation of emissions to sectors or differences in the use of the primary or secondary sources. The model documentation was insufficient to understand the nuances in creation of the satellite tables to further ascertain what led to

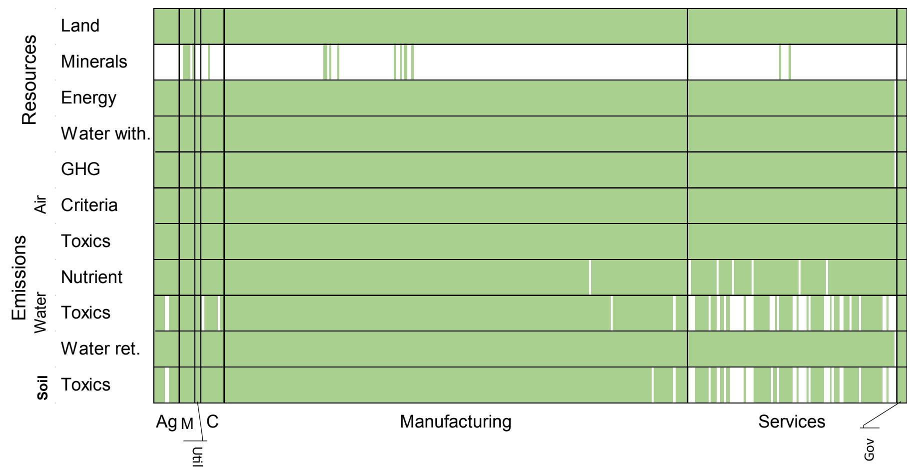

Fig. 1. Presence of environmental flows from satellite tables (rows) in USEEIO sectors, with green cells indicating presence and blank cells absence. The 385 commodities are in classes: Ag – agriculture, forestry, fishing and hunting (13); M – mining and energy (8); Util – utilities (3); C – construction (12); Manufacturing (237); Services (107); Gov – government (5). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Flow data quality scores for 2013 US life cycle inventory totals for selected flows.

Flow	Satellite table	Data reliability	Temporal correlation	Geographical correlation	Technological correlation	Data collection methods
1,2,4-trimethylbenzene/soil	TRI	5(0)	1(0)	1(0)	1(0)	4.14(0.9)
1,2-butylene oxide/air	NEI	3.9(0.3)	2(0)	1(0)	1(0)	4.7 (0.58)
2,4-D	Pesticide	4(0)	1.1(0.35)	1.4(1.1)	1.57(1.4)	3.2(0.5)
Ammonia/air	NEI	3(0)	2(0)	1(0)	1.6(1.1)	3.8(1.4)
Barite	Minerals	1(0)	1(0)	1(0)	1(0)	1(0)
Crude oil	Energy	1(0)	1(0)	1(0)	1(0)	1(0)
Nitrogen/water	N&P	3.3(1)	1(0)	1(0)	1(0)	4.9(0.5)
Phosphorus/water	N&P	2.5(0.8)	1(0)	1(0)	1(0)	4.8(0.7)
Nitrogen oxides/air	NEI	2.5(0.5)	2(0)	1(0)	1(0)	2.9(1.3)
Sulfur dioxide/air	NEI	2.1(0.3)	2(0)	1(0)	1(0)	4.1(1.2)
Volatile organic compounds/air	NEI	3(0)	2(0)	1(0)	1(0)	3.7(1.6)
Occupation, forest	Land	2(0)	3(0)	1(0)	1(0)	1(0)
Occupation, industrial area, built up	Land	4(0.2)	2(0.1)	1(0)	3(0)	1(0)
Occupation, annual crop	Land	2(0)	3(0)	1(0)	1(0)	1(0)
Water, fresh (withdrawal)	Water	2(1.1)	2(0.2)	1(0)	4(0.2)	2(0)
Water, fresh (discharge)	Water	2(0.8)	2(0.2)	1(0)	3.8(0.6)	2(0)
Carbon dioxide/air	GHG	3.9(0.3)	2(0.1)	1(0)	3.9(0.4)	1(0)
Methane/air	GHG	3.9(0.4)	2(0.2)	1(0)	3.9(0.6)	1(0)

Note: Scores in the form of mean (standard deviation). 1 is the best quality score and 5 is the worst quality score.

these differences, as the original files in which the satellite tables were made are not publicly available or sufficiently described.

3.3. An example use of USEEIO – good & service hotspot analysis

Organizations without extensive knowledge of their supply chain environmental performance may be interested in first performing a "hotspot" analysis to determine in which categories the commodities they produce may have greater relative environmental impact, whether these impacts occur from their direct emissions or use of resources or whether they are embedded in their purchases, and what types of purchases are associated with which impacts. This knowledge could assist in prioritization of impacts and associated activities or purchases that could potentially be modified to reduce those impacts.

Hospital services are services not commonly associated with direct environmental impacts in comparison with primary sectors. But the final demand for hospital services is the third highest amongst the 389 sectors included in USEEIO, and these purchases drive significant environmental impacts, as it was ranked 9th in the Road Ahead report from the final consumption perspective (USEPA, 2009a). Thus, it provides a rich example which proves USEEIO can be used to assess life cycle impacts of an average service.

A hotspot analysis for hospital services could be conducted in the following series of steps using USEEIO, illustrated in Fig. 2 and described below.

Step 1. Determine impact categories of concern.

