Uncertainty Estimation in Matrix-based Life Cycle Assessment Models

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Abstract

Life Cycle Assessment (LCA) has been applied to help decision-makers understand quantitative environmental effects and impacts through the life stages of a product or process. Matrix-based LCA models are widely incorporated to LCA software tools to simplify the assessment and provide straightforward results. However, these tools do not sufficiently provide the uncertainties that arise from the inventory data as well as from the matrix-based models. To address this problem, in this thesis I use a range method to explore three types of uncertainties (parameter, scenario, and model uncertainties) present in matrix-based LCA models. These three types of uncertainties are assessed separately for two different types of LCA models: the Input-Output- based LCA model, and the process-based LCA models analyzed with matrix methods. IO-based LCA models are studied with the Environmental Input-Output Life Cycle Assessment (EIO-LCA) model, and the US LCI database incorporated to matrix methods is used as an example of process-based LCA models. I selected two demonstrate the results with two environmental effects (greenhouse gas emissions and energy consumptions) and five environmental impacts (global warming, ozone depletion, acidification, eutrophication and ecotoxicity).

First, I analyzed the parameter uncertainty in the EIO-LCA model. Publicly available data sources and assumptions are used to estimate the parameter uncertainties of the direct energy consumption in the US industrial sectors. The direct and indirect energy consumption ranges are estimated through the EIO-LCA model. The results show that the parameter uncertainties are generally within -40% to 40% from the default values, with several outliers. Second, I examined the scenario uncertainties in total carbon dioxide emissions by using alternative inputs in the US LCI database. I found that the US LCI database fails to take full advantage of matrix-based methods; when incorporated to matrix-based LCA models, less than 10% of the processes contribute to the indirect environmental effects. The results of scenario uncertainty estimation in the US LCI database show that on average, the total carbon dioxide emissions across all processes are between -30% to -30%. Finally, I addressed the model uncertainty by using different Life Cycle Inventory Assessment (LCIA) methods incorporated in the matrix-based models. The results show that when the US LCI inventories are applied, the uncertainties due to choosing different impact

methods are within 5%. This is possibly caused by the incompleteness of the inventories: more than 50% of the characterized substances are excluded in the inventory, resulting in the neglect of some impact values.

The results from this study emphasize the importance of estimating uncertainties in matrix-based LCA models. The variability in the LCA results is caused by all three types of uncertainties, as well as the incomplete inventories embedded in the matrix-based LCA models. Future LCA database and software should focus on including uncertainty estimation in the features and improving the inventory data to take full advantage of the matrix-based LCA models.

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1. Chapter 1. Introduction and Background

1.1 Motivation

Life cycle assessment (LCA) is a decision-support technique for practitioners, including policy makers and industry, to assess the environmental impacts of a product or process. The results from LCA studies can aid the decision-makers by providing quantitative environmental impact results (Hellweg and Canals 2014). LCA software tools, such as OpenLCA, SimaPro, and CMLCA, have been designed for conducting LCA studies and are popularly used by environmental specialists and decision makers. These tools provide accessible LCA results and have lower barriers to be understood and handled compared to the scattered scientific LCA reports published in academic journals. However, the user-friendly interfaces of LCA tools have insufficient uncertainty information to make the users fully understand the underlying information behind the data and the results. This lack of sufficient uncertainty information limits the accuracy of decision-making based on the results provided by the LCA tools.

The LCA tools often incorporate matrix-based methods in the analyses of LCA results. Due to the complexity of matrix-based methods, the uncertainty estimation in the LCA tools are hard to be addressed. The existing tools use only empirical judgments and simulations to estimate the uncertainties in the LCA tools. The estimated uncertainties from such methods are hard to interpret and can be easily ignored by the users. In order to provide the users with more reliable uncertainty results in LCA tools, more robust uncertainty estimation methods for matrix-based models need to be developed. More accurate uncertainty information for LCA tools needs to be provided.

This dissertation attempts to analyze the uncertainty associated with the data inputs and model outputs of matrix-based LCA tools. A method using real-life data rather than empirical estimation based on the quality of the deterministic data is developed, and the uncertainties of matrix-based LCA tools are estimated based on the new method. In addition, the uncertainties from the empirical estimation method are applied to current available full datasets used in the input-output matrix-based model to compare with the uncertainty results estimated from the new method.

In this study, a new method to estimate the uncertainty in matrix-based LCA models will be provided. The method is based on more reasonable estimation and assumptions, and provides more robust uncertainty results in matrix-based LCA models. The proposed method can be easily applied to both process matrix LCA and input-output LCA models. The uncertainty results will help matrix-based LCA tool users have an insight of the importance of uncertainty in LCA models, and provide more understandable uncertainty results to support the decision-making process associated with LCA.

1.2 Introduction

1.2.1 Life cycle assessment

Life Cycle Assessment (LCA) is a method that computes and evaluates the inputs, outputs, and environmental impacts from design to disposition of a product or process (Guinee 2002; ISO 2006a). The guidelines developed by the International Organization for Standardization (ISO) regulate the minimum requirements in the principles and framework of LCA studies (ISO 2006b). Based on the ISO standards ISO 14040 and 14044, LCA studies involve four main phases: 1) the goal and scope definition that defines the context of the study, 2) the life cycle inventory (LCI) that creates an inventory of stages and flows, 3) the life cycle impact assessment (LCIA) that evaluates the environmental impacts based on the inventory, and 4) the interpretation that systematically interprets the results (ISO 2006a). Three primary types of LCA methodologies have been applied to determine environmental impacts and help in decision making: process-based LCA that analyzes the impacts from the processes involved in a study, economic input-output LCA (IO-LCA) that uses economic exchange values to trace the total impacts from the supply chain, and hybrid LCA that combines process-based and input-output-based methods to combine and expand the perspective of the two methods (Hendrickson et al. 1998) (Hertwich 2005) (Finnveden et al. 2009) (Pairotti et al. 2014).

Following the four stages and conducting an LCA study in each of the three primary types is time consuming; this is a complex processes that requires data gathering, study scoping, inventory and impact estimation as well as result interpretation (Ong et al. 2001). Different LCA databases and

LCA tools have been developed to help the users perform LCA studies in more efficient and convenient ways. LCA software tools such as Gabi, SimaPro, BEES, EIO-LCA and LCA databases such as Ecoinvent and U.S. LCI use existing inventory data, and include various models and methods to quickly generate systematic results for users (GmbH 2006) (Consultants 2008) (NIST 2009) (National Renewable Energy Laboratory 2012).

1.2.2 Matrix-based LCA models

The efficiency of LCA analysis can be improved by scaling the inventory in matrix-based models. Compared to scattered scientific LCA models, matrix-LCA models provide accessible results and have lower barriers to be understood and handled. The Life Cycle Inventory (LCI) data from existing LCA databases (U.S. LCI, ELCD and Ecoinvent) can be mapped on to a matrix model. Recently, the matrix-based LCA models have been widely accepted and incorporated to LCA software tools (Heijungs and Suh 2006).

Matrix-based methods are applied to Input-output (IO) LCA models. IO LCA is a method that combines LCA and the economic input-output approach, which is applied in the principles of Input-output models developed by Leontief (Leontief 1970). The IO method scales the direct requirement exchanges in dollar values between industrial sectors into matrix $\boldsymbol{A}$, and uses Leontief inverse $(\boldsymbol{I}-\boldsymbol{A})^{-1}$ to include the upstream requirements of the sectors. The $\boldsymbol{A}$ matrix can be the regionally specified input-output table from economic surveys. For example, the 2002 Standard Use Table provided by the US BEA is used in the IO-LCA model developed at Carnegie Mellon University. IO-LCA applies the environmental effects from the industries to the Leontief inverse and estimates the total environmental effects from productions in the industries.

The process-based LCA can also apply the matrix methods to scale the inventories and provide both direct and indirect effects. The principles are the same for the two different models with slight differences. First, the process-based LCA considers the exchanges between product flows, not industrial sectors. Second, in process-based LCA, the direct requirements are scaled into the $\boldsymbol{A}$ matrix based on physical units. In this way, the exchanges between processes are based on the functional units of the production, instead of dollar values as used in IO-LCA models. Third, instead of Leontief inverse $(\boldsymbol{I}-\boldsymbol{A})^{-1}$, the inverse of the $\boldsymbol{A}$ matrix is used in estimating the total requirements. Despite the three minor differences, the two models have the same advantage of efficiently providing both direct and indirect effects. However, both models also suffer from the lack of uncertainty information.

In this study, the parameter uncertainties of these two models are accessed. I use the US 2002 Economic input-output life cycle assessment (EIO-LCA) model's energy consumption category to implement and demonstrate the utility of the uncertainty estimation method in the IO LCA model. The US LCI database are incorporated into matrices to provide the uncertainties in the process-based LCA methods.

1.2.3 Uncertainty in LCA

LCA practitioners have long been trying to consider uncertainty information in LCA studies to give more robust conclusions (Huijbregts 1998; Lloyd and Ries 2007; Williams et al. 2009). Huijbregts et al. (2003) outlined three sources of uncertainty: parameter uncertainty, scenario uncertainty, and model uncertainty. Parameter uncertainty arises from using inaccurate data and weighting factors in the LCI analysis (Huijbregts 1998). Scenario uncertainty includes different choices such as scope, system boundaries, and allocation methods. Model uncertainty is caused by spatial differences as well as characterization factors.

These types of uncertainties are propagated to the life cycle results via different methods, such as probabilistic (Bullard et al. 1988; Raa and Steel 1994; Ali and Santos 2014), fuzzy (Tan 2008; Cruze et al. 2012), and range analysis (Chevalier and Téno 1996; Geisler et al. 2005; Deng et al. 2011; Bawden et al. 2015). In probabilistic methods, random samples are generated by distributions that are defined to represent uncertainties in the inventory data. Each distribution is estimated or chosen based on its parameters such as mean, standard deviation, and distribution type (e.g., normal or uniform). The parameters and type of distribution can be estimated with different methods, including: applying the regression results of various data sets (Lenzen 2001; Yamakawa and Peters 2009; Lenzen et al. 2010), assumptions made for estimating the impact multipliers (Zhang, et al 2014), or by using the pedigree matrix approach (Weidema and Wesnæs 1996). The fuzzy number approach uses fuzzy logic to estimate uncertainty in the degree of plausibility of data (Tan 2008). The range method applies multiple values for each process to represent the uncertainty. The multiple values are collected for each process and are treated equally as possible inputs in the inventory resulting in a range of possible values in the final answer.

In current practice, parameter uncertainty in matrix-based LCA models has been addressed by using a pedigree matrix approach (Weidema and Wesnæs 1996). This approach determines the parameter uncertainty from the data indicator scores, which quantitatively estimate the quality of the data sources. In practice, this approach requires a considerable number of assumptions and simulations. Some LCA software tools like SimaPro, include this analysis. However, estimating parameter uncertainty in this way is problematic, in two ways. First, the uncertainty distributions from the inventory data are arbitrary. The data indicator scores and pedigree matrix approach focus on quantifying the quality of each data point's data source, rather than the quality of the data points. The distributions are not estimated from real data samples, but rather empirical judgement. Second, the uncertainty results are hard to interpret. Generally, LCA practitioners are not capable to easily understand the methodology of parameter estimation and simulation. It is hard to interpret the uncertainty in the results without knowing the causes.

Scenario and model uncertainties have not yet been addressed in matrix-based LCA models. Here, the scenario uncertainty can be caused by scaling inventories with different goal and scope to the same matrix; while the model uncertainty can come from different impact assessment methods being incorporated into the software. Compared with the parameter uncertainty, the scenario and model uncertainties from matrix-based LCA models are more easily overlooked. When a matrix-based model scales inventories with different goal and scope together without any distinction, the users are unable to realize the result contains scenario uncertainty. Similarly, the model uncertainty cannot be identified unless the potential uncertainty results are given directly to the users. In current practice, LCA tools that apply matrix-based methods generally do not clearly provide potential scenario and model uncertainties to the users.

1.2.4 Life cycle impact assessment (LCIA)

Life cycle impact assessment (LCIA) is a phase of life cycle assessment (LCA) (ISO 2006b). This phase seeks to evaluate the environmental impacts from a product system (Owens 1997). To achieve this evaluation, Life cycle inventory (LCI) data are associated with environmental impact categories (ISO 2006b).

Multiple impact assessment methods have been developed for different purposes of the LCA studies. Early impact assessment developments were based on the only available reference - ISO standard (Baumann and Rydberg 1994). In 1999, the SETAC-Europe working group provided guidance to impact assessment method developments, in order to model the best available impact assessment method (Udo de Haes et al. 1999). The concepts of impact assessment framework, and principles of characterization factor modeling are widely accepted and adapted in LCIA developments. Many LCIA methods have been developed since, some of which are updated regularly. These methods provide characterization factors to transform environmental effects to quantified environmental impacts. In matrix-based LCA models, to evaluate the total environmental impact results for products under study, the LCIA methods are applied to the inventories and effects.

LCIA methods provide different characterization vectors to transform the effects. The differences in the characterization factors are the contributors to the model uncertainties in matrix-based LCA models. LCA studies have focused on the uncertainties in the LCIA results regarding the differences in LCIA methods. Baumann and Rydberg (1994) compared three early LCIA methods: ecological scarcity (ECO), environmental theme (ET), environmental priority strategies in product design (EPS). For these three methods, Baumann and Rydberg looked at the differences between the calculation methods for characterization factors. Pennington et al. (2004) also systematically reviewed the differences between multiple impact assessment methods regarding their models and methodologies. More recently, some LCA studies have considered the variances in the impact results caused by choosing different impact methods (Brent and Hietkamp 2003; Bovea and Gallardo 2006; Cavalett et al. 2013; Owsianiak et al. 2014; Martinez et al. 2015). All of these studies emphasized the importance of choosing the best-suit impact assessment method for the goal and scope of the study. However, no LCA study has focused on understanding the model uncertainty caused by using different LCIA methods in matrix-based LCA models.

1.3 Dissertation outline and research questions

In this study, I introduce methods to comprehensively address the three types of uncertainties in matrix-based models. For reference, I have applied our methods to two different matrix-based models: the IO-LCA model, and the process-based LCA model.

Following the introduction (Chapter 1), the dissertation is divided into three research chapters and a concluding chapter, followed by appendices and references. The main chapters and the research questions they explore are outlined below.

In chapter 2, the parameter uncertainty in matrix-based LCA models is estimated using an IO LCA model. Key research questions include:

- What are the uncertainty ranges of direct and indirect life cycle energy consumptions over the supply chain of the U.S. industries based on economic input-output models with public available data?
- What is the impact of each individual industry's uncertainty on results of other industries?
- Which industries have the largest uncertainties in the model? How to reduce the uncertainties of these industries?

In chapter 3, the parameter uncertainty is estimated for process-based LCA inventories incorporated into the matrix-based LCA model. Chapter 3 also introduces the scenario uncertainty in the same model. Key research questions include:

- In the current US LCI database, how many processes flows contribute to the indirect environmental effects when applied to matrix-based LCA models?
- What are the total CO_2 emissions ranges from US industrial processes by considering different scenarios from current process-based life cycle inventory databases?
- What are the ranges of total CO_2 emission ranges from aggregated US industrial processes calculated from current process-based life cycle inventory databases?

In chapter 4, the model uncertainty is estimated based on the differences in the LCIA methods. Key research questions include:

- In current LCIA methods, how many substances are covered? How many of these substances are included in elementary flows in the US LCI database? Does the US LCI database have enough flows that are characterized in impact assessment methods to build a robust inventory?
- For processes in current process-based LCA databases, what are the uncertainties of direct and indirect environmental impacts caused by different impact characterization factors used in LCIA?
- What are the contributions of different characterization factor values and coverages of substances from different methods to the LCA result?
- What should be the new reported value in LCI for different substances considering impact assessment results?