Final perspective LCIA results are calculated for total US private consumption expenditures in 2013 (see Eq. 10 in SI 1). A process contribution analysis is performed to show the proportional contribution of each of the 389 sectors to each impact category score. The results may be used to understand which impact categories are "hotspots," in that for certain impact categories the impacts are higher relative to other sectors. For hospitals, it appears that Acidification, Water use, Global warming potential, Human health toxicity – non-cancer, Human health toxicity – cancer, Land use, Energy use, and Smog formation are relatively higher than the others (Fig. 3a).

Step 2. Determine what proportion of impacts is derived from on-site operation versus purchases.

Step 2a. To estimate on-site operation impacts of hospitals, a final perspective LCIA calculation (see equation 10 in SI 1) is

Table 3
Environmental Data and Sources Used in openIO and CEDA compared with USEEIO.

Data	openIO			CEDA			USEEIO		
	Present	Source	Year	Present	Source	Year	Present	Source	Year
GHG emissions - All sectors	✓	GHGI	2002	✓	GHGI	2002	✓	GHGI	2013
CAPs/HAPs	✓	NEI	2002	✓	NEI	2002	✓	NEI	2011
Toxic releases	✓	TRI	2002	✓	TRI	2002	✓	TRI	2013
Pesticide releases - Agriculture	✓	NASS, NCFAP	2005–2007, 1997	✓	NASS, NCFAP	?, 1997	✓	NASS	2009–2014
Nutrient releases - Agriculture	✓	NASS	2005–2007	✓	NASS	2005-2007	✓	NASS	2009–2014
Nutrient releases - Util, Man, Serv							✓	DMR	2013
Water withdrawal - Ag, Min, Util, Water	✓	FRIS	2008	✓	WUUS, FRIS	2000& 2005, 2002	✓	WUUS, FRIS	2010, 2008
Water withdrawal - Manufacturing	✓	PI	2000				✓	CWUS	2007
Water return - All sectors							✓	WUUS	2010
Primary energy extraction - Fossil fuels	✓	EIA	?	✓	EIA	?	✓	EIA	2014
Primary energy capture - Renewables							✓	CBECS, MECS	2014, 2014
Mineral extraction				✓[a]			✓	MYB	2014
Land use - Ag and Forestry, Mining	✓	CA	2002	✓	MULUS	2002	✓	CA, MULUS, PLS	2007, 2007, 2007
Land use – Transportation	✓	Lit					✓	MULUS	2007
Land use - Manufacturing and Service							✓	CBECS, MECS	2014, 2014
Waste generation				✓	NBHWR	2002			
Harvested products (wood, fish)				✓	FDC,THUS	?, 1950-2002			

Note: Check marks indicate that one or more flows of that type are included. Only primary sources are included. Data years, not publication years, are provided under year. The sources are as follows, with general links provided and reference information for most recent year used. GHGI = US Greenhouse Gas Inventory (USEPA, 2016a), NEI = National Emissions Inventory (USEPA, 2015c), TRI = Toxic Release Inventory (USEPA, 2015b), NASS = Various resources of the National Agriculture Statistical Service (USDA, 2016a; USDA, 2016b), NCFAP = National Center for Food and Agricultural Policy's Pesticide Use in US Crop Production (USDA, 2000), DMR = Discharge Monitoring Report (USEPA, 2016b), EIA = various Energy Information Administration fossil energy use reports (EIA, 2016a; EIA, 2016b; EIA, 2013a; EIA, 2013b; EIA, 2015), FRIS = Farm and Ranch Irrigation Survey (USDA, 2009b), WUUS = Water Use in the US (Maupin et al., 2014), MYB = Mineral Year Book (USGS, 2016); MULUS = Major Uses of Land in the United States (Nickerson et al., 2011), CA = Census of Agriculture (USDA, 2014; USDA, 2009a), Lit = various literature sources, NBHWR = National Biennial Hazardous Waste Report (USEPA, 2015a), PI = Pacific Institute's Potential for Urban Water Conservation in California Report (Pacific Institute, 2014), CWUS = Canadian Water Use Survey (Statistics Canada, 2010), CBECS = Commercial Building Energy Use Survey (EIA, 2015), MBECS = Manufacturing Building Energy Consumption Survey (EIA, 2013a), PLS = Public Land Use Survey (BLM, 2008), THUS = Timber Harvest by US Region (USDA, 2006a).
[a] includes iron ore extraction but no other minerals.

performed for 1 USD demand for the hospital sector with the A matrix (Equation 3 in SI 1) set equal to unity to calculate only direct hospital sector impacts of 1 USD demand.

Step 2b. To estimate impacts of purchases associated with 1 USD impact, the column of the direct requirements matrix representing purchases for output is used as the demand vector, y, and final perspective LCIA calculation results are performed.

The impact category totals are summed from step 2a and 2b, and ratios are created. For hospitals, purchases embed more impacts than direct operations at the hospitals for all impact categories (Fig. 3b).

Step 3. Determine which purchases lead to the most impacts in the hotspot categories.

For a selection of the impact categories identified in step 1 – GWP, Land, and Water (Fig. 4) – a process contribution analysis is performed for the result from Step 2b. The 389 sectors are aggregated into purchase categories that are more understandable to an end user. The electricity purchase embeds ~38% of water use and ~30% of GWP. Purchases of industrial equipment embed a significant portion of water, GWP, and land use (12%, 14%, 15%). A number of other smaller supplies and services contribute portions to the impact categories, like food and food services, plastic/rubber and nonmetallic mineral products, and technical, administrative, rental, and medical services.

An expert may want to inspect or audit the above results in more detail. For instance, it may be of interest to understand the particular processes that lead to impacts of interest, the environmental flows (resources or emissions) responsible for those impacts, and then to understand the sources of the data and associated data quality of these estimates. Additional steps can support this form of detailed inspection.

Step 4. Determine which sectors and environmental flows are responsible for the direct impacts for hospitals.

Step 4a. A direct perspective LCIA result is calculated for 1 USD demand for hospitals. A process contribution analysis is performed on this result. For GHGs for hospitals, the electricity sector contributes ~50% of the direct impact. Direct emissions from hospitals contribute 9%, which is seen in Fig. 3b. For land use, beef cattle ranching and forestry contribute 45% and 31%, respectively.

Step 4b. For sectors with high direct impact in the category of interest, determine which flows contribute to impacts.

For the sectors that contribute the most direct impact to the impact category of interest, perform a final perspective calculation for 1 USD demand for that sector, with the A matrix set to unity to zero out indirect emissions. Then for that result, perform a flow contribution analysis. For direct GHG emissions in the electricity and hospital sectors, it appears that CO_2 emissions dominate the results. For direct land use in the beef and cattle ranching, 'Occupation, pasture and meadow' and 'Occupation, forest' are the dominant flows.

Step 5. Determine the origin and sources for the environmental flows of interest.

Determine the appropriate source satellite table files for the flows of interest (links to satellite table files can be found in SI 1). The 'Exchanges' can be filtered or searched for the sector and emission of interest. The GHG Satellite file shows the carbon dioxide flows for the electricity sector and hospitals sectors are from 2013 data from the US EPA Greenhouse Gas Inventory. The

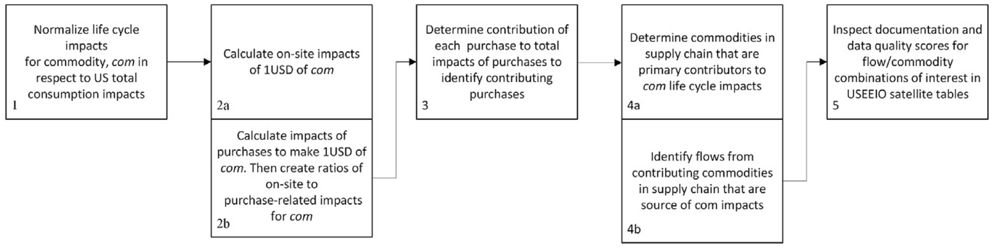

Fig. 2. Framework for good & service hotspot analysis using USEEIO.

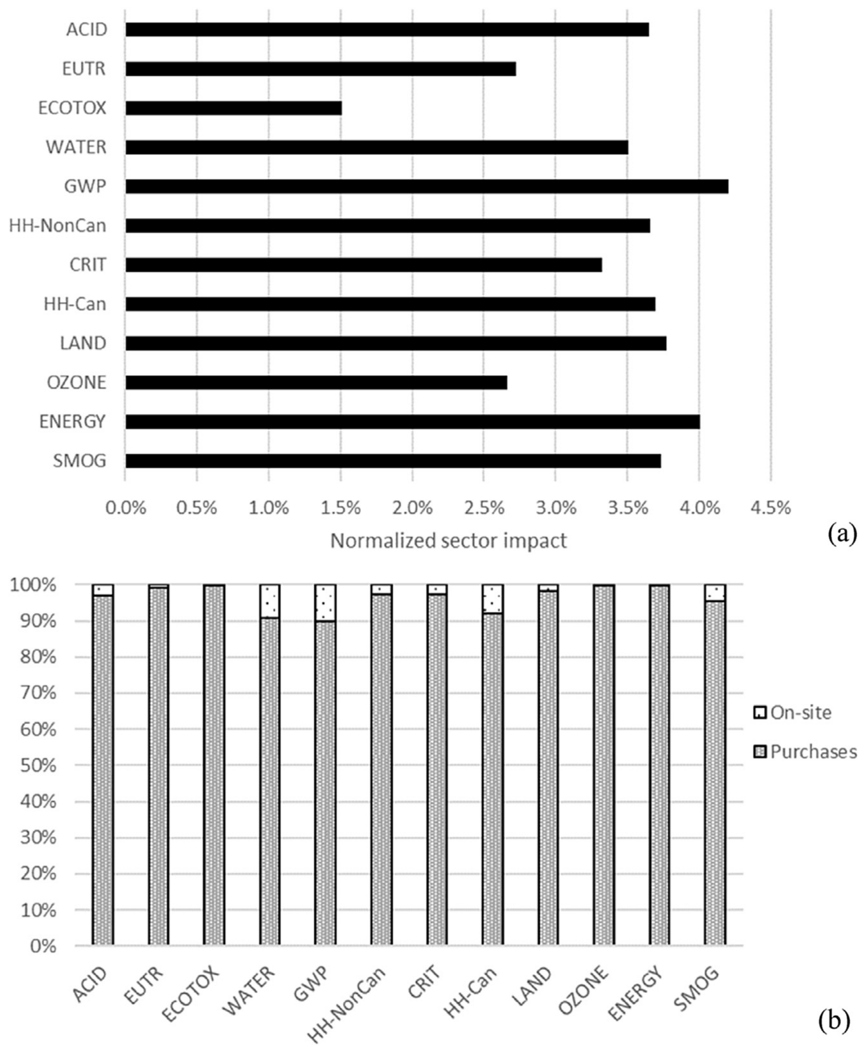

Fig. 3. Hospital sector analysis. (a) Normalized impact scores of hospitals relative to other sectors. (b) Breakdown of each impact score into contribution from on-site operations or purchases.