2. Chapter 2. Parameter uncertainty in the EIO-LCA model

2.1 Parameter uncertainty in matrix-based tools

Parameter uncertainty arises from using inaccurate data and weighting factors in life cycle inventory analysis (Huijbregts 1998). The parameter uncertainties in the LCA inventories are propagated to life cycle results via different methods, such as probabilistic (Bullard et al. 1988; Raa and Steel 1994; Ali and Santos 2014), fuzzy (Tan 2008; Cruze et al. 2012), and range analysis (Chevalier and Téno 1996; Geisler et al. 2005; Deng et al. 2011; Bawden et al. 2015). In probabilistic methods, random samples are generated by distributions that are defined to represent uncertainties in the inventory data. Each distribution is estimated or chosen based on its parameters such as mean, standard deviation, and distribution type (e.g., normal or uniform). The parameters and type of distribution can be estimated with different methods, including: applying regression results of various data sets (Lenzen 2001; Yamakawa and Peters 2009; Lenzen et al. 2010), assumptions made for estimating the impact multipliers (Zhang, et al 2014), or by using the pedigree matrix approach (Weidema and Wesnæs 1996). The fuzzy number approach uses fuzzy logic to estimate uncertainty in the degree of plausibility of data (Tan 2008). The range method applies multiple values for each process to represent the uncertainty. The multiple values are collected for each process and are treated equally as possible inputs in the inventory resulting in a range of possible values in the final answer.

In this study, I introduce a method that adapts principles of the range method to propagate uncertainty in matrix-based models, as such methods are used in most LCA software tools to manage data and generate results. The focus in this study is on propagating and representing data (parameter) uncertainty, as applied to an input-output matrix based model. A range of alternative values developed based on different data sources with different assumptions are considered in the inventory. The data are derived from publicly available data sources such as government agencies, published research articles, and reports. Different assumptions are used to convert or estimate the raw data from these sources to derive values in an appropriate form for the model. Values calculated were used to estimate changes in results from the model's current deterministic values. A new way of visually presenting results is also introduced.

I use the US 2002 Economic input-output life cycle assessment (EIO-LCA) model's energy consumption category to implement and demonstrate the utility of the method. The EIO-LCA model is used because it has a clear boundary, which includes all US industrial sectors (428 in total), providing consistency for comparison between sectors. Although, there are many potential impacts that could be model choosing energy consumption i s based on the on the high degree of data availability, and because it is a fundamental component to estimate other inventory categories, such as greenhouse gas emissions.

In an IO-based matrix model, Equation 1 is used to estimate the environmental effects from all sectors defined in the system. In Equation 1, $\boldsymbol{f}$ is a vector of requirement defined by the users; it is the amount of direct purchase from the industry in dollar value. For an economic system that has n industries, the $\boldsymbol{f}$ vector has n by 1 dimensions. The $\boldsymbol{A}$ matrix is n by n, each column or row represents an industry in the system. The $\boldsymbol{A}$ matrix can be the regionally specified input-output table from economic surveys. For example, the 2002 Standard Use Table (the Use Table) provided by US BEA (ref) is used in the IO-LCA model developed Carnegie Mellon University (ref). The $\boldsymbol{B}$

matrix is an m by n matrix, the rows are m different environmental effects cause by producing dollar units of product in each industry (represented by impact/$). The resultant vector $\boldsymbol{g}$, has m by 1 dimensions and contains the m total environmental effects for the final demand $\boldsymbol{f}$. For each environmental effect ($\boldsymbol{i = 1, \ldots, m}$), the direct and indirect effects can be separated by the Hadamard (entrywise) product of the transpose of row $\boldsymbol{i}$ in the $\boldsymbol{B}$ matrix and $(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{f}$:

Equation 1: $\boldsymbol{g} = \boldsymbol{B}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{f}$

Equation 2: $\boldsymbol{h_i} = \boldsymbol{B_i}^{\boldsymbol{T}} \circ (\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{f}$

This approach provides a method to quickly scale large inventory data to estimate the final impact, saving users time and effort. As the direct and indirect effects can be separated, the large indirect effects contribute to the total effects can be sorted to identify the hotspots in the upstream production. LCA tools, such as EIO-LCA, can provide the users these hotspots in the results; the hotspots are straightforward and can help to identify the important upstream industry to reduce the effects. However, LCA tools fail to emphasize uncertainty, which is critical in determining the impact of LCA results and conclusions (Wang and Work 2014). Common LCA tools typically show only deterministic results; since no uncertainty is displayed, users or the study audience may assume that there is no relevant uncertainty.

The following sections describe the methods used in developing these uncertainty-based estimations in the 2002 EIO-LCA model with respect to energy consumption. The detailed information of sectors in the EIO-LCA model are provided in Table S1 in the Appendix.

2.2 Material and Methods

This section explains the method used to evaluate $\boldsymbol{B}$ matrices. I also provide a description of the data sources and assumptions. Finally, the method used for propagating the uncertainty are introduced.

2.2.1 Values in the R matrix

In a deterministic input-output model, an energy $\boldsymbol{B}$ matrix contains the unit energy consumption of each industry sector based on the economic exchange between industries, making the unit in the energy $\boldsymbol{B}$ matrix Joules/$. Two steps are involved in estimating values in a $\boldsymbol{B}$ matrix: first, annual energy consumption values for each industry are estimated from available data sources; second, the energy values are normalized (divided) by the total annual economic output of the industry sector. In the new method, instead of a single deterministic value, multiple energy consumption values were derived by using various available data sources to generate an energy consumption range for each sector. Those different consumption values were estimated from different sources like survey reports, e.g., with different assumptions about fuel prices. The detailed estimations of data points are discussed below.

2.2.2 Data sources

Energy consumption values were calculated from various publically available data sources. From the different data sources as well as various assumptions (see section Assumptions and Calculations), multiple values were developed for each sector. For the energy consumption category in the 2002 EIO-LCA model, data from 6 publicly available government agency sources were used:

U.S. Bureau of Economic Analysis (US BEA)

U.S. Census Bureau (Census)

U.S. Department of Energy, Energy Information Administration (US EIA)

U.S. Environmental Protection Agency (US EPA)

U.S. Department of Agriculture (USDA)

National Transportation Research Center (NTRC).

The *2002 Standard Use Table* (the Use Table), provided by US BEA, has expenditure data for the energy production sectors (in million $) for all 428 US industrial sectors. An advantage of the Use Table is the availability of sectoral level data for electricity, coal, petroleum fuels and natural gas consumption for all 428 sectors. Due to the completeness of the data, the Use Table has traditionally been used as a major data source in IO-based LCA models (including the EIO-LCA model). Values in the Use Table were converted from expenditure values to physical units with various price assumptions.

Table 2-1 shows the prices used in all the sectors when no more specific price data is available. Values are provided by U.S. Energy Information Administration (Forms EIA-782A, "Refiners'/Gas Plant Operators' Monthly Petroleum Product Sales Report" and EIA-782B, "Resellers'/Retailers' Monthly Petroleum Product Sales Report). The prices were used to convert fuel expenditure values in U.S. dollars to energy consumption values in physical units.

Table 2-1: Energy prices used in this study

Fuel type	Value	Unit
Coal	1.25	$/MBtu
Natural Gas	4.02	$/1,000 cu. Ft
Motor Gasoline	0.947	$/gal
Kerosene-Type Jet Fuel	0.721	$/gal
Kerosene	0.99	$/gal
No. 1 Distillate	0.828	$/gal
No. 2 Distillate	0.759	$/gal
No. 2 Diesel	0.762	$/gal
No. 2 Fuel Oil	0.737	$/gal
No. 4 Distillate	0.657	$/gal
Residual Fuel Oil	0.569	$/gal

The U.S. Census Bureau was another major data provider across nearly all sectors. Detailed reports including *Industry Series Reports* for mining, construction, and manufacturing sectors; *Core Business Statistics Series*; and *the Business Expenses Survey* were applied to evaluate energy consumption values for agriculture, mining and mineral, construction, utility, manufacturing, transportation and service industry categories. Values from the Census required conversion from North American Industry Classification System (NAICS) codes to IO codes, as well as from expenditure values to physical units with price assumptions, if the values were provided by expenditure value.

Some data sources were used only for a broad industry category. For instance, two energy surveys, the US EIA’s Manufacturing Energy Consumption Survey (MECS) and Commercial Buildings Energy

Consumption Survey (CBECS) were major data sources for manufacturing and service sectors. MECS provides detailed fuel and electricity usage in both physical units and expenditure dollar values. CBECS provides energy consumption and expenditure values for commercial buildings. The values are in a form of building types aggregated by principal building activities, such as education, food services and health care. These two surveys have the disadvantage that some of the values were aggregated to higher-level sectors, which required allocation in order to provide values at the 428 industrial sector level.

Values from US EPA, USDA and the Transportation Energy Data Book published by National Transportation Research Center (NTRC) were used for energy estimation for utility, agriculture, and transportation sectors. The data gathered from these different data sources were processed by recalculating, allocating or aggregating with assumptions. A full report of how the data were processed can be found at http://www.eiolca.net/docs/ (Chen et al. 2016).

2.2.3 Assumptions and calculations

Applying the range method, different values were calculated to form alternative $\boldsymbol{B}$ matrices, rather than using one deterministic $\boldsymbol{B}$ matrix to estimate a deterministic $\boldsymbol{g}$ vector. These $\boldsymbol{B}$ matrices were calculated from different data sources with different calculation assumptions. The methods vary across sectors, but generally include price assumptions for unit conversion, allocation for aggregated values in raw data, and missing raw data evaluation.

Energy consumption values from different data sources were not necessarily in physical energy units. For instance, expenditure values were commonly provided, as in the Use Table. In these cases, data were converted to physical units of energy with fuel prices. As price values were not always available for individual sectors, sectors were grouped into categories where one of its members' energy price was known. For instance, CBECS provided fuel prices based on building types, the price values for the building type "education" was assigned to three sectors: education services, social assistance, and national security & international affairs. This assignment was based on the definition of the building type "education" from CBECS (US EIA 2003).

Allocation was required when the energy data was at an aggregate level compared to that needed for the EIO-LCA model. These values were allocated into their sub-sectors using allocation factors that were situation dependent. For example, while MECS provided energy consumption values for manufacturing sectors, they were often at the 3-digit NAICS code level rather than the 6-digit level needed for the model. In these cases, fuel expenditures in dollars from the detailed Use Table were used as allocation factors to estimate the 6-digit sectoral fuel consumption. The assumption presumes that sectors within an aggregate industry sector have similar costs of energy. Fuel use values were allocated from the 3-digit to 6-digit sector level by considering the dollar purchases of the fuels of each commodity sector in the model from the relevant industry. For example, in the Food sector (3-digit NAICS code 311), if sector 311111 (6-digit NAICS code) represented 90% of purchases from the *Coal mining* sector for all the sectors beginning with 311, then 90% of the coal use would be allocated to sector 311111.

Some data sources provide reports with partially withheld data, in these cases, missing data were estimated using different methods, such as adapting data from previous years. In the US Census' *Industry Series Reports* for mining, the physical units of energy consumption for a few sectors were withheld. Two general methods were used to estimate the missing values: 1) deriving missing values based on logical deductions; 2) the energy expenditure ratio of the sector to the total mining category.

The uncertainties in the $\boldsymbol{B}$ matrix are then propagated through the model to calculate the life cycle final results. The direct and indirect (total) consumption is the value in the $\boldsymbol{g}$ vector, calculated by Equation 1. Instead of using only one $\boldsymbol{B}$ matrix, I used various $\boldsymbol{B}$ matrices to estimate different $\boldsymbol{g}$ vectors; those ***B*** vectors were used to form the ranges. Besides the default matrix, which was chosen as a set of values falling in the middle of all the available data sources, and is generally the current EIO-LCA deterministic results with a few exceptions[1], alternate $\boldsymbol{B}$ matrices were formed using data from one data source and calculated with the one assumptions. This enables investigators to make different assumptions to select the $\boldsymbol{B}$ matrix values that meet the purpose of their analyses. Presenting results calculated from same data source/assumptions can more clearly present the overall uncertainty for users, and avoid weighting methods. Table 2-2 and Table 2-3 show the summary of different assumptions and data sources used in each alternative $\boldsymbol{B}$ matrix (USDA 2002a; Census 2007a; MECS 2002; NTRC 2014; EIA 2004).

A brief description of data sources and assumptions used to convert values are listed below; a more detailed document can be found at http://www.eiolca.net/docs (Chen et al. 2016).

- USDA: United States Department of Agriculture (USDA) 2002 Census of Agriculture provided the expense of total gasoline, fuel and oil (but not electricity) in dollar values for agriculture sectors in its report (USDA 2002b). Prices in Table S1 are used to convert the energy expenditure values to physical units.
- Use Table 1: the US 2002 Standard Use Table (the Use Table) provided by Bureau of Economic Analysis (BEA 2002) has the detailed expenditure values from other sectors to one sector (in million dollars). In the Table, the purchases from Coal mining, Power generation, Natural gas distribution, and Petroleum refinery sectors for all other remaining sectors are used as the energy purchase values. Prices in Table S1 are used to convert the energy expenditure values to physical units.
- Use Table 2: values in the Use Table are used as the energy purchase values. Different prices are used to estimate energy consumption values. The prices are provided by the 2002 Manufacturing Energy Consumption Survey (MECS 2002), and the Commercial

[1] A default value in the analysis represents the base case of the percentage change. The default value for each sector was chosen as a set of values falling in the middle of all the available data sources. In most of the cases, the default value is the value used in the current EIO-LCA model. In two cases, default values in this study are not equal to those in the current EIO-LCA model: 1) values that are updated with new evaluated withheld data, a few manufacturing and mining sectors have these updated values; and 2) values that calculated based on more specific price assumptions, these values are used in natural gas and gasoline product consumption for service sectors.

Buildings Energy Consumption Survey (CBECS 2003). MECS provides the unit prices of different fuel types in its reports: *Average Prices of Purchased Energy Sources 2002*, with the unit dollar per physical unit and dollar per million BTU. CBECS provides fuel expense values and energy consumption values based on the types of the building, these values are used to calculate the unit price of the fuels regarding individual building types. These less aggregated unit price values are used to convert the energy expenditure values to physical units.

- US Census mining 1,2,3,4,5: US Census of Bureaus' 2002 Economic Census Industry Serious Reports (2007) provided fuel and electricity usage in physical units (e.g., short ton, barrel, cubic feet, gallon and kWh) as well as economic expenditures in some cases for the mineral sectors in 2002. Two different allocation methods are used for the withheld data points in the source. Method 1 was used in estimating current values in EIO-LCA mode; method 2 involves some new assumptions and re-evaluation. Two major differences are: 1) various fuel prices were used, rather than fixed fuel price; 2) withheld data were re-estimated in order to better fix the total fuel expenditure values provided by Census Mining Report.
- US Census construction 1,2: US Census of Bureau's reports "Construction: Subject Series - Industry General Summary: Detailed Statistics for Establishments by Subsector: 2002" and "Construction: Industry Series: Detailed Statistics for Establishments: 2002" are used to estimate the energy consumption values for construction sectors. The two reports provide energy consumption values in four different categories: Gasoline and Diesel, Natural gas, Electricity, and Other fuels in dollar value; Prices in Table S1 are used to convert the energy expenditure values to physical units. In addition, the values in the reports are provided by NAICS code, a bridge developed by Sharrard (2007) was used to convert the NAICS code to IO code: each NAICS construction industry was allocated into one or more different IO industries based on a mathematical method.
- CBECS 1,2: the Commercial Buildings Energy Consumption Survey (CBECS 2003) conducted by US Energy Information Administration (US EIA) is used for energy consumption values, allocation is needed. The values provided by CBECS are in both energy consumption value in physical units and expenditure value in dollars. The values are based on the types of the

building, such as education, rather than industrial codes. Therefore, values from CBECS are allocated into different sectors based on the “crosswalk between CBECS buildings and NAICS industries”. In this file, different types of building activities were allocated to its likely corresponding NAICS sectors. For example, the building type category “education” was considered to be most likely allocated into 611 Education services, as well as two other sectors 624 Social assistance and 928 National security and international affairs. Then the NAICS sectors were converted to IO based sectors.