electricity sector data quality scores for CO_2 are {2,1,1,1,1}[3], indicating good reliability and excellent temporal, geographical and technological correlation and sector coverage. The hospital sector has the CO_2 flow data quality scores {4,2,1,4,1}, representing less reliability, temporal and technological correlation than for the electricity sector. The GHG SI file can be further examined to see the calculation details for an environmental flow, and in this case can identify why the data quality of the hospital CO_2 estimate is poorer than for electricity. For hospitals, it reveals the CO_2 emissions come from data reported for total US commercial combustion CO_2 emissions for coal, natural gas, and petroleum. These emissions are allocated across the commercial sectors according to their use of these fuels in the Use table. Examination of the land flows in the land satellite table reveals that for beef and cattle ranching there are multiple 'Occupation, pasture and meadow' because they are compiled at a state level of resolution. Sorting by state reveals that TX has three times the land occupation than that of the next largest

[3] Scores are in this format: {data reliability, temporal correlation, geographic correlation, technological correlation, and data collection methods}.

Commodity	GWP	WATER	LAND
Electricity	29.9%	37.7%	1.7%
Industrial equipment	14.0%	12.0%	15.1%
Nonmetallic mineral products	8.5%	2.8%	4.6%
Transport	7.8%	1.2%	2.8%
Fuel	3.5%	3.4%	1.2%
Rental services	3.4%	3.2%	5.7%
Technical services	3.4%	4.0%	6.2%
Admin & support services	3.0%	3.5%	6.1%
Chemicals	3.0%	2.6%	3.8%
Plastic/rubber products	3.0%	3.2%	6.9%
Primary metals	2.4%	1.5%	1.0%
Other services	2.2%	2.7%	3.6%
Medical services	2.1%	2.6%	5.0%
Wholesale & Retail	2.0%	2.4%	3.8%
Food services	1.9%	3.0%	7.5%
Food	0.9%	4.6%	5.5%
Buildings	0.2%	0.4%	2.5%

Fig. 4. Heatmap of sources of Water Use, GWP, and Land Use impacts in hospital sector purchases.

states (MT, NM, WY, OK). The source for these flows is the USDA agricultural census and the data quality scores {2,3,1,1,1} reveal these data to be very reliable although moderately old (2007). For the forestry occupation of forested land, two exchanges are found, one for federal land and one for non-federal timberland. The data scores are the same as that for the previous flow {2,3,1,1,1}, but the data source for land occupied is the Major Uses of Land. In both cases, the original data for these land uses with their original names in the sources can be found in the satellite table file.

This example of a sector hotspot analysis is only appropriate for characterizing an average hospital, but could be tailored to a specific hospital using hospital-specific environmental performance data (e.g., water and land use, emissions) and purchases.

USEEIO, assembled and used with the IO Model Builder, can provide this type of analysis for each of the goods and services in the model along with extensive and detailed process and flow contributions for any results found within the result analysis. The source of the data points that influence the analysis results can be found through inspection of the flow details in the satellite table files and data quality scores for those data points can be scrutinized as well as more details found regarding the original data.

Furthermore, the model can be exported in JSON-LD format from the IO Model Builder and imported into openLCA software. Fig. S1 in SI 1 presents screenshots of USEEIO in openLCA. In LCA software, the USEEIO processes could be used to generate results on their own, or linked to process LCI as a background database to create hybridized life cycle inventory models. The availability of the model in this standard LCA format along with metadata documentation addresses some of the needs previously expressed for harmonization of traditional process LCA and EEIO LCA data (Schuerch et al., 2012).

3.4. Reflecting current conditions and uncertainty

Despite the temporal inconsistency between IO tables and satellite tables, the model may provide adequate estimates of commodities' cradle-to-gate environmental impacts in more recent years, such as in 2013 as demonstrated in the hotspot analysis example, if the structure of the economy as defined in the Make and Use tables is determined to be similar enough to the target year to satisfy the study goals. More recent year estimation requires deriving final demand and adjusting it to the same year price as the satellite tables, which are prepared in USD 2013. Using the final demand for a more recent year, like 2013, with direct requirements coefficients derived from the industry exchanges and value added in the Make and Use tables from an earlier year, like 2007, is not uncommon in input-output analysis (Miller and Blair, 2009). This approach assumes that a USD 2007 $input/$output requirement is a good approximation of a more recent year, and is referred to as a current price approach (Miller and Blair, 2009). This approach is in contrast to a constant price approach in which the values in the Make and Use tables are adjusted to the same year currency, which in this case would be the 2007 tables in USD 2013 $input/$output.