- MECS 1,2,3: 2002 Manufacturing Energy Consumption Survey (MECS 2002) provides energy consumption values for manufacturing sectors. The survey also provided standard errors for the values. These values are all used in the scenario ranges. Data provided by MECS are in physical units, but generally aggregated at the 3-digit NAICS level, values were allocated from the 3-digit to 6-digit sector level by considering the dollar purchases of the fuels of each commodity sector in the model from the relevant industry sectors.
- EPA: Data from National Greenhouse Gas Emissions Data (Table A-21 “2002 Energy Consumption Data and CO_2 emissions from Fossil Fuel Combustion by Fuel Type”) reported by EPA (2014) were used as coal, natural gas and petrol consumptions for Power generation sector. These values are provided in physical units, merely for electricity generation; no further calculation and conversion are needed.
- NTRC: Transportation Energy Data Book (2014) conducted by Oak Ridge National Laboratory and published by the U.S. Department of Energy. Its 24th edition reported the consumption of energy in physical units by fuel type and transportation mode for the year 2002. The energy consumption values are used for the transportation sectors.

Figure 2-1 tries to more visually describe the substitution process used (as first mentioned in the paper) for when a data source does not cover all 428 sectors. Three different substitutes are used to replace the missing values. For example, if one data source (US Census) only provides data for sectors No. 20 to 30, the rest of 418 sectors need substitutes in the ***R*** matrix. Three different cases of choosing three different substitutes will result in three different ***B*** values: asterisk, plus, and circle symbol shows the result of using default values, minimum values, and maximum values for each sector as substitute, respectively.

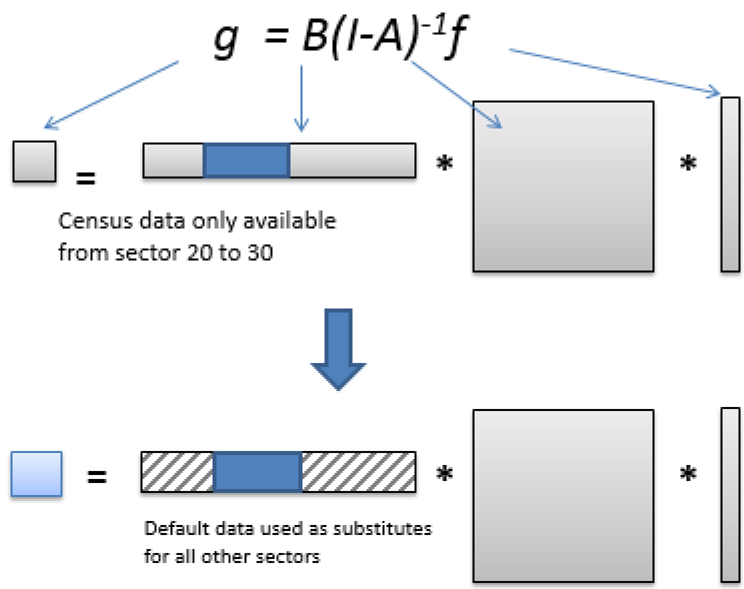

Figure 2-1: Method used to calculated different B values from different R matrices that has substitutes

In the cases where partial data were available, such as $\boldsymbol{B}$ matrix No. 3 in Table 2-2, All the results are chosen as they could be helpful to understand possible outcomes caused by different assumptions.

Table 2-2: Summary of different data sources and assumptions used in the uncertainty range model. Default value is annotated.

<table>
<tr><th rowspan="2">B matrices</th><th colspan="7">Sector categories</th></tr>
<tr><th>Agri-culture</th><th>Mining</th><th>Utility</th><th>Construction</th><th>Manu-facturing</th><th>Trans-portation</th><th>Service</th></tr>
<tr><td>Default</td><td>USDA[d]</td><td>US Census Mining 1[d]</td><td>EPA[d]</td><td>US Census Construction 1[d]</td><td>MECS1[d]</td><td>NTRC[d]</td><td>CBECS 1[d]</td></tr>
<tr><td>1</td><td colspan="7">Use Table 1</td></tr>
<tr><td>2</td><td colspan="7">Use Table 2</td></tr>
<tr><td>3</td><td rowspan="8">USDA[d]</td><td>US Census Mining 2</td><td rowspan="8">EPA[d]</td><td rowspan="7">US Census Construction 1[d]</td><td rowspan="4">MECS1[d]</td><td rowspan="8">NTRC[d]</td><td rowspan="6">CBECS 1[d]</td></tr>
<tr><td>4</td><td>US Census Mining 3</td></tr>
<tr><td>5</td><td>US Census Mining 4</td></tr>
<tr><td>6</td><td>US Census Mining 5</td></tr>
<tr><td>7</td><td rowspan="4">US Census Mining 1[d]</td><td>MECS 2</td></tr>
<tr><td>8</td><td>MECS 3</td></tr>
<tr><td>9</td><td rowspan="2">MECS1[d]</td><td>CBECS 2</td></tr>
<tr><td>10</td><td>US Census Construction 2</td><td>CBECS 1[d]</td></tr>
</table>

[d] default value used as substitute

The values used in the $\boldsymbol{B}$ matrices are not necessarily independent. Results could be from the same data source, but with different assumptions. Two alternative $\boldsymbol{B}$ matrices are both calculated from the Use Table, with different price assumptions. The same energy purchase values are used for each sector, only the fuel price (divisor) for each sector changes; therefore the energy consumption results are highly interdependent. Also, some raw data used in the data sources were derived from common economic surveys. The values for mining sectors, construction, and agriculture sectors were all derived from the US Economic Census, meaning that the data sources are not entirely independent. All the results are chosen as they could be helpful to understand possible outcomes caused by different assumptions.

Table 2-3: Detailed descriptions of assumptions used in data sources

Abbreviation	Calculation description	Calculation methods
Use Table 1	Fix fuel prices provided by EIA are applied to convert values for all sectors	Price assumptions for unit conversion
Use Table 2	Different fuel prices to convert individual sectors, the prices values are gathered from different data sources, such as CBECS and MECS	Price assumptions for unit conversion
US Census Mining 1	Withheld fuel expenditure are estimated based on the sum of rows and columns, different fuel prices (from Census Mining) are used to convert values for each sector	Missing raw data evaluation, price assumptions for unit conversation
US Census Mining 2	Withheld fuel expenditure are estimated based on the sum of rows and columns, fixed fuel prices are used to convert values for each sector	Missing raw data evaluation, price assumptions for unit conversation
US Census Mining 3	Withheld fuel expenditure are estimated based on the ratios from total, different fuel prices (estimated for individual sector from Census Mining) are used to convert values for each sector	Missing raw data evaluation, price assumptions for unit conversation
US Census Mining 4	Withheld fuel expenditure are estimated based on the ratios from total, fixed fuel prices (estimated for all sectors in the category from Census Mining) are used to convert values for each sector	Missing raw data evaluation, price assumptions for unit conversation
US Census Mining 5	Withheld fuel expenditure are estimated based on the ratios from total, fixed fuel prices (from EIA) are used to convert values for each sector	Missing data evaluation, price assumptions
MECS 1	Default values provided by MECS are used, some values are calculated based on allocation, expenditure values from the Use Table are used as allocation factor	Allocation for aggregated values in raw data

MECS 2	Minimum values provided by MECS are used, some values are calculated based on allocation, expenditure values from the Use Table are used as allocation factor	Allocation for aggregated values in raw data
MECS 3	Maximum values provided by MECS are used, some values are calculated based on allocation, expenditure values from the Use Table are used as allocation factor	Allocation for aggregated values in raw data
CBECS 1	Some values are calculated based on allocation, 'converting bridge' provided by CBECS is used allocation factor; different fuel prices to convert individual sectors, the prices values are gathered from different data sources, such as CBECS and MECS	Allocation for aggregated values in raw data, price assumptions for unit conversation
CBECS 2	Some values are calculated based on allocation, 'converting bridge' provided by CBECS is used allocation factor; fixed fuel prices to convert individual sectors, the prices values are gathered from different data sources, such as CBECS and MECS	Allocation for aggregated values in raw data, price assumptions for unit conversation
USDA	Some values are calculated based on allocation, expenditure values from the Use Table are used as allocation factor; fix fuel prices provided by EIA are applied to convert values for all sectors	Allocation for aggregated values in raw data, price assumptions for unit conversation
EPA	Some values are calculated based on allocation, values from the same data source are used as allocation factor	Allocation for aggregated values in raw data, price assumptions for unit conversation
NTRC	Some values are calculated based on allocation, expenditure values from the Use Table are used as allocation factor	Allocation for aggregated values in raw data

2.3 Results and discussion

This section shows how the method is implemented in the 2002 EIO-LCA model, using IO Sector No. 120, *Petrochemical manufacturing*, as an example. Additionally, three case studies are used to demonstrate the potential improvement in decision support considering the uncertainties and results.

2.3.1 Uncertainty results for single sectors

Figure 2-2 shows the results for total energy consumption across the supply chain as well as separated by fuel for IO Sector No. 120, *Petrochemical manufacturing*. The names in the legend indicate different alternative $\boldsymbol{B}$ matrices used to estimate the result (Table 2-2). All the results are chosen as they could be helpful to understand possible outcomes caused by different assumptions.. Three other $\boldsymbol{B}$ matrices that use each sector's minimum/maximum/default value generalized from all alternative results are also provided. The results are based on one million dollars of final demand input in sector 120. Since IO-LCA models are linear, the relative uncertainty for a different input of final demand would be the same. In this case, the sector's total energy consumption varies from 21 TJ to 62 TJ, resulting in the range of -50% to 40% compared to the default value of 42 TJ. Figure 2-2 shows that the uncertainties of natural gas and petroleum usage are the major contributors to the large discrepancy of total energy consumption. They are also estimated to be the highest fuel inputs in the total.

The causes of the uncertainties are also displayed in Figure 2-2. The red symbols are the values calculated from the $\boldsymbol{B}$ matrix using values from the Use Table. All of the red symbols are larger than the value calculated from the default $\boldsymbol{B}$ matrix, which demonstrates that the values in the Use Table tend to be the upper values within the ranges. In addition, the uncertainty in the total energy consumption is mostly caused by the large uncertainty of petroleum consumption associated with data from the Use Table, of which possible reasons are discussed later in this paper. The results calculated from the US Census data (blue symbols in Figure 2-2) are closer to the default value. Since only a small proportion of data come from the Census, and a majority of the data are substitutes, the results are similar to the results calculated from default values.

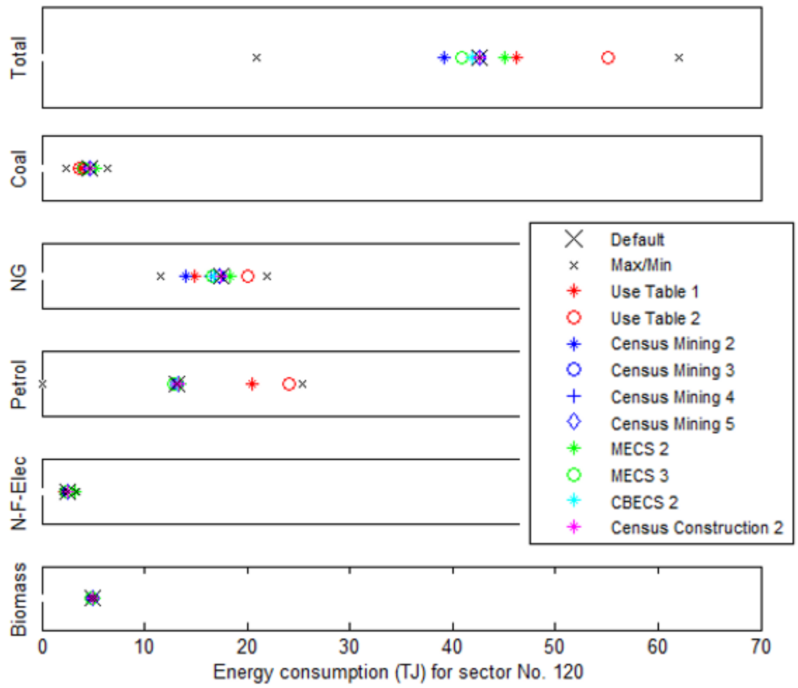

Figure 2-2: Scaled results for 1 million dollars of final demand of sector No. 120 (Petrochemical manufacturing). Total energy as well as separated fuel consumptions are provided. Abbreviation: NG as natural gas, Petrol as petroleum products, N-F-Elec as non-fossil fuel electricity.

As a hotspot analysis tool, IO models like EIO-LCA can deterministically list the highest sectors across the supply chain for an industry. Figure 2-3 shows the results of the top 15 most energy intense sectors in the supply chain for 200 thousand dollars of final demand in sector 120, sorted by the values in the deterministic $\boldsymbol{B}$ matrix used in current EIO-LCA model. As can be seen, sector 120 (*Petrochemical manufacturing*), 115 (*Petroleum refineries*) and 126 (*Other basic organic chemical manufacturing*) are the top 3 energy intense sectors, contributing an estimated 64% to the total energy consumption. These three sectors are also major contributors to the uncertainty of total energy consumption; however, the rankings of the top 5 energy intense sectors could change when uncertainties are considered. The red symbols for the top 3 sectors remind us that the Use Table is the data source leading to the high end of the ranges. As these sectors belong to the Petroleum Product Manufacturing category, this finding indicates that the Use Table provides greater energy consumption values for some petroleum products. Similar conclusions can be made for values from CBECS, which provides relatively smaller values for petroleum products. The reason for these differences is discussed in the following section.

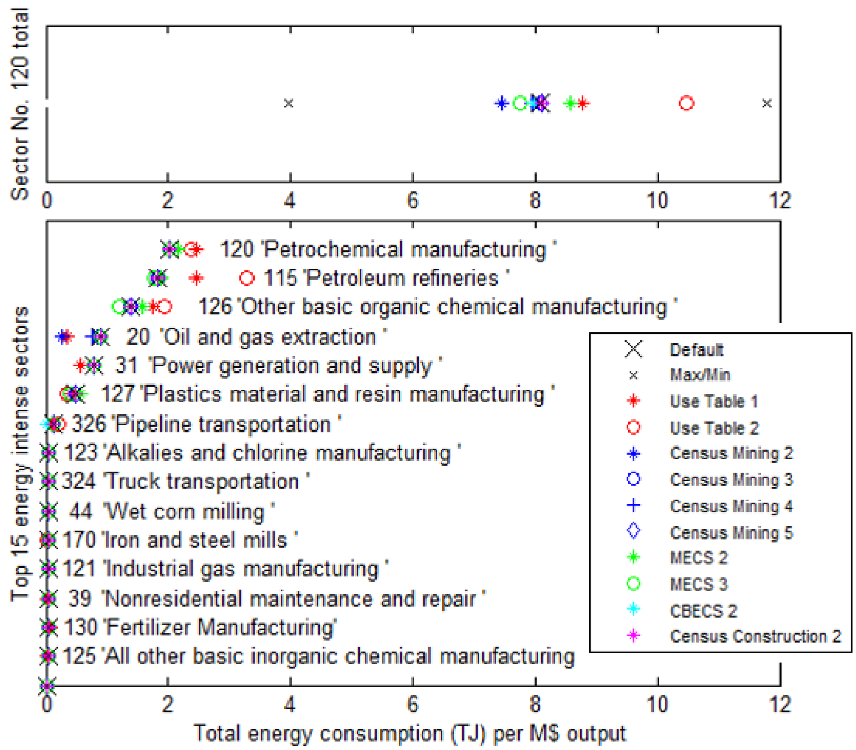

Figure 2-3: Scaled results of total energy consumption and top 15 energy intense sectors for $200k final demand of sector No. 120 (Petrochemical manufacturing). Graph on top is the g values (direct and indirect); the bottom shows the top 15 energy intense sectors for the g values.