To explore changes in the structure of the US economy from 2007 to 2013, as reflected in the input-output tables, we performed an analysis comparing published 2007 and 2013 US input-output tables at a less-resolved level of sectors (71). Our analysis and findings, including the high correlation between 2007 and 2013 direct requirements ($R^2 = 0.96$), are described in SI 1. This finding is also consistent with previous studies of structural change in the US economy that have shown that the structure is slow to change, particularly within a short period of time (e.g. Carter, 1970). The high correlation of the 2007 and 2013 direct requirements suggests that the 2007 structure model is largely appropriate for 2013. We also tested a constant price approach, by adjusting the 2007 direct requirements to 2013 dollars (see SI 1), but found this approach for the 71-sector data did not yield any better correlation than the current price approach. Our conclusion mirrors the recommendation by Miller and Blair (2009) to use the current dollar approach, because it generally yields more stable input/output coefficients.

Ideally, USEEIO would use the more current IO tables – were they available – to increase the accuracy of input structure and modeling of indirect impacts. The drawback of using data on resource use and emissions normalized by output in a different year than the direct requirements is that the inputs to making a commodity may not temporally match the emissions and resources associated with that process. This can lead to potential errors in modeling of indirect, supply-chain impacts, if the input structure for the production of a particular commodity changes significantly. However, the benefits of using the most current environmental data outweigh the drawback of this potential imbalance. Take for instance, the US electricity sector between 2007 and 2014, which has experienced changes in input structure and emissions. The US grid reduced generation from coal from 48.4% to 38.7% and increased generation from natural gas from 21.6% to 27.5%, and wind from <1% to 4.4%, among other minor changes (USEPA, 2017). Due to fuel source changes but also other industry changes such as increased emission controls, the NO_x, SO_2 and GHG emission intensities decreased 41%, 64% and 12% respectively from 2007 levels. USEEIO captures the more recent changes in emissions in this sector, which are particularly important to accurately model in that they potentially contribute to a number of environmental impacts, as reflected in the hospital example. Using 2007 emissions data would miss these changes and lead to less accurate modeling of potential environmental impacts of current conditions, which is the principal goal of the model. In the same light, USEEIO can, through use of more current environmental data, provide a more accurate measure of total resource use and emissions in the US economy if final demand is set to equal economy totals from a consumption or production perspective. It should be noted that in the documentation, the data quality of the technosphere flows reflects this current lack of high temporal correlation in the model metadata.

Including confidence intervals on flow amounts is valuable for use in uncertainty or variability modeling. It is still not common to evaluate uncertainty in EEIO models because there are no established methods for doing so, but USEEIO offers the extensive data quality information as an alternative. It is not recommended the data quality scores be used for quantitative uncertainty analysis (see Edelen and Ingwersen, in review), but they can be used for identifying potential weaknesses in underlying data both from the "bottom-up" through review of data quality of particular exchanges and from a results-oriented perspective, to indicate the data quality of the inventory data driving the results.

4. Conclusions

This paper presented the USEEIO model, a new and transparent environmentally-extended input-output model of the US. USEEIO includes several major improvements on its predecessors. USEEIO provides an up-to-date picture of environmental aspects of the US economy with most of the environmental data reflective of 2013 conditions. In comparison to previous models, USEEIO covers more environmental releases with improvements to nutrient releases which include industrial sources and wastewater treatment plants omitted from earlier models, water discharges, comprehensive mineral use, renewable energy use, industrial and commercial land use, and more detailed characterization of pesticide releases to air, water, and soil. Understanding the sources of differences between results for emissions in previous EEIO models of the US such as CEDA and openIO when they used the same data sources was not possible due to lack of adequate documentation, but the sector hotspot example showed how with USEEIO it is possible to understand and find in the original data the source of a value and assumptions behind it. The previous models restricted their data year to the most recently available year for the detailed input output tables. However, USEEIO integrates more recent economic and environmental data to be more relevant for current decision making. The scope, preparation, model builder, and formatting in standard templates and as software-ready LCI are novel for EEIO models. Extensive data quality assessment was performed and data quality scores are included in the dataset to increase understanding of data quality for use in interpretation. Considering these improvements and the quality of US government statistics, USEEIO is arguably the most comprehensive, transparent, and reproducible national EEIO model to date.

USEEIO supports EPA's prioritization of opportunities to manage goods and services more sustainably using a life cycle approach. However, as with EEIO models in general, it can be applied as a systems approach to address many other environmental questions. Moreover, estimates of resource use and emissions by different industries in USEEIO may shed light on individual environmental problems. The complete coverage of nutrient emissions, for example, helps identify the major direct emitters, which may lead to more effective policy design or improvement opportunities.

There is continuous effort at EPA to make USEEIO more comprehensive and up-to-date. Currently, the use and end-of-life management phases for commodities consumed by US households are being incorporated into USEEIO, and regionalized versions of the model are being constructed. As economic and environmental data sources are updated, USEEIO will in turn undergo periodic updates.

Disclaimer

This article does not reflect the endorsement or opinion of the US Environmental Protection Agency.

Acknowledgments

This research was part of the EPA Office and Research and Development's Sustainable and Healthy Communities Program. The EPA Office of Resource Conservation and Recovery's Sustainable Materials Management program established the need for this research. The research was supported by EPA contracts EP-C-15-012 and EP-C-12-021. Troy Hawkins, Sangwon Suh, and Greg Norris served on a technical advisory panel for the model. Theresa Garvey (USEPA), Matt Bergmann (ORAU), and Donnie Vineyard (ORISE) helped in preparation of the impact methods and with dataset review. Ben Morelli and Sarah Cashman (ERG) also reviewed the environmental satellite tables. Katelyn Gilkey (ORAU) assisted with table preparation for the manuscript. Diana Bless and Jennifer Cashdollar (USEPA) were contract officer's representatives for EP-C-12-021. Andreas Ciroth and Sebastian Greve (GreenDelta) supported the IO Model Builder development and integration with openLCA software and Cristina Rodriguez (GreenDelta) performed quantitative comparison tests between the openIO and CEDA models.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jclepro.2017.04.150.

References

Bare, J., 2012. Tool for the Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI): TRACI Version 2.1-User's Manual. National Risk Management Laboratory, U.S. Environmental Protection Agency, Cincinnati, OH.
BEA, 2015. Input-output Accounts Data. https://www.bea.gov/iTable/index_industry_io.cfm.
Blackhurst, B.M., Hendrickson, C., Vidal, J.S., 2010. Direct and indirect water withdrawals for US industrial sectors. Environ. Sci. Technol. 44, 2126–2130.
BLM, 2008. 2007 Public Land Statistics (No. BLM/OC/ST-08/001+1165). U.S. Department of Interior, Bureau of Land Management, Washington DC.
Brown, M.T., Ingwersen, W.W., Pfahler, D., Rajvanshi, N., Rothrock, H., Evans, J.M., Hodges, A., Dwivedi, P., 2009. Clean Energy for Florida Transportation: Assessment of Greenhouse Gas Emissions for Selected Renewable Fuels. Prepared for the Florida Energy and Climate Commission, Tallahassee, FL.
Carter, A.P., 1970. Structural Change in the American Economy. Harvard University Press, Cambridge, MA.
Cashman, S.A., Meyer, D.E., Edelen, A.N., Ingwersen, W.W., Abraham, J.P., Barrett, W.M., Gonzalez, M.A., Randall, P.M., Ruiz-Mercado, G., Smith, R.L., 2016. Mining available data from the United States environmental protection agency to support rapid life cycle inventory modeling of chemical manufacturing. Environ. Sci. Technol. 50, 9013–9025. http://dx.doi.org/10.1021/acs.est.6b02160.
Cooper, J., Kahn, E., Ingwersen, W.W., 2015. US Federal LCA Commons Life Cycle Inventory Unit Process Template, 1.0 ed.
Cox, R.W., Norris, G., 2011. Open IO: Developing a Transparent, Fully Accessible Economic Input-output Life Cycle Assessment Database. The Sustainability Consortium, Tempe, AZ, USA.
Edelen, A., Ingwersen, W., 2016. Guidance on Data Quality Assessment for Life Cycle Inventory Data (No. EPA/600/R-16/096). National Risk Management Laboratory, U.S. Environmental Protection Agency, Cincinnati, OH.
Edelen, A., Ingwersen, W., 2017. Recommendations on the Creation, Management and Use of Data Quality Information for Life Cycle Assessment. submitted for publication.
EIA, 2013a. 2010 Manufacturing Energy Consumption Survey (MECS). Energy Information Administration. https://www.eia.gov/consumption/manufacturing/data/2010/ (Accessed 3 March16).
EIA, 2013b. Annual Energy Review. Energy Information Administration. http://www.eia.gov/totalenergy/data/annual/ (Accessed 9 June 2016).
EIA, 2015. 2012 Commercial Buildings Energy Consumption Survey (CBECS). Energy Information Administration. http://www.eia.gov/consumption/commercial/ (Accessed 11 January 2015).
EIA, 2016a. Monthly Energy Review. Energy Information Administration. http://www.eia.gov/totalenergy/data/monthly/ (Accessed 12 July 2016).
EIA, 2016b. Electric Power Annual. U.S. Energy Information Administration. http://www.eia.gov/electricity/annual/ (Accessed 9 June 2016).
Goebes, M.D., Strader, R., Davidson, C., 2003. An ammonia emission inventory for fertilizer application in the United States. Atmos. Environ. 37, 2539–2550.
GreenDelta, 2014. openLCA 1.4 (Accessed 30 November 2016).
Hendrickson, C.T., Lave, D.L.B., Matthews, H.S., 2006. Environmental Life Cycle Assessment of Goods and Services: an Input-output Approach. Resources for