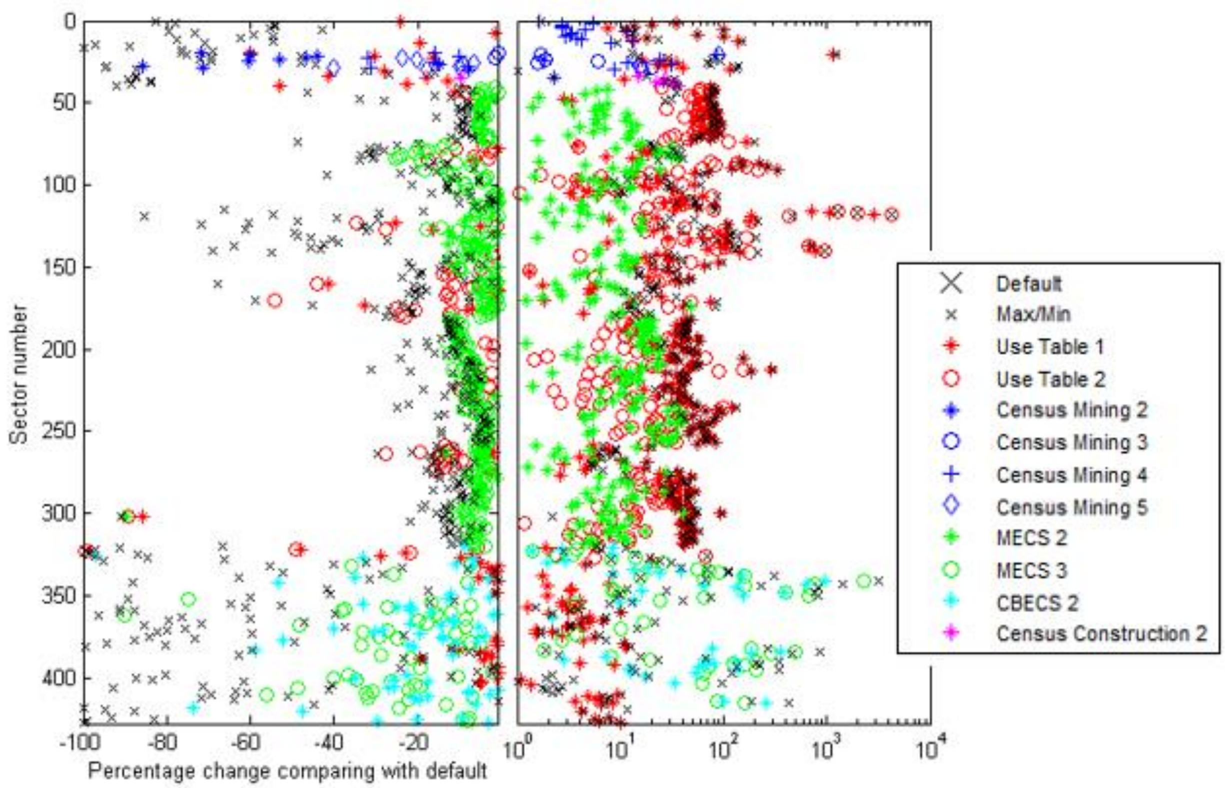

Figure 2-4: Results of the B matrices for all 428 sectors, based on percentage changes comparing with default value. Linear scale is used for negative values while base 10 logarithmic scale is used for positive values.

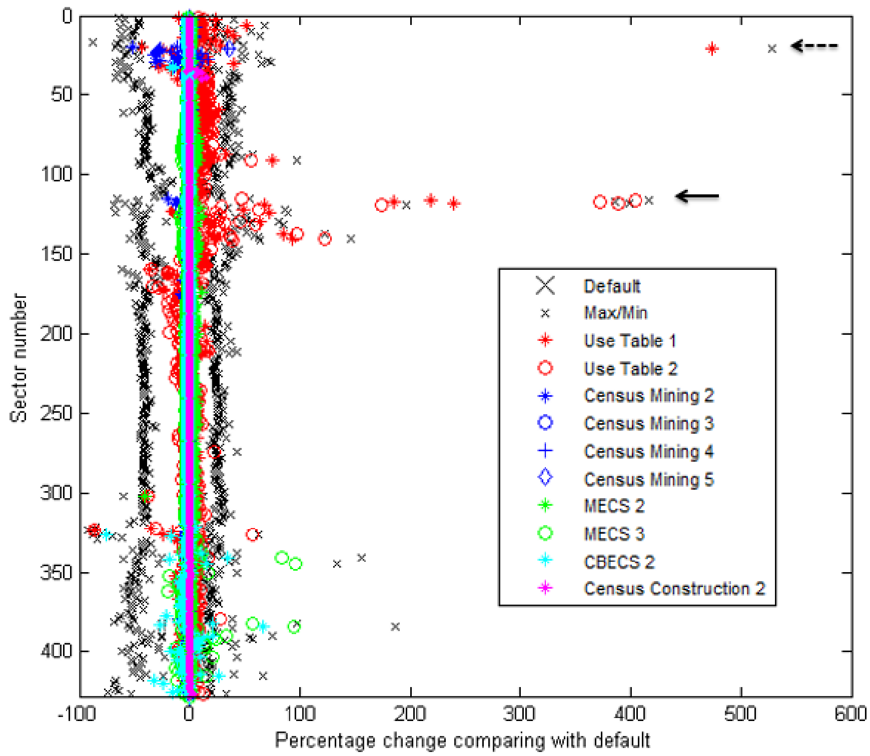

Figure 2-5: Results of g values for all 428 sectors, based on percentage changes compared to default value. Linear scale is used for negative values while base 10 logarithmic scale is used for positive values.

While Figure 2-3 suggests sectors with high default values also have high uncertainty for Sector 120, this is not a general rule - uncertainty varies across many dimensions. Figure 2-4 shows the uncertainty results of all 428 sectors in all $\boldsymbol{B}$ matrices, based on each sector's percentage change, compared to its default value. Note that the positive side of the x-axis is transformed to log scale for legibility. Results suggest that in general, the sectoral uncertainty for direct and indirect energy consumption in the $\boldsymbol{B}$ matrix is approximately ±50% overall. In some extreme cases, the values reach over 40 times larger than the default value. For example, the value for *Coal mining* (No. 21, noted by the dashed arrow in Figure 2-5) varies from 5 to 70 TJ/M$, and *Petroleum lubricating oil and grease manufacturing* (No. 118, noted by the solid arrow in Figure 2-5) varies from 3 to 110 TJ/M$. Such outcomes demonstrate how different data sources and assumptions can result in a significantly larger range for some sectors, which would not be currently expressed in such models, like EIO-LCA. Results from Figure 2-4 also show that Use Table (red) and MECS (green) generally lead to values larger than the default while US census of construction (purple) generally lead to lower values.

This analysis suggests that the uncertainty in the energy $\boldsymbol{B}$ matrix can be large. Thus using only a single data source for a sector in the $\boldsymbol{B}$ matrix (as typically done in IO-LCA models) could ignore important information about the system.

2.3.2 Uncertainties of the $\boldsymbol{g}$ vector

Figure 2-5 shows the results of the $\boldsymbol{g}$ values, which include the total of direct and indirect energy consumption calculated from Equation 1 for \$1 million final demand for each industry, based on different $\boldsymbol{B}$ matrices. Detailed percentage changes for all 428 sectors are shown in Table S1 of the Appendix. The results were calculated based on the total economic output in 2002 for each sector. The overall uncertainty in total energy consumption for a sector varies from about -40% to 40%; however, for several extreme cases, the result is approximately 5 times larger than the default value. The percentage changes are smaller compared to changes in the $\boldsymbol{B}$ matrix, especially for the extreme cases, given the interconnectedness of supply chains. The results show that the percentage changes in the $\boldsymbol{g}$ vector are generally less than the changes in the $\boldsymbol{B}$ matrix, based on the composition of the overall supply chain.

The different patterns of uncertainties are caused by the discrepancies in the values of the $\boldsymbol{g}$ vector, which are taken from various data sources. Using this information, potential sectors with large uncertainties could be identified or adjusted after further investigation, in order to reduce the uncertainty in the model. The next section briefly discusses how to investigate the reasons for large discrepancies, by re-evaluating data sources.

2.3.3 Sectoral impact to overall model

In matrix-based LCA models, the change of one sector's value in $\boldsymbol{B}$ matrix can have impacts on the whole model. In order to show the impacts from single sector to the overall model, controlled tests are conducted and compared with base case results. The controlled tests are performed by setting the value of one of the 428 sectors in $\boldsymbol{B}$ matrix as upper or lower bound while holding all other 427 sectors constant at their default values, and the results are compared with base case, which uses default value for each sector. A top ten detailed sectoral results is shown in Table 2-4.

Not surprisingly, Power generation has the most impact to the model; and considering both sides from the default value, Pipeline transportation is another very important sector cause the total changes is 3 million TJ. These sectors, though have relatively smaller uncertainties, have the largest impacts on the model. The controlled test of the study provides information of the importance of the sectors to the model. The importance of the sector does not depend on the energy intensity or the uncertainty of the sector, but the relations of each sector to the rest 427 sectors in the model. Hospital sector has a total 2 million TJ energy consumption value and more than 500% upper uncertainty results, however it has negligible impacts over other sectors as well as the model

On one hand, this information will benefit the decision makers by providing supporting information of selecting the most sensible sectors, user will be able to choose the best suitable information to reduce the uncertainty in their LCA analysis. Values provided in Table 2-4 show both the changes of each sector and the changes of the rest of the sectors caused by the sector. For a sector such as hospital that has big sectoral change but small impact over the rest sectors, the uncertainty is only important when this sector's result is investigated in a LCA study. On the contrary, coal mining sector, which has both big sectoral change and big impact over the model, needs to be taken serious account anytime. On the other hand, as matrix-based LCA model involves a great amount of calculation, the information will help the user to decide with sectors should be taken into more serious account to limit the calculation time in matrix-based LCA models. So far the high uncertainty flows have not been addressed in uncertainty analyses in matrix-based LCA models. The results in this study will support further uncertainty estimation and sensitivity analysis in matrix-based LCA models.

Table 2-4: Result from controlled tests, sectoral results (Million TJ)

I-O number	Sector name	Change without sectoral change (real)	Change with sectoral change	Sectoral change	Change Default value to
221100	Power generation and supply	-15.2	-27.9	-12.7	Min
324110	Petroleum refineries	4.3	7.0	2.7	Max
211000	Oil and gas extraction	-4.0	-4.9	-0.9	Min
331110	Iron and steel mills	-2.7	-3.5	-0.8	Max
212100	Coal mining	2.6	3.8	1.2	Max
325190	Other basic organic chemical manufacturing	2.2	3.1	0.8	Max
486000	Pipeline transportation	1.5	2.2	0.7	Max
486000	Pipeline transportation	-1.5	-2.2	-0.7	Min
324191	Petroleum lubricating oil and grease manufacturing	1.0	1.5	0.5	Max
324121	Asphalt paving mixture and block manufacturing	1.0	1.6	0.7	Max
325190	Other basic organic chemical manufacturing	0.7	1.1	0.3	Min

The analyses above are based on the exchanges between sectors within the boundary set by the IO table (the entire production of the economy), thus the results are limited to the energy consumption within the system boundary set for a certain year and geographic area. For example, several studies suggested that energy embedded in infrastructure should be included in the supply chain of a process (Chester and Horvath 2009; Lucas et al. 2012; Turconi et al. 2013). However, this part of the energy is not within the system boundary of the EIO-LCA model. Several industrial sectors such as "Nonresidential manufacturing structures" are included in the IO table; however, the exchange between other sectors and these construction sectors are based on the year 2002, excluding energy embedded in the infrastructure already built. Therefore, the results in Table 2-4 are limited to the system boundary of the EIO-LCA model; if the users need to include processes outside the boundary, the results might change depending on the boundary drawn for the new analysis.

2.3.4 Uncertainty values re-evaluation

The existence of major discrepancies for some of the sectors is one of the novel results presented. Tracking the reasons for these can provide decision makers with a clearer concept of how or when to use the various data given the uncertainties. An example is shown in Figure 2-3. Larger than default values were calculated from the Use Table (red), while smaller than default values were calculated from CBECS (light blue). A possible explanation is the insufficient documentation of the data source. Values provided by the Use Table were based on the purchase of all fuels for the sector, rather than energy consumed specifically in production phases. For example, these purchases could include fuels used as both energy and feedstocks. The resulting uncertainty can be reduced as better-documented data are provided (I note that MECS separates fuel and feedstock usage but is more aggregated than values in the Use Table).

An extreme example of data induced uncertainty can be found in the *Coal mining* sector. The minimum value of coal consumption for the *Coal mining* sector was calculated from the Census, while the maximum value was from the Use Table. Comparing the Use Table with other data sources, it was found that coal purchases between coal companies included coal undergoing beneficiation, which was accounted as an energy source purchase in the Use Table.

The values generated from these data sources, including those not well-documented, were used in the analysis. As all the data sources are government agency surveys or peer-reviewed published articles, the possible reason for the differences among sources could not always be confirmed. With all the data sources separately noted in the result, users can make decisions based on all the information provided. For example, a data source for a particular sector may be excluded by the user, changing that range accordingly. An example of the utility and impact of data exclusion can be seen in case study 2.

2.4 Decision support considering uncertainty

The results propagated from the uncertainties in the inventory in the EIO-LCA model can improve the utility of this source of information. As shown below, adding representations of uncertainty enables two-dimensional hotspot screening tools. The first dimension relates to the most important effects, and the second is their relative uncertainty. Either or both can indicate where additional data (e.g., primary data or sector-specific data) could be useful in subsequent efforts. Three case studies are shown that demonstrate how the information from our results can be used. All are based on previously published LCA work; I update the studies using the 2002 EIO-LCA model and present results with consideration of uncertainty. These case studies demonstrate that with such uncertainty results, 1) the LCA conclusions can be strengthened; 2) the uncertainty source can be identified; and 3) hotspots can change.

2.4.1 Case Study 1 – Illustrating impact of uncertainty on the results

LCA was at the center of the paper vs. plastic debate of the early 1990s (Hocking 1991). In a previous study, Lave and colleagues compared the toxic releases and energy use (electricity only) of plastic and paper cups using a 1987 EIO-LCA model (Lave et al. 1995). They estimated that 170,000 plastic cups consumed almost 50% less electricity (4,400 kWh vs. 8,600 kWh) than paper cups.

The *Paperboard container manufacturing* and *Plastics material and resin manufacturing* sectors were chosen to represent paper and plastic cups respectively; total energy rather than only electricity was evaluated. The deterministic results using the models' default values show that total energy consumption for 170,000 paper cups and plastic cups are 0.4 and 0.5 TJ, respectively, suggesting that plastic cups consume more energy than paper cups, different than previously stated perhaps due to exclusion of fuels.

Adding uncertainty, total energy consumption for a plastic cup and a paper cup varies from 0.25 TJ to 0.69 TJ, and from 0.28 TJ to 0.45 TJ, respectively, as shown in Figure 2-6. The results with the consideration of uncertainty suggest that plastic cups use energy at the same level or higher than the paper cup production. The plastic cup has a larger range of possible energy use values than the paper cup. When results are compared on a data source by data source basis, the plastic cup always consumes more energy than the paper cup, except for the minimum value. These results suggest strongly that beyond the previous simple deterministic results, it is very likely that plastic uses more energy, e.g., when all individual (mostly independent) data sources suggest higher values for a plastic cup, the comparison between two types of cup is more robust.

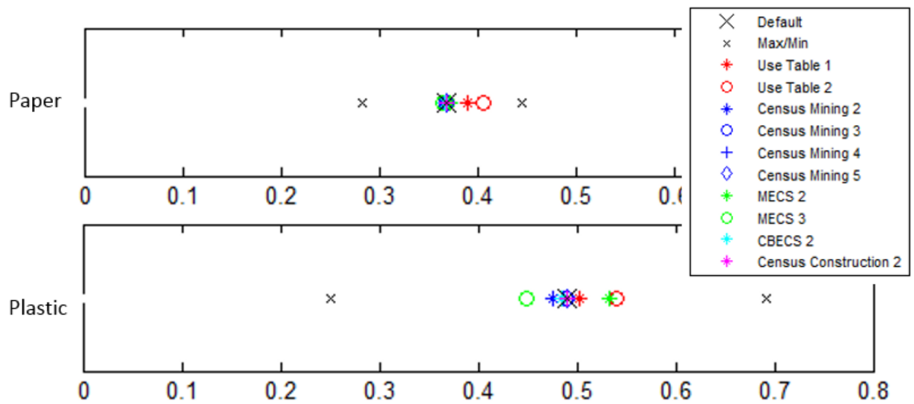

Figure 2-6: Scaled results of total energy consumption for approximately 170,000 paper and plastic cups

2.4.2 Case Study 2 – Identifying uncertainty related to specific fuel use

Similar to case study 1, all the assumptions except for the price values from the old study are adapted to the new study.

In Horvath and Hendrickson's study (1998), the concrete pavement is made of 78,066 kg steel bars and 720 square meters of concrete, while the asphalt pavement takes 5,018 MT of asphalt.

In this study, new price assumptions are used. U.S. Department of Transportation's report Price Trends for Federal-Aid Highway Construction provides the material prices for highway constructions from 1972 to 2006 (USDOT 2002). According to the data, prices of steel, concrete and asphalt were \$0.61/lb, \$25.86/sq.yd., and \$34.14/ton in 2002. Therefore, the expenditures of one kilometer-long cement concrete and asphalt pavement are \$0.13 million (\$106,000 steel and \$22,270 concrete) and \$0.19 million. Applying these expenditure values to EIO-LCA model, Iron and steel mills, Ready-mix concrete manufacturing, Asphalt paving mixture and block manufacturing sectors are used for three components, energy consumption results for two types of pavements are shown in Table 2-5 and Table 2-6, respectively.

Table 2-5: Energy Consumption for 1km concrete pavement

Fuel types	Min (GJ)	Default (GJ)	Max (GJ)	Upper uncertainty (%)	Lower uncertainty (%)
Coal	3.29	2.64	0.84	24%	-68%
Natural gas	1.51	1.38	0.99	9%	-28%
Petroleum products	0.71	0.39	0.00	81%	-100%
Non-fossil electricity	0.63	0.60	0.41	5%	-32%
Biomass	0.10	0.09	0.09	3%	-3%
Total	6.23	5.11	2.33	22%	-54%

Table 2-6: Energy Consumption for 1km of asphalt pavement

Fuel types	Min (GJ)	Default (GJ)	Max (GJ)	Upper uncertainty (%)	Lower uncertainty (%)
Coal	0.70	0.50	0.30	41%	-40%
Natural gas	2.18	1.70	1.23	28%	-28%
Petroleum products	14.50	0.88	0.00	1546%	-100%
Non-fossil electricity	0.32	0.26	0.22	27%	-15%
Biomass	0.12	0.11	0.11	3%	-3%
Total	17.81	3.45	1.86	417%	-46%

Updating to the 2002 EIO-LCA model and using the *Iron and steel mills, Ready-mix concrete manufacturing,* and *Asphalt paving mixture and block manufacturing* sectors to represent the pavement products, it was found that the deterministic total energy consumption for 1 km of asphalt and concrete pavement changed to 4 TJ and 5 TJ, respectively, favoring the choice of asphalt on an energy basis. As the analysis based on EIO-LCA model relies on the prices of the products, the differences from the prior analysis are possibly due to the significant change of the prices of asphalt and concrete over 10 years. However, the results remain deterministic, encouraging users to make assertive decisions; the question becomes whether considering uncertainty in the model can better assist the LCA analyses.

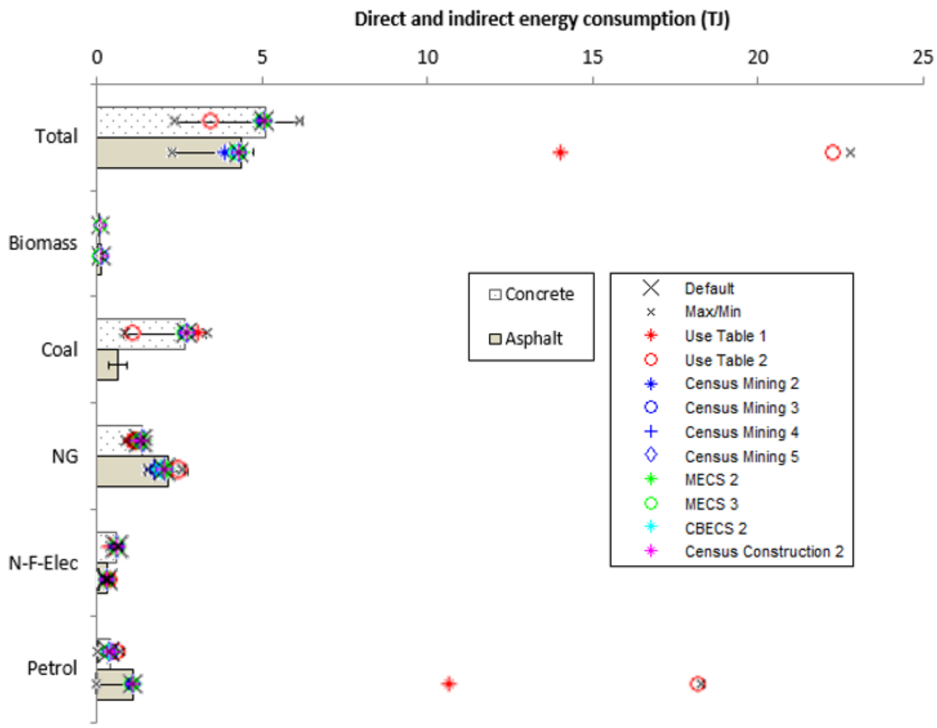

Figure 2-7: Results of energy consumption for 1 km concrete and asphalt pavement, error bars are the max/min values without outliers

As shown in Figure 2-7, considering all values, the energy consumption for 1 km of asphalt pavement has a range from 1.9 TJ to 17.8 TJ, larger than that of concrete pavement (2.3 TJ to 6.2 TJ). Asphalt pavement could be nearly 8 times (17.8/2.3) more energy intense, in contrast to the conclusion based on simple deterministic values. The large range in total energy use for asphalt pavement is mostly associated with the uncertainty of petroleum usage. As mentioned previously, the Use Table indicates larger petroleum purchase values for petroleum product manufacturing industries due to potential feedstock use. The uncertainty could be reduced if improved documentation was available. Providing all the results can allow users to make decisions based on all available data. The users can choose to ignore the big outliers caused by insufficiently documented data. For instance, if the values from the Use Table are ignored, the ranges for asphalt pavement change to 1.9 TJ to 3.7 TJ, resulting in a maximum value for asphalt pavement smaller than the maximum value for concrete pavement.

2.4.3 Case Study 3 – Identifying hotspots given uncertainty

LCA models, specifically IO-LCA models, are often used as a hotspot screening tool to help decision-makers access quick and simple relative results. The importance of sectors regarding environmental impact rankings helps determine what and where to look for potential impacts in a supply chain. Ukidwe and Bakshi (2008) developed a model to evaluate the environmental impacts of the chemical industry. In one step of the analysis, an economic input-output (EIO) model was used to identify the most significant supplier in an industry's supply chain. EIO models provide the economic outputs for all sectors in the supply chain; the most significant supplier can be found by sorting the outputs. Ukidwe and Bakshi identified that the most important supplier is the *Petroleum refineries* sector regarding economic output for the *Petrochemical manufacturing* sector.

Inspired by Ukidwe and Bakshi's study, I use the 2002 EIO-LCA model to evaluate the energy consumption for *Petrochemical manufacturing.* In our analysis, rather than economic output, energy consumption is evaluated and shows that the most energy intense sector is *Petrochemical manufacturing*.

When considering uncertainty, the most significant supplier can change. As shown in Figure 2-3 (which is the relevant result to use for this case study), when all possible data points are considered, *Petrochemical manufacturing*, *Petroleum refineries*, or *Other basic organic chemical manufacturing* could be the most energy intensive sector in the supply chain. If uncertainties are not considered, the possibility of the other two sectors being the most significant supplier may be ignored, and they could be left out of the analysis or not be a focus of study.

2.5 Conclusion

This study develops a method that propagates and visualizes uncertainty, focusing on inventory data uncertainty, in matrix-based LCA models. The uncertainty results provide additional insight to understand how a screening tool framework can be used to identify both the importance and the uncertainty of the results. Considering the uncertainty can provide better decision support for LCA studies, leading to more robust decisions as compared to those using only deterministic values. Different data sources and assumptions were used to build different underlying matrices of direct and indirect energy consumption values for each sector. The different consumption values provide information that can be used to identify the source of the uncertainties. A benefit of this approach is that it can be extended easily as additional relevant data sources are identified.

Results show that uncertainty in the $\boldsymbol{B}$ matrix in the EIO-LCA model is generally around 50%, with some extreme cases that reach over 40 times the default value. The overall uncertainty of each sector considering both direct and indirect impacts is smaller; total energy consumption, considering all 428 industries, is generally within -40% to 40%, with a few extreme cases that have over 4 times more impact. Outliers show that even reliable data sources can lead to large uncertainty, especially when underlying assumptions are not well documented or understood.

Another contribution of this paper is the visualization of all possible values calculated for one sector. The results visually show all possible results calculated from different data sources and/or assumptions, rather than merely the maximum and minimum values for a sector. There are several advantages of this visualization. First, results emphasize all possible results, which cannot be indicated in simple bounding results. Second, more information can be provided when possible results are shown to users. Users can make judgments based on all the information shown in the visualization. Third, users can track the source(s) of uncertainty in the inventories by reading the possible results.

The general method used here for energy consumption can be applied to other inventory categories of an IO-LCA model, can be expanded to consider scenario and model uncertainties.

The method described here can be used to inform an uncertainly analysis in process matrix models as well and could consist of known ranges of values for a sub-process input into the $\boldsymbol{B}$ matrix or simply deriving a range of data from the various complementary available process datasets. As an example, if electricity is important in the process and the model has various data to represent electricity generation (grid average, renewable, fossil fuel-based, etc.), a range can be generated to help an analyst to explore and present the impacts. Future work will focus on adapting the method to the uncertainty estimation in the technology and intervention matrices of process-based models.

3. Chapter 3. Data analysis in the US LCI database and scenario uncertainty in matrix-based models

3.1 Introduction of the matrix-based method

Process-based data is typically used in LCA, and when implemented in software using existing databases, is often modeled with matrix-based methods. The method scales life cycle inventories from existing databases into matrices, and uses formulas (such as Equation 1) to calculate the direct and indirect environmental effects for any user-defined final demand in the system (Heijungs et al. 1992; Heijungs 2010; Heijungs and Suh 2006; Wang and Work 2014). The results calculated from the matrix-based LCA method can separately provide environmental effects of direct (onsite) and indirect (upstream) processes in the system under study.

The system under study may consist of all processes provided in a LCA database. These databases, such as US LCI (United States Life Cycle Inventory) and Ecoinvent, often provide LCI data for a significant amount of processes. The LCI data generally includes direct (gate-to-gate) energy, materials used, and emissions from the production of the processes (NREL et al. 2004).

To assess the direct environmental effects from production, the LCI of each process can be used individually. The LCI data of different processes can also be grouped together using matrix-based methods to include both direct and indirect environmental effects. A brief description of how inventories are mapped into matrices is provided below.

The inputs and outputs in a unit process from a LCA database are one of two types: product flows or elementary flows. The product flow is an input or output from the technosphere (technical system or the economy) (NREL et al. 2004). Electricity generated from coal is an example of a product flow. An elementary flow is an environmental effect to the biosphere (nature or ecosystem) without previous human transformation (ISO 2006b) (NREL et al. 2004). Carbon dioxide emitted to air is an example of an elementary flow. In process-based LCI databases, each unit process has its product flow mapped on to the technology matrix ($\boldsymbol{A}$), and its elementary flow mapped on to the intervention matrix ($\boldsymbol{B}$). These two matrices are used in Equation 3 (Heijungs 2010) to calculate direct and indirect environmental effects.

Equation 3: $\boldsymbol{g} = \boldsymbol{B}\boldsymbol{A}^{-1}\boldsymbol{f}$

Where $\boldsymbol{f}$ is a vector representing the final demand defined by the users; it is the amount of product output in its functional unit. For a system that has n unit processes and m elementary flows, the $\boldsymbol{f}$ vector has n by 1 dimensions. The $\boldsymbol{A}$ matrix is n by n, each column represents a unit process and each row indicates the input/output product flow. The $\boldsymbol{B}$ matrix is an m by n matrix, here the rows are m different elementary flows, such as carbon dioxide emissions. $\boldsymbol{A}^{-1}\boldsymbol{f}$ gives an n by 1 vector of the total input/output product flows. The resultant vector $\boldsymbol{g}$, has m by 1 dimensions and contains the m total environmental effects for the final demand $\boldsymbol{f}$. For each environmental effect ($\boldsymbol{i} = \boldsymbol{1}, \ldots, \boldsymbol{m}$), the direct and indirect effects can be separated by the Hadamard (entrywise) product of the transpose of row $\boldsymbol{i}$ in the $\boldsymbol{B}$ matrix and $\boldsymbol{A}^{-1}\boldsymbol{f}$:

Equation 4: $\boldsymbol{h}_i = \boldsymbol{B}_i{}^{\boldsymbol{T}} \circ \boldsymbol{A}^{-1}\boldsymbol{f}$

Where $\boldsymbol{h}_i$ is an n by 1 vector containing the $\boldsymbol{i}^{\text{th}}$ environmental effect from n unit processes for the final demand $\boldsymbol{f}$.

3.2 Definitions of connections and processes

Two directed connection categories among processes are defined: downstream and upstream (Figure 3-1). The downstream connections of a process indicate the relative role of the process in the database. An electric power generation process, for example, was typically used as an energy input in industrial productions, thus many downstream connections would be expected. Figure 3-1 shows the downstream and upstream connections for a hypothetical process A. On the right panel, two input product flows are related to Process A via upstream connections (Process B and C). The left panel shows the definition of a downstream connection. When a process serves as an input to another process, I say that the input process has a downstream connection to the receiving process. Process A has one downstream connection, to Process B, which of course then has an upstream connection to Process A. As shown in this example, an upstream connection could be another process' downstream connection, or vice versa.