the Future, Washington DC.
Horowitz, K.J., Planting, M.A., 2006. Concepts and Methods of the U.S. Input-output Accounts. Bureau of Economic Analysis, U.S. Department of Commerce, Washington, DC.
Huang, Y.A., Weber, C.L., Matthews, H.S., 2009. Categorization of scope 3 emissions for streamlined enterprise carbon footprinting. Environ. Sci. Technol. 43, 8509–8515. http://dx.doi.org/10.1021/es901643a.
Huppes, G., Koning, A., Suh, S., Heijungs, R., Oers, L., Nielsen, P., Guinée, J., 2006. Environmental impacts of consumption in the European Union: high-resolution input-output tables with detailed environmental extensions. J. Ind. Ecol. 10, 129–146.
Kerkhof, A.C., Nonhebel, S., Moll, H.C., 2009. Relating the environmental impact of consumption to household expenditures: an input–output analysis. Ecol. Econ. 68, 1160–1170.
Kim, J., Yang, Y., Bae, J., Suh, S., 2013. The importance of normalization references in interpreting LCA results. J. Ind. Ecol. 17 (3), 385–395.
Krauter, C., Goorahoo, D., Potter, C., Klooster, S., 2002. Ammonia emissions and fertilizer applications in California' s Central Valley. In: Presented at the 11th International Emission Inventory Conference - "Emission Inventories - Partnering for the Future," Atlanta GA.
Kucukvar, M., Egilmez, G., Tatari, O., 2014. Sustainability assessment of U.S. final consumption and investments: triple-bottom-line input–output analysis. J. Clean. Prod. 81, 234–243.
Lenzen, M., 1998. Primary energy and greenhouse gases embodied in Australian final consumption: an input–output analysis. Energy Policy 26, 495–506.
Lenzen, M., Moran, D., Kanemoto, K., Geschke, A., 2013. Building Eora: a global multi-region input–output database at high country and sector resolution. Econ. Syst. Res. 25, 20–49. http://dx.doi.org/10.1080/09535314.2013.769938.
Leontief, W., 1941. The Structure of American Economy, 1919-1929: an Empirical Application of Equilibrium Analysis. Harvard University Press.
Liang, S., Feng, T., Qu, S., Chiu, A.S., Jia, X., Xu, M., 2016. Developing the Chinese environmentally extended input-output (CEEIO) database. J. Ind. Ecol. http://dx.doi.org/10.1111/jiec.12477.
Lovelace, J.K., 2009. Method for Estimating Water Withdrawals for Livestock in the United States, 2005. US Geological Survey, Reston, VA.
Lutter, S., Giljum, S., 2014. Demand-based measures of material flows. A review and comparative assessment of existing calculation methods and data options. In: Presented at the OECD International Expert Workshop "Demand-based Measure of Material Flows and Carbon," Paris.
Macknick, J., Newmark, R., Heath, G., Hallett, K.C., 2011. A Review of Operational Water Consumption and Withdrawal Factors for Electricity Generating Technologies. National Renewable Energy Laboratory, Golden, CO.
Maupin, M.A., Kenny, J.F., Hutson, S.S., Lovelace, J.K., Barber, N.L., Linsey, K.S., 2014. Estimated Use of Water in the UnitedStates in 2010. US Geological Survey, Reston, VA.
Miller, R., Blair, P., 2009. Input-output Analysis: Foundations and Extensions. Cambridge University Press, Cambridge, England.
Nansai, K., 2009. Environmental input-output database building in Japan. In: Suh, S. (Ed.), Handbook of Input-output Economics in Industrial Ecology, Eco-efficiency in Industry and Science. Springer Netherlands, pp. 653–688. http://dx.doi.org/10.1007/978-1-4020-5737-3_31.
Nickerson, C., Ebel, R., Borchers, A., Carriazo, F., 2011. Major Uses of Land in the United States, 2007 (Economic Information Bulletin No. 89). U.S. Department of Agriculture, Economic Research Service.
Orszag, P.R., 2009. Open Government Directive.
Pacific Institute, 2014. Urban Water Conservation and Efficiency Potential in California. http://pacinst.org/app/uploads/2014/06/ca-water-urban.pdf (Accessed 17 March 2017).
Pairotti, M.B., Cerutti, A.K., Martini, F., Vesce, E., Padovan, D., Beltramo, R., 2015. Energy consumption and GHG emission of the Mediterranean diet: a systemic assessment using a hybrid LCA-IO method. J. Clean. Prod. 103, 507–516.
Pauliuk, S., Majeau-Bettez, G., Mutel, C.L., Steubing, B., Stadler, K., 2015. Lifting industrial ecology modeling to a new level of quality and transparency: a call for more transparent publications and a collaborative open source software framework. J. Ind. Ecol. 19, 937–949. http://dx.doi.org/10.1111/jiec.12316.
Pascual-González, J., Guillén-Gosálbez, G., Mateo-Sanz, J.M., Jiménez-Esteller, L., 2015. Statistical analysis of global environmental impact patterns using a world multi-regional input–output database. J. Clean. Prod. 90, 360–369.
Pelton, R.E.O., Smith, T.M., 2015. Hotspot scenario analysis. J. Ind. Ecol. 19, 427–440. http://dx.doi.org/10.1111/jiec.12191.
Peters, G., Weber, C., Liu, J., 2006. Construction of Chinese Energy and Emissions Inventory. Nor. Univ. Sci. Technol. (Ind. Ecol. Programme Rep. Work. Pap).
Rebitzer, G., Loerincik, Y., Jolliet, O., 2002. Input-output life cycle assessment: from theory to applications 16th discussion forum on life cycle assessment Lausanne, April 10, 2002. Int. J. Life Cycle Assess. 7, 174–176.
Schuerch, R., Kaenzig, J., Jungbluth, N., et al., 2012. 45th Discussion forum on LCA—environmentally extended input–output analysis and LCA, September 15, 2011, Berne, Switzerland. Int. J. Life Cycle Assess. 17, 840. http://dx.doi.org/10.1007/s11367-012-0428-5.