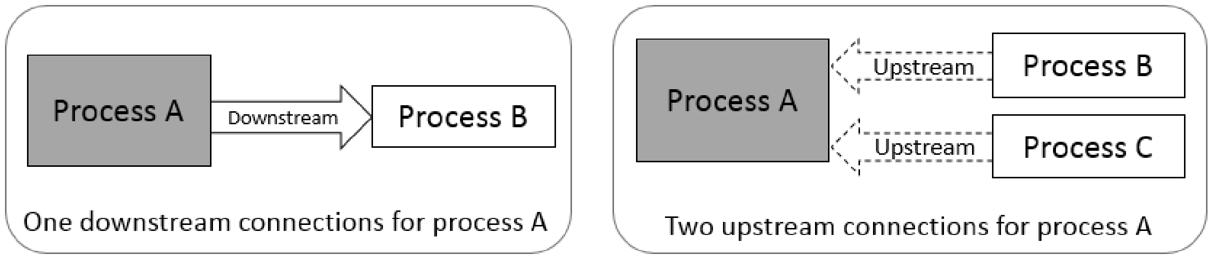

Figure 3-1: Definitions of upstream and downstream connections in this study, shown with one downstream connection and two upstream connections for a hypothetical Process A.

As the LCI for each process only provides direct inputs or outputs, the indirect inputs or outputs calculated from the matrix-based LCA method rely on the interconnections between processes in the system under study. These interconnections are links between processes based on their respective inventories. In the matrices, a link between two processes is represented by a non-zero value. In recent years, the interconnections in the LCI database have become interesting to LCA practitioners. Using graphical methods, Kuczenski (2015) estimated the interconnections between processes in several LCI databases; this study concluded that all the databases under consideration shared similar internal structure. Network analysis methods have also been used in input-output models to determine the key processes in the system (Singh and Bakshi 2011; Kagawa et al. 2013; Nuss et al. 2016). These studies generally focused on determining the strongly connected processes in the system with the purpose of categorizing processes in the databases, and identifying important processes in particular industries. However, the question of how the database interconnections affect the results from matrix-based LCA method remains unanswered.

Substantial connections are crucial to evaluate direct and indirect environmental effects. The coverage of connections determines whether the indirect environmental effects can be fully captured. This study demonstrates a method to evaluate the effects from the interconnections in matrix-based methods. The US LCI database is used as a case study. The latest version of the US LCI database provides 1060 unit processes. These unit processes have inputs or outputs from 1466 elementary flows and other processes. In this study, first, the processes from the US LCI database were mapped on to the A and B matrices. Then, the inputs and outputs for each process were evaluated and quantified to demonstrate the coverages of connections in the database. Last, I compared the connections with the input-output table and the results from EIO-LCA

(Environmental Input-Output Life Cycle Assessment) model to identify possible missing connections for some processes. In addition, I analyzed the uncertainties resulting from using alternative utilities for each process.

3.3 Matrices mapped from unit processes in the US LCI database

At the time this analysis was conducted, the US LCI database provided 701 unit processes. The inventories of these unit processes could be obtained individually from the US LCI website compiled by the National Renewable Energy Laboratory (NREL 2012). To apply the inventories into matrix-based LCA model, I downloaded the inventory data for all available unit processes and used Matlab software to map their inventories into the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices (code is provided in the Appendix). Following the terminology from above, the results from the mapping showed n=1471 product flows and m=2701 elementary flows in the matrices. I observed some potentially problematic processes in the matrix mapping and results. These problematic processes affect the consistency of the inventories in the matrices and could result in inaccurate interpretations in the matrix-based LCA model. Therefore, before the interconnections in the matrices were evaluated, I screened potential problematic processes according to three categories: the cut-off processes, the system boundary, and the flow types.

3.1.1 Cut-off processes

In US LCI, "cut-off" processes, previously labeled as "Dummy" processes, are input products whose inventories are not yet provided in the current version of the database. For example, the inventory information of one secondary steel production process ("CUTOFF Steel, secondary, at plant") is not yet included in the database. Currently, 525 or 35% of the total number of processes in US LCI database are cut-off processes. The cut-off processes cover diverse products and generally can be found in all US industries, see Table S3 for a list of all cut-off processes. When the database is applied to a matrix-based LCA model, the presence of cut-off processes, as inputs to a process under study, results in the neglect of upstream effects. This is because the cut-off processes do not contribute to the indirect effects.

3.1.2 Cradle-to-gate and gate-to-gate processes

Based on the inclusiveness of the processes' system boundaries, data in the US LCI database is associated with two different types of unit processes: "gate-to-gate" and "cradle-to-gate". Gate-to-gate processes are unit processes for the production only; the word "gate" indicates the entry or exit threshold of a factory. Whereas the cradle-to-gate processes also include upstream inputs and outputs; the word "cradle" indicates the origin of a product.

The US LCI database has around 10% cradle-to-gate processes among the total number of unit processes provided; the identification of these processes are introduced later in this section. Here, Polyethylene terephthalate (PET) is used as an example product to illustrate how the two types of processes are listed in the US LCI database. The cradle-to-gate and gate-to-gate inventories for producing PET were provided in a LCA study (Franklin Associates 2010), and are shown in Table 3-1. For PET, the cradle-to-gate process and gate-to-gate process differ in their material usage and transportation inputs. The four material inputs for the gate-to-gate process are products from other factories that are incorporated to the production of PET. The cradle-to-gate PET process is composed of crude oil, natural gas, and oxygen; these are the raw production materials for the four inputs in the gate-to-gate process. There are transportation inputs in the cradle-to-gate process, because compared to the gate-to-gate process, there are more product exchanges between factories or industrial sites.

In the US LCI database, the published inventories in Table 3-1 were modified to produce two different unit processes, as shown in Table 3-2.

Table 3-1: Inputs in the gate-to-gate and cradle-to-gate processes for PET production from Franklin Associates' original LCA study. The two processes differ in material usage and inputs.

Gate-to-gate PET inventory, for 1000kg PET, provided by Franklin Associates study		Cradle-to-gate PET inventory, for 1000kg PET, provided by Franklin Associates study	
Material		**Material**	
Paraxylene	521 kg	Crude oil	568 kg
Ethylene glycol	322 kg	Natural gas	215 kg
Acetic acid	37.2kg	Oxygen	223 kg
Methanol	35.2 kg		
Water consumption	0.537 cubic meter		
Energy use		**Energy use**	
Electricity (grid)	558 kWh	Electricity (grid)	882 kWh
Electricity (cogeneration)	9.59 cubic meter	Electricity (cogeneration)	12.1 m3
Natural gas	98.1 cubic meter	Natural gas	352 m3
Bit./Sbit. Coal	18.9 kg	Bit./Sbit. Coal	35.9 kg
Distillate oil	12.8 liter	Distillate oil	13.8 liter
Residual oil	26.8 liter	Residual oil	80.1 liter

		Transportation	
		Combination truck	28.5 tkm
		Rail	1633 tkm
		Barge	139 tkm
		Ocean freighter	2717 tkm
		Pipeline-natural gas	382 tkm
		Pipeline-petroleum	395 tkm

Table 3-2: Inputs in the gate-to-gate and cradle-to-gate processes for PET production provided by the US LCI database. Italics are used to mark the differences from Table 3-1. The inputs for the cradle-to-gate process are broken into upstream raw elementary flows, as opposed to the inputs as product flows from the original LCA study.

Gate-to-gate PET inventory, for 1000kg PET, provided by the US LCI database		**Cradle-to-gate PET inventory, for 1000kg PET, provided by the US LCI database**	
Material		**Material**	
Paraxylene, at plant	521 kg	*Coal, lignite, in ground*	*25.3 kg*
CUTOFF Ethylene glycol, at plant	322 kg	*Coal, unprocessed bituminous, in ground*	*326 kg*
Acetic acid, at plant	37.2kg	*Gas, natural, in ground*	*222 kg*
Methanol, at plant	35.2 kg	*Oil, crude, in ground*	*587 kg*
		Oxygen, in air	*243 kg*
		Uranium oxide, 332 GJ per kg, in ore	*6.46 g*
Water, process, unspecified natural origin/m3	*0.244 m3*	*Water, process, unspecified natural origin/m3*	*12.1 m3*

Energy use		**Energy use**	
Electricity, at grid, US, 2008	558 kWh	*Gas, natural, in ground*	*504 m3*
Electricity, at cogen, for natural gas turbine	9.59 m3	*Oil, crude, in ground*	*151 kg*
Natural gas, combusted in industrial boiler	98.1 m3	*Energy, from biomass*	*5.37 MJ*
Bituminous coal, combusted in industrial boiler	18.9 kg	*Energy, from hydro power*	*24.8 MJ*
Diesel, combusted in industrial equipment	12.8 liter	*Energy, geothermal*	*13 MJ*
Residual fuel oil, combusted in industrial boiler	26.8 liter	*Energy, kinetic (in wind), converted*	*12.9 MJ*
		Energy, solar	*0.547 MJ*
		Energy, unspecified	*17.4 MJ*
Transportation		**Transportation**	
Transport, barge, diesel powered	*0.655 tkm*		
Transport, barge, residual fuel oil powered	*2.18 tkm*		
Transport, pipeline, natural gas	*0.0876 tkm*		
Transport, train, diesel powered	*1610 tkm*		
Disposal		**Disposal**	
CUTOFF Disposal, solid waste, unspecified, to municipal incineration	*0.31 kg*	*CUTOFF Disposal, solid waste, unspecified, to municipal incineration*	*128 kg*
CUTOFF Disposal, solid waste, unspecified, to sanitary landfill	*4.19 kg*	*CUTOFF Disposal, solid waste, unspecified, to sanitary landfill*	*31.8 kg*

CUTOFF Disposal, solid waste, unspecified, to waste-to-energy	*0.59 kg*	*CUTOFF Disposal, solid waste, unspecified, to waste-to-energy*	*0.595 kg*
		CUTOFF Disposal, solid waste, process, to municipal incineration	*1.03 kg*

As shown in Table 3-2, the gate-to-gate process provided by the US LCI database links to four other processes flows ("Paraxylene, at plant", "CUTOFF Ethylene glycol, at plant", "Acetic acid, at plant", and "Methanol, at plant") in the model as inputs, and the inputs are identical to the inventory provided in the original LCA study (Table 3-1). On the other hand, cradle-to-gate processes in the US LCI database (Table 3-2) link to other elementary flows as inputs, and do not have product flows. The US LCI database (Table 3-2) also includes further decompositions, derived from Table 3-1, of the inputs' raw materials represented as only elementary flows. For example, "Electricity (grid)" is decomposed into upstream inputs such as "energy from solar", and "energy from geothermal". This decomposition requires additional assumptions on electricity generation methods; however, the assumptions used are not stated in the metadata of the process (or any other cradle-to-gate process in the database), making the interpretation impossible for any user. It can only be assumed that the grid electricity used in the production is a mix of electricity generated from different types of power plants. The power plants themselves use different energy sources, such as solar power, to generate electricity. Thus, in this example, the resulting cradle-to-gate PET inventory is a mix of raw energy inputs. In general, this type of decomposition allows the cradle-to-gate process to have only elementary flows as inputs. When mapping processes on to matrices, a representation of only elementary flows avoids double-counting. Double-counting occurs when matrix $\boldsymbol{A}$ includes upstream inputs; the double-count of inputs propagates to $\boldsymbol{A}^{-1}\boldsymbol{f}$ in Equation 3. On the contrary, without double-counting, the results calculated from $\boldsymbol{A}^{-1}\boldsymbol{f}$ correspond to only one unit of the process under study and the cradle-to-gate emissions in the $\boldsymbol{B}$ matrix represent the total emissions. The effects calculated from gate-to-gate processes can be separated into direct and indirect effects in each upstream input using Equation 4. In this way, I can trace the locations of the upstream effects. The CTG decomposition prevents the double-counting issue. However, the necessary assumptions as well as the decomposition methods are not documented in the US LCI database. As a result, the users are unable to fully interpret the cradle-to-gate inventory.

The cradle-to-gate processes and gate-to-gate processes have different system boundaries. The two types of processes should be separated when mapped into matrices to avoid potential scenario uncertainty in matrix-based LCA models. Hence, in this analysis I distinguish the cradle-to-gate processes from the unit processes in the US LCI database.

To categorize cradle-to-gate and gate-to-gate processes, I consider each process' metadata. The metadata information includes system boundary, location, and other notes of the LCA studies. First, the cradle-to-gate processes were identified by parse matching keywords "Cradle-to-gate", "cradle to gate" and "CTG" in the metadata via MATLAB software (code available in the Appendix). Then, the identified processes' full descriptions were individually assessed to avoid errors in parse matching. Last, the processes with all elementary flows but no product flows as inputs were separately identified; these processes could be cradle-to-gate processes whose inventories have been simulated into elementary flows.

Keyword matching identified 125 potential cradle-to-gate processes in the original LCA study (Table 3-1). This database investigated the inventories for several different plastic resins. Individual assessments revealed 61 false positives; the cradle-to-gate misclassification was due to errors in the metadata, see Table S2. From the correctly classified 64 cradle-to-gate processes, 10 processes only had cradle-to-gate inputs in part of their inventories. For instance, the "Soy-based resin, at plant" process was listed as "part cradle-to-gate, part unit process" in its metadata. Despite the lack of clarity in these inventories, I assumed it is reasonable to consider all 64 processes as cradle-to-gate.

In the $\boldsymbol{A}$ matrix mapped from all US LCI processes, I observed elementary flows as sole inputs in the remaining processes. By individual assessment I found that 6 were actually cradle-to-gate processes. Four of these six misclassifications were identified as having simulated upstream energy inputs, such as PET, CTG process in Table 3-2. I assumed that gate-to-gate processes did not have to break inputs into upstream raw materials. These processes were: "Corn steep liquor", “Forest residue, processed and loaded, at landing system”, “Wood fuel, unspecified”, and “Zinc, Special High Grade”. The other two misclassifications were “Polylactide Biopolymer Resin, at plant” and “Zinc, sheet”; they had other simulated upstream inputs. The final classification count was 70 cradle-to-gate processes (approximately 4% of the total). Furthermore, 48 out of the 70 cradle-to-gate processes had simulated upstream inputs in the form of raw materials, such as the PET, CTG process in Table 3-2, meaning the remaining 22 processes could cause double-counting when applied to matrix-based models.

The cradle-to-gate processes can provide total environmental effects without needing to use the matrix-based method, making them seemingly more convenient to use than the gate-to-gate processes. However, a disadvantage of the cradle-to-gate processes is that they fail to provide effects on different stages of the production. For example, the cradle-to-gate PET process provided in Table 3-2 indicates that the total (direct and indirect) fossil CO_2 emissions, for producing 1 kg of PET, is 2.419 kg. I cannot know the amount of fossil CO_2 emissions from different inputs of the production (and thus cannot evaluate sources of differences if there were alternative production processes). In comparison, by running the gate-to-gate PET process in the matrix-based model, I calculate the direct and indirect emissions from the upstream processes (the upstream processes with the highest 10 emissions are listed in Table 3-3). Gate-to-gate processes can take the full advantage of the matrix-based method by separately listing the emissions from different stages. For the PET example, the users can tell that the onsite fossil CO_2 emissions (excluding emissions from burning fossil fuel) was 72.4 kg, only 6% of the total emissions, while the most intensive emissions were from burning fossil fuel in the production or upstream energy use. As seen in this example, gate-to-gate processes allow the LCA practitioners to efficiently interpret the LCA results. On the contrary, cradle-to-gate processes fail to deliver an equivalent breakdown of results.

Another limitation of the undocumented cradle-to-gate processes is that when applied to the matrix-based method, it is impossible to improve the inventory by reducing the uncertainty in each input. For the PET example, the total fossil CO_2 emissions from the cradle-to-gate and gate-to-gate differ by 1.242 kg, with the cradle-to-gate process (not surprisingly) having a larger emission value. As the emissions by inputs from the cradle-to-gate process are not available, it is impossible to identify what produced these discrepancies. Alternatively, in the case of gate-to-gate processes, improving the data quality for an input also improves the uncertainty in the total emission. For example, the largest part of fossil CO_2 emissions for producing PET is from burning natural gas in the production, therefore when this input is switched to another fuel, or the data quality of emissions from the natural gas combustion is improved, the total fossil CO_2 emissions can be updated accordingly. This update could not be possible for cradle-to-gate processes, because their emission sources cannot be tracked.

Table 3-3: top ten fossil CO_2 emissions processes for producing 1 kg of Polyethylene terephthalate, resin, at plant (PET), calculated from the gate-to-gate PET process.

Process name	Fossil CO_2 emissions (g)	Parentage of the total
Natural gas, combusted in industrial boiler	508.18	41.0%
Residual fuel oil, combusted in industrial boiler	140.02	11.3%
Electricity, natural gas, at power plant’	95.72	7.7%
Bituminous coal, combusted in industrial boiler	94.78	7.6%
Polyethylene terephthalate, resin, at plant	72.40	5.9%
Electricity, bituminous coal, at power plant	44.94	3.6%
Transport, ocean freighter, residual fuel oil powered	40.34	3.3%
Diesel, combusted in industrial equipment	37.34	3.0%
Transport, train, diesel powered	32.04	2.6%
Methanol, at plant	29.28	2.4%
Other	142.26	11.5%
Total	1,237	100%

3.1.3 Product flows and elementary flows

As mentioned before, a gate-to-gate process should include all the possible inputs within the technosphere. This would maximize the interconnections and include all possible indirect effects. For example, when mapping the inventory from a coal power plant on the US LCI database, one should make sure that all the associated intermediate processes have been included. For example, Coal power plants use coal as their energy input, thus a product flow that represents coal combusted for energy should be chosen as one of the inputs. Choosing “coal as a raw material” as an input would result in ignoring potentially large emissions from the coal mining process. Note that some cradle-to-gate processes in the US LCI database have already included all inputs in the elementary flows, thus the cradle-to-gate processes do not have the same problem.

In this study, all 474 raw material input elementary flows were used to identify the processes that had skipped intermediate product flows. First, I distinguished the processes with any of these raw material flows as an input. Then, the distinguished processes were individually evaluated to identify the processes that had used these raw material elementary flows directly without the intermediate process.

The results show that among all 1471 processes, 136 had at least one of these raw material elementary flows as inputs. After evaluating these 136 processes individually, it was found that 131 processes were either cradle-to-gate processes (54) or correctly connected to the biosphere gate-to-gate processes (77). The 54 cradle-to-gate processes had the raw material elementary flows listed in Table 3-4 as inputs due to a separate issue discussed above. The remaining 77 gate-to-gate processes were correctly connected to the biosphere. For example, the "Coal, in ground (hard, 30.7 MJ per kg)" elementary flow is an input to "Anthracite coal, at mine". The "Anthracite coal, at mine" process is a product (product flow) which is directly produced using "coal in ground" as raw material. Thus, no intermediate flow was skipped. In conclusion, there are only 5 processes that possibly skipped the intermediate processes (Table 3-4).

Table 3-4: process and resource elementary flows

Product flow	Functional unit	Elementary flow as inputs, skipping intermediate processes	Value for 1 functional unit (positive as inputs, negative as outputs)
Winter wheat straw, production, average, US, 2022	1 kg	Energy, from biomass	15.0 MJ
Corn stover, production, average, US, 2022	1 kg	Energy, from biomass	15.4 MJ

Switchgrass, production, US, 2022	1 kg	Energy, from biomass	15.3 MJ
Portland cement, at plant	1 kg	Clay, unspecified	-59.7 g
		Gypsum	-61.5 g
		Iron ore	-13.5 g
		Limestone	-1400 g
		Raw material, unspecified	-26.4 g
		Sand, unspecified	-40.5 g
		Shale	-52.2 g
		Slate	-1.13 g
Iron, sand casted	1 kg	Coal, bituminous, 24.8 MJ per kg	-14.6 g
		Limestone	-76.7 g
		Sand, unspecified	-1100 g

Skipping intermediate processes can result in neglecting the upstream environmental effects. The processes fail to reach the utmost connections for the matrix-based LCA studies. Hence there is a need to resolve the inconsistencies in flow types in order to improve the database. The next section will discuss additional connection issues found in the US LCI database.

3.4 Connections in the US LCI database

To understand the processes and whether they can take full advantage of matrix-based LCA models, the connections between processes were analyzed using the definition of upstream and downstream connections introduced in section 3.2. The results show that 791 out of 1471 product flows have no upstream connections; this number includes 525 cut-off processes (Figure 3-2). The absence of upstream connections neglects potential indirect effects, as discussed previously. Similarly, 503 out of the 1471 product flows had no downstream connections (Figure 3-3). The lack of upstream connections in cut-off processes is due to inventory unavailability, not zero inputs. The matrix-based models (and databases) are less useful when the inventories include cut-off processes; when the cut-off processes are replaced by other processes with full inventories, they will have non-zero upstream connections. It is important to be aware of cut-off processes because they are used as inputs in other processes' inventories (but again, have no upstream inventory). Figure 3-3 shows that almost all cut-off processes have more than one downstream connection; in fact, 28 of them have more than 10 downstream connections – meaning 10 processes would otherwise benefit from them having real inventories. These cutoff processes may hide total environmental effects. Therefore, when new inventory data are incorporated in the US LCI database, the cut-off processes' inventories, especially the ones with large number of downstream connections, should be prioritized to maximize the utility and completeness of the database, and avoid potentially missing total environmental effects.

The results also show that global average (upstream and downstream for all processes) was 4 connections. In general, processes had more downstream connections than upstream connections; 69 processes had more than 20 downstream connections, one process ("Transport, train, diesel powered") had 250 downstream connections. In comparison, no process had more than 51 upstream connections. Individual processes did not necessarily have more downstream than upstream connections.

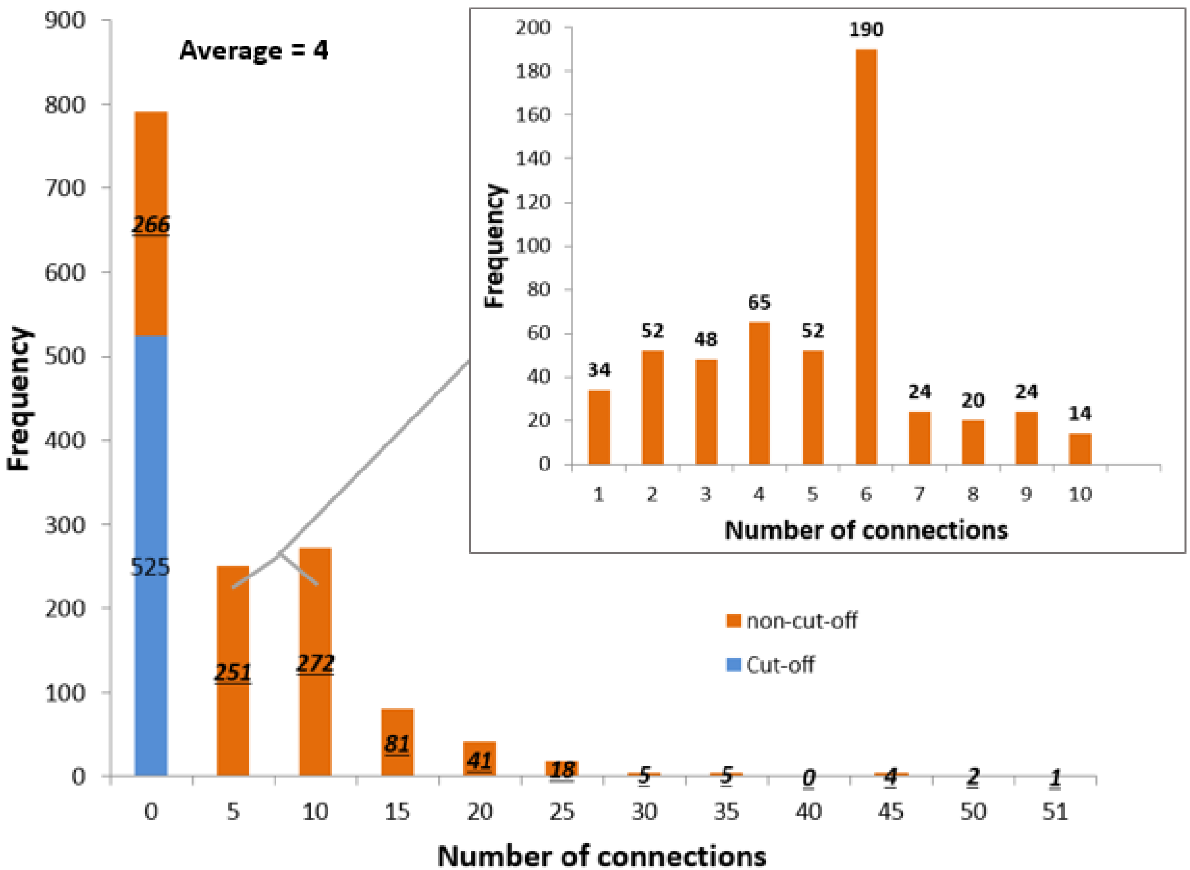

Figure 3-2: Number of upstream connections for each process in the US LCI database. The inset provides greater detail for those processes with 10 or less process inputs. Values on the x axis indicate the number of connections in which each process falls. For example, the third bar on the main graph shows that there are 272 processes that have a range from 6 to 10 upstream connections. Results are shown separately for Cut-off (blue), and non-Cut-off processes (orange). The bar on the zero value is the number of processes with no upstream connection. All Cut-off processes have zero upstream connections, due to the inventory unavailability.

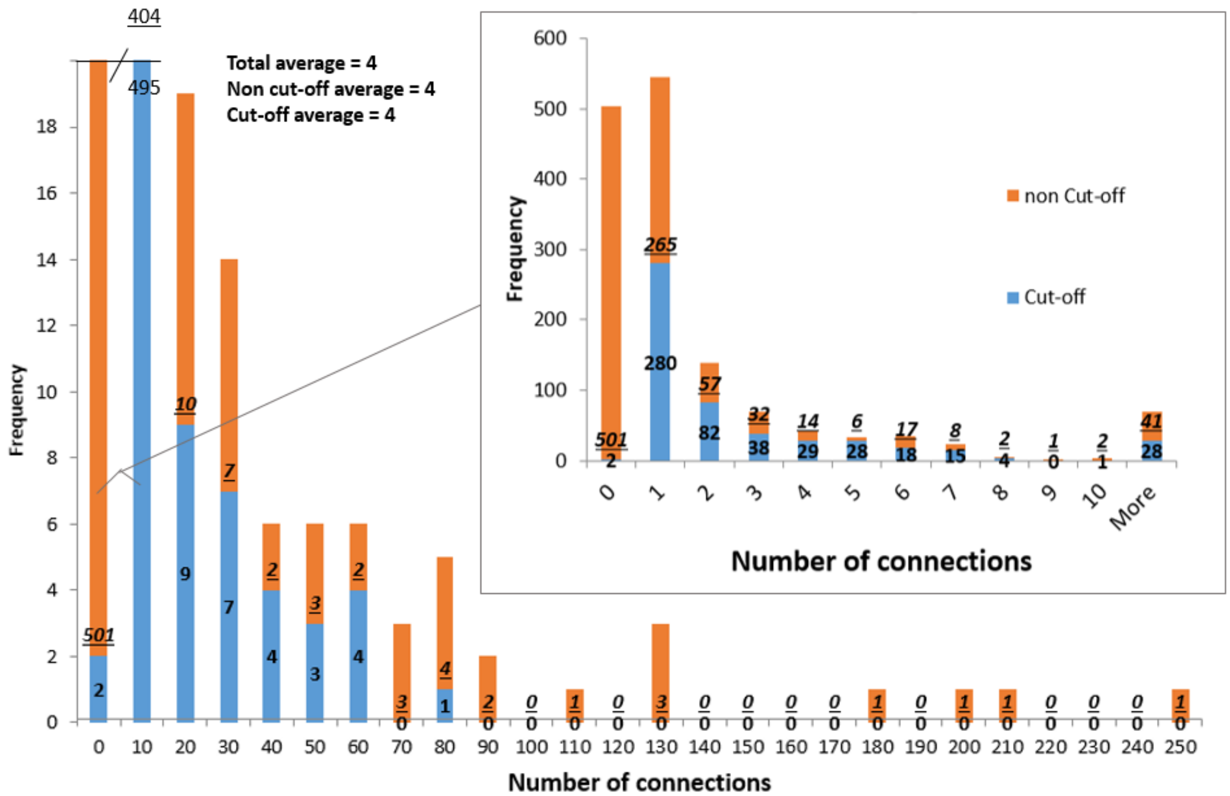

Figure 3-3: number of downstream connections for each process in the US LCI database. The inset shows processes with 10 or less downstream connections. Result are shown separately for cut-off (blue) and non-cut-off processes (orange). Values on the x axis indicate the number of connections in which each process falls. For example, the third bar on the bottom graph shows that there are 19 processes that have connections ranging from 11 to 20; 9 of these processes are "cut-off" processes. The bar on the zero value is the number of processes with no downstream connections.

Table 3-5 lists the non-cutoff processes with more than 20 downstream connections. Many of these processes represent very similar alternative processes, often with minor differences. For example, "Electricity, at grid, US, 2000" (No. 15 in

Table 3-5) and "Electricity, at grid, US, 2008" (No. 11) each represent an overall US average grid mix of electricity. Here, these input processes differ only by the year. If there are multiple versions for a given type of electricity process, only one should be chosen as the input. Table 3-4 includes the numbers of downstream connections for some similar processes, such as the two electricity examples discussed above. To understand the downstream connections from each type of input process, the connections of these similar processes were aggregated, the processes are listed by their categories in Table 3-6. The results show that energy or transportation accounted for the majority of processes with large numbers of downstream connections. These processes are similar and are often used as inputs by other processes. When one of these processes is used as an input, it is possible to consider other similar processes as alternatives. Including these possible alternatives can potentially improve the inventories and the LCA results. This is the subject of the second topic in this chapter.

The upstream connections can be subdivided into three individual types based on the characteristics of their inputs: 1) cutoff or non-cutoff inputs, 2) within or without the same industrial category based on the ISIC (The International Standard Industrial Classification of All Economic Activities) code, and 3) whether energy or transportation is included. Cut-off inputs to a process, in the first type, were distinguished because they do not contribute to the indirect effects. The ISIC code used in the second type is a classification structure based on industrial economic activities (UN 2008). I chose to use the ISIC code to categorize the processes because it associates industrial products with economic activities, and its categories are more detailed than the input-output industrial sectors. In the ISIC code, the industries are categorized in broad structures called divisions; these broad structures are further separated into detailed structures called classes. The inputs arising from outside the same category were identified to show whether the processes were connected to other industries, as processes that only have inputs from the same industry could be merely the mix of similar processes. For example, the grid electricity process in the US LCI database is a mix of different electricity processes generated by different types of fuels. For the processes that had at least one downstream or upstream connection, their inputs were evaluated separately to identify whether they were fuel, electricity, and/or transportation. It can be assumed that the production of most products needs certain types of energy and transportation as inputs, therefore the processes without any energy and transportation input should be identified. I note that this is another inconsistency in the inventories of LCI databases. For example, some processes include transportation in their scope, while others do not. However, the users are generally unaware of this inconsistency and might use a process that does not align with their scope assumptions. The proper identification of this inconsistency can lead to improvements on the processes' inventories.

Table 3-5: Processes with more than 20 downstream connections in the US LCI database.