SRA International, IERS, 2014. Opportunities for Improving the Environmental Profile of GSA Expenditures. Prepared for the US General Services Administration.
Statistics Canada, 2010. Table 153-0047-Water Use Parameters in Manufacturing Industries, by North American Industry Classification System (NAICS), Every 2 Years (Cubic Metres). 2007. http://www5.statcan.gc.ca/cansim/ (Accessed 5 January 2015a).
Stone, R., 1961. Input-output and National Accounts. Organisation for Economic Cooperation and Development, Paris.
Suh, S., 2005. Developing a sectoral environmental database for input–output analysis: the comprehensive environmental data archive of the US. Econ. Syst. Res. 17, 449–469.
Suh, S., 2010. Comprehensive Environmental Data Archive (CEDA). In: Murray, J., Wood, R. (Eds.), The Sustainability Practitioner's Guide to Input-output Analysis. Common Ground Publishing LLC, Champaign, Illinois, pp. 109–122.
Suh, S., Weidema, B., Schmidt, J.H., Heijungs, R., 2010. Generalized make and use framework for allocation in life cycle assessment. J. Ind. Ecol. 14, 335–353.
Torcellini, P.A., Long, N., Judkoff, R., et al., 2003. Consumptive Water Use for U.S. Power Production. National Renewable Energy Laboratory, Golden, CO.
Tukker, A., 2006. Identifying priorities for environmental product policy. J. Ind. Ecol. 10, 1–4.
Tukker, A., de Koning, A., Wood, R., Hawkins, T., Lutter, S., Acosta, J., Rueda Cantuche, J.M., Bouwmeester, M., Oosterhaven, J., Drosdowski, T., Kuenen, J., 2013. EXIOPOL—development and illustrative analyses of a detailed global MR EE SUT/IOT. Econ. Syst. Res. 25 (1), 50–70.
USDA, 2000. Pesticide Use in U.S. Crop Production: 1997. http://www.ncfap.org/documents/nationalsummary1997.pdf (Accessed 17 March 2017).
USDA, 2006a. Estimated timber harvest by U.S. Region and ownership, 1950-2002. http://www.viewcrafters.com/pdffiles/pnw_gtr659.pdf (Accessed 17 March 2017).
USDA, 2006b. Model Simulation of Soil Loss, Nutrient Loss, and Change in Soil Organic Carbon Associated with Crop Production. Natural Resource Conservation Service, US Department of Agriculture.
USDA, 2009a. 2007 Census of Agriculture (No. AC-07-a-51). US Department of Agriculture, Washington DC.
USDA, 2009b. Farm and Ranch Irrigation Survey (2008). United States Department of Agriculture, Washington, DC.
USDA, 2014. 2012 Census of Agriculture (No. AC-12-a-51). US Department of Agriculture, Washington DC.
USDA, 2016a. Agricultural chemical use program. http://www.nass.usda.gov/Surveys/Guide_to_NASS_Surveys/Chemical_Use/ (Accessed 12 December 2013).
USDA, 2016b. Quick Stats, National Agricultural Statistics Service. US Department of Service. http://quickstats.nass.usda.gov/ (Accessed 20 December 2013).
USEPA, 2009a. Sustainable Materials Management: the Road Ahead. US Environmental Protection Agency, Washington, DC.
USEPA, 2009b. Guidance on the Development, Evaluation, and Application of Environmental Models (No. EPA/100/K-09/003). Council for Regulatory Environmental Modeling, U.S. Environmental Protection Agency, Washington, DC.
USEPA, 2015a. National Biennial Hazardous Waste Report. https://www.epa.gov/hwgenerators/biennial-hazardous-waste-report (Accessed 17 March 2017).
USEPA, 2015b. Toxics Release Inventory (TRI) 2014. https://www.epa.gov/toxics-release-inventory-tri-program (Accessed 17 March 2017).
USEPA, 2015c. National Emissions Inventory (NEI) 2011 v2. https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei (Accessed 14 November 2016).
USEPA, 2016a. U.S. Greenhouse Gas Inventory Report: 1990-2013. http://www3.epa.gov/climatechange/ghgemissions/usinventoryreport.html (Accessed 1 April 2016).
USEPA, 2016b. Discharge Monitoring Report (DMR) Pollutant Loading Tool. https://cfpub.epa.gov/dmr/ (Accessed 13 April 2016).
USEPA, 2016c. Environmental Dataset Gateway. https://edg.epa.gov/metadata/catalog/main/home.page (Accessed 20 October 2016).
USEPA, 2017. Emissions & Generation Resource Integrated Database (eGRID). https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid (Accessed on 12 February 2017).
USGS, 2015. Mineral Commodity Summary 2013. U.S. Geological Survey, Reston, VA.
USGS, 2016. Mineral Commodity Summary 2014. U.S. Geological Survey, Reston, VA.
Vineyard, D.L., Ingwersen, W.W., Bergmann, M., Yang, Y., 2017. Modeling Agricultural Pesticide Emissions at a National Scale.
Weber, C., Matthews, D., Venkatesh, A., Costello, C.H., Scott, M., 2009. The 2002 US Benchmark Version of the Economic Input-output Life Cycle Assessment (EIO-LCA) Model. Green Design Institute, Carnegie Mellon University, Pittsburgh, PA.
Wiedmann, T.O., Lenzen, M., Barrett, J.R., 2009. Companies on the scale. J. Ind. Ecol. 13, 361–383.
Yang, Y., Suh, S., 2011. Environmental impacts of products in China. Environ. Sci. Technol. 45, 4102–4109.
Yienger, J.J., Levy, H., 1995. Empirical model of global soil-biogenic NO_χ emissions. J. Geophys. Res. Atmos. 11447–11464, 1984–2012 100.
Zhang, Y., Baral, A., Bakshi, B.R., 2010. Accounting for ecosystem services in life cycle assessment, Part II: toward an ecologically based LCA. Environ. Sci. Technol. 44, 2624–2631.