No.	Process name	Number of downstream connections
1	Transport, train, diesel powered	250
2	Transport, pipeline, unspecified petroleum products	191
3	Transport, barge, average fuel mix	176
4	Natural gas, combusted in industrial boiler	130
5	Transport, ocean freighter, average fuel mix	129
6	Diesel, at refinery	128
7	Transport, combination truck, diesel powered	102
8	Transport, combination truck, average fuel mix	93
9	Diesel, combusted in industrial equipment	89
10	Gasoline, combusted in equipment	83
11	Electricity, at grid, US, 2008	71
12	Electricity, residual fuel oil, at power plant	66
13	Liquefied petroleum gas, combusted in industrial boiler	63
14	Gasoline, at refinery	55
15	Electricity, at grid, US, 2000	54
16	Diesel, combusted in industrial boiler	45
17	Electricity, at grid, Eastern US, 2000	42
18	Residual fuel oil, combusted in industrial boiler	42
19	Transport, pipeline, natural gas	31
20	Natural gas, combusted in industrial equipment	30
21	Transport, barge, diesel powered	26
22	Electricity, at grid, Western US, 2000	25
23	Quicklime, at plant	25

24	Bituminous coal, combusted in industrial boiler	24
25	Transport, barge, residual fuel oil powered	23

Table 3-6: Processes with more than 20 downstream connections in the US LCI database, sorted by three industrial categories

Category	Process name	Number of downstream connections
Fossil fuel and electricity as energy	Electricity, at grid	192
	Natural gas, combusted	160
	Diesel, combusted	89
	Gasoline, combusted	83
	Liquefied petroleum gas, combusted	63
	Residual fuel oil, combusted	42
	Bituminous coal, combusted	24
Transportation	Transport, train	249
	Transport, pipeline	222
	Transport, barge	225
	Transport, combination truck	195
	Transport, ocean freighter	129
Materials	Diesel, at refinery	128
	Gasoline, at refinery	55
	Quicklime, at plant	25

Figure 3-4 shows the different types of connections for the 1471 processes in the database. Also included in Figure 3-4 is the analysis of energy and transportation inputs for the processes that have at least one upstream or downstream connection. The results show that 342 (233+284-194+19) processes (23% of the total) have at least one upstream or downstream connection. 248 (342-94) out of these 342 processes have either transportation or fuel as input. If transportation is considered as an important input to decide whether a given process' inventory is fully established, there are 76 (61+9+6) processes (5% of the total) that have both energy and transportation as inputs. On the other hand, more than 50% of the total processes have no upstream connections; this percentage includes the cut-off processes. I also note that more than 34% of the total processes do not have downstream connections.

The results also show that 165 processes in the database have neither upstream nor downstream connections. Most of these processes were by-products from the production of other products, thus their inputs were not considered. For example, "Steam, at uncoated freesheet mill" is a by-product of "uncoated freesheet". For this production, I assumed that allocation was not necessary. Thus, the number of inputs for this by-product was zero; consequently, the number of upstream connections was also zero. Additionally, this by-product was not used as an input in any other processes' inventories, resulting in zero downstream connections.

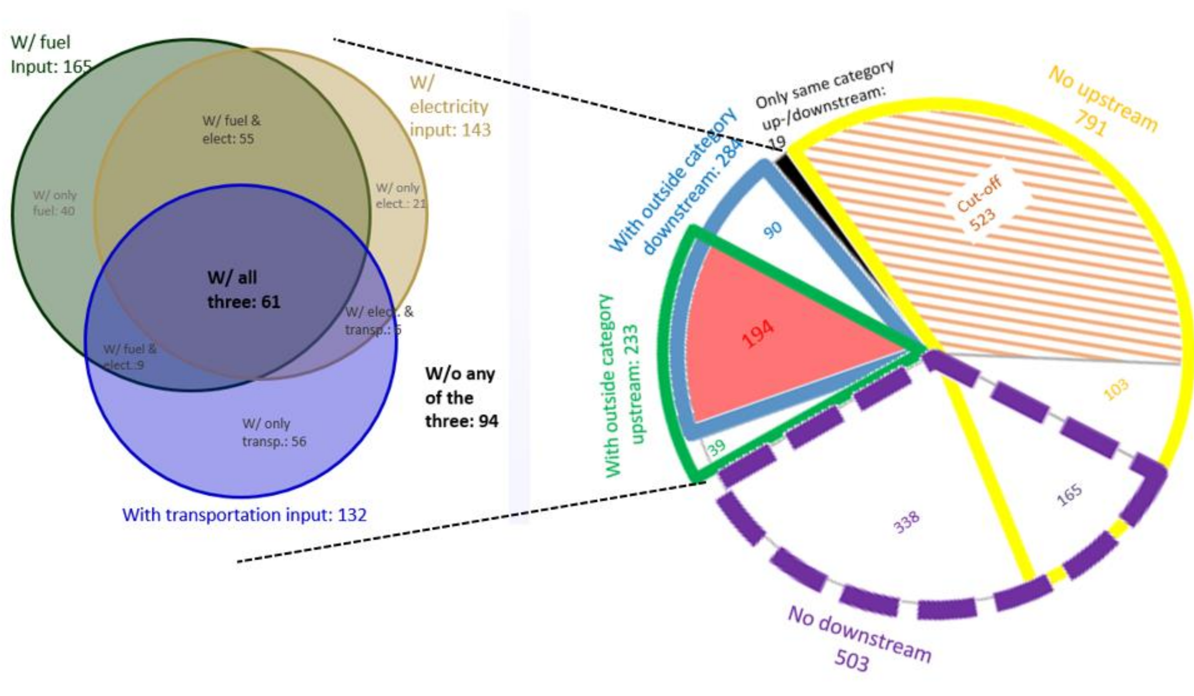

Figure 3-4: different types of connections among the 1471 processes in the US LCI database. The chart on the right shows the different types of connections shared by the 1471 processes, the figure on the left shows processes that have fuel (green circle), electricity (brown circle) or transportation (blue circle) as inputs, for the processes that have one or more than one upstream or downstream connections.

Let us define a “useful process” as one that effectively contributes to the indirect values in the matrix-based LCA model. A “useful process” requires 1) at least one upstream and downstream connection, and 2) at least one energy (fuel or electricity) and at least on transportation as input. This definition is made for several reasons. First, most processes without upstream connections neglect indirect effects in the matrix-based LCA model. Second, processes without downstream connections can be seen as only a product , rather than a contributor in the database (previous studies have defined these processes as “foreground processes” (UNEP 2011)). Processes without downstream connections are just modeled products from the matrix; these processes do not contribute to the indirect effects for other processes when incorporated in the matrices, therefore they do not affect the results of any other process in the database. Third, processes without energy or transportation as inputs are assumed to have missed these two inputs in the inventory; in this case, it is quite possible to neglect both direct and indirect upstream environmental effects. I found only 76 “useful processes” in the current version of the US LCI database. It is assumed that compared to the rest of the processes, the “useful processes” can cover more indirect effects in the matrix-based LCA method. I believe that the processes that are not “useful processes”, especially the processes without upstream connections or no energy/transportation input should not be included in the matrix. The processes without upstream connections do not contribute to the indirect environmental effects when used in the matrix-based model framework, and the lack of interconnections may mislead users to assume that there are no upstream effects.

Similarly, a process without energy inputs is problematic. In the production of a process, it is unlikely that no energy is used, thus, missing energy inputs in the inventory ignores the upstream effects from energy consumption. In addition, transportation can be defined to be inside or outside of the system boundary of a process. In a database, the system boundaries for all processes should be consistent to avoid ignoring neglects of effects from transportation. However, in the US LCI database, some processes have transportation as inputs while others do not; the exclusion of transportation inputs results in missing upstream effects. The missing of energy inputs and inconsistency in transportation inputs are problematic when the processes are incorporated into a matrix-based framework. It is difficult (sometimes impossible) for users to realize when upstream effects are missing.

On the other hand, when updating the database, priority should be given to the processes that have downstream connections without upstream connections, such as some cut-off processes. For these processes, if the inventories are updated, more upstream effects can be included when modeling processes that connect to them. To maximize the connections, processes with no energy inputs should be prioritized for updates. I suggest that to gather the most indirect environmental effects, the processes in the US LCI database should be updated and maintained with a matrix-based LCA framework in mind. Identifying potential missing inventories can be helpful to the inventory updates. I use an input-output table as a reference to spot locations of the potential missing inventories and identify neglected connections in the US LCI database. In the next section, I introduce methods and results for the comparison between the IO model and the US LCI database.

3.5 Comparisons of the interconnections between the US LCI database and the EIO-LCA model

The technology matrix (**A**) in the current US LCI database is structured by mapping the physical inventory data from all processes; the processes are comprised of a wide range of industries in the US. It is ordered alphabetically. However, the analyses above show that there are processes without upstream or downstream connections, which suggests a lack of interconnections in the technosphere. To better understand the interconnections in the database, the 2002 US input-output table (IO table) is used as a reference to identify potentially missed connections in the US LCI database.

The interconnections in the (**A**) matrix from the US LCI database were compared with the interconnections in the IO table; both represent exchanges in the technosphere. The interconnections in the US LCI database were then referenced with the hotspots of exchanges between industries identified in the IO table. In the IO table, the exchanges between sectors are based on direct requirements in dollar values. In this way, all purchases between industries can be translated into product exchanges. These exchanges can be good references for interconnections. In the US LCI database, the exchanges in the technosphere are based on individual products or processes in physical unit operations. In the IO table, the exchanges are based on industry sectors with purchase values in dollars. Because the industrial categories classified by the ISIC are more comparable with the industrial sectors in the IO table, categorized the processes in the US LCI database were categorized into industrial divisions via the ISIC code. The categorization was based on the descriptions of industries provided by the ISIC code documentation and the industrial categories of the processes in the US LCI database. The industry-classified US LCI processes were aggregated and fitted into a new technology matrix that have the same format with the IO table to make a more feasibly comparison.

3.5.2 Classification based on ISIC code

The International Standard Industrial Classification of All Economic Activities (ISIC) is a classification structure based on industrial economic activities (UN 2008). The industries are categorized in broad structures called divisions; the broad structures are further separated into detailed structures called classes.

I categorized the processes in the US LCI database into different categories that are comparable with IO sectors. Then, the inventories of the processes were mapped to a smaller matrix that was comparable with the IO table by aggregation. The inventories for processes were aggregated to inventories for industries using the following two steps. First, for a process, the inputs from the same categorized ISIC industrial class were summed to represent the input from the industrial class. For example, the inputs of all types of electricity, such as coal and natural gas electricity, were summed to a total electricity consumption (one single number of the electricity input). Second, within each industrial class, a process was chosen to represent the industry. For instance, the “Iron, sand cast” process was chosen to represent the Iron and steel manufacturing industry. As the choice of a representative process can be arbitrary, this section uses the maximum input values across all processes as the values in the new inventory. The aggregated upstream inputs were mapped into a new matrix with equal rows and columns corresponding to the number of industrial classes. The industry on each row represented an industry that provided input; each column had the chosen process’ inventory and represented the inventory for that industry.

The 1471 processes in the US LCI database fell into 83 categories, including 76 ISIC classes and 7 fuel combustion categories. The 7 fuel combustion categories were separately listed as they represent different stages of the energy inputs. One fuel combustion category is "Natural gas, combusted in industrial boiler". The corresponding upstream fuel input in this case was "Natural gas, at extraction site". The process names and ISIC categories are listed in Table S3.

When categorized by the ISIC code, the IO table has 136 equivalent industries, including 54 service and government sectors. Again, the service and government sectors were not included in the analysis because they were not present in the US LCI database. From the remaining 82 industries, 6 did not have equivalent correspondences in the US LCI database. Thus, only 76 industries from the IO table were compared with their corresponding aggregated US LCI industrial categories.

3.5.1 Number of interconnections in the IO table

Let us first consider the number of connections from the detailed level industries in the IO table; this should provide a general idea of how different the connections are at this detailed level.

I used the same method provided in section 3.4 Connections in the US LCI databaseto evaluate the number of upstream and downstream connections of the sectors in the IO table. In the detailed level IO table, there are 428 industrial sectors; 97 of these are service and government sectors that are not part of the US LCI database. I focus on the remaining 331 agricultural, industrial, and transportation sectors, because these categories are also present in the US LCI database, and thus their connections can be compared.

Results show that the average number of connections in the IO table is 277 for both upstream and downstream connections. I note that connection values less than $50,000 were not provided in the table (rounded down to $0), thus the actual number of the connections could be larger. Figure 3-5 shows the histograms of downstream and upstream connections for the 331 sectors. Most of the sectors had more than 250 upstream connections, no sector had less than 150 upstream connections in the IO table. On the other hand, 57 (5+15+18+6+13) sectors had less than 200 downstream connections, among which 5 had zero downstream connections (hunting, and construction sectors).

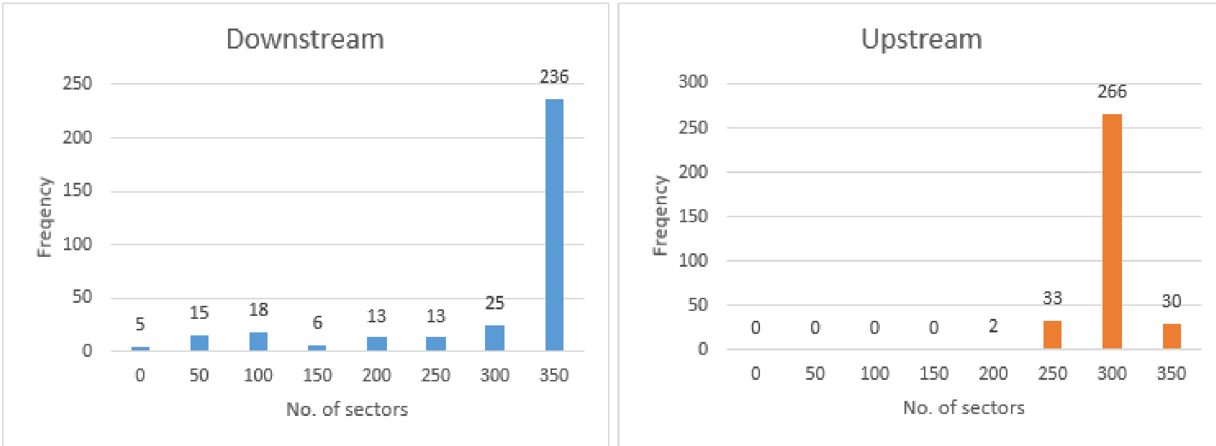

Figure 3-5: Numbers of connections for agriculture, industrial and transportation sectors (331 in total) in the IO table (service sectors not considered). The left histogram shows the numbers of downstream connections; the right histogram shows the numbers of upstream connections.

While the IO table benefits from aggregation of sectors, the results indicate that the IO table differs from the US LCI database in number and pattern of connections. The number of connections in the IO table are significantly larger (277 on average) than the connections in the US LCI database (4 on average). The average number of connections in the US LCI database is significantly smaller despite its larger total number of processes. The IO table also differs on the pattern of connections. For instance, the majority of the sectors had upstream inputs, and only a few sectors were not used as inputs to other sectors. The number of processes with downstream connections in the IO table was higher than the number of processes with upstream connections in the US LCI database. This indicates that unlike the processes in the US LCI database, the IO table includes mostly foreground sectors (products but not contributors).

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3.5.3 Hotspots in the EIO-LCA and comparison results

In this section, the connections in the US LCI database and the IO table are compared on the aggregated level of the matrices.

Figure 3-6 provides an overall comparison, using connection hotspots, between the IO table (left) and the technology matrix in the US LCI database (right). Both tables represent the **A** matrix in the matrix-based LCA method. The IO sectors were bridged to 76 ISIC classes from the previously categorized US LCI processes. The grey areas in the figure were US LCI categories that did not have equivalent sectors in the IO table, such as “natural gas, combusted in industrial boiler”. The cells in each table represent the total contributions directed from rows to columns. The relative percentages from the entries in each row (contributing sectors) are indicated with a color map, in this scale white is 0%, yellow is 0.01%, and red is 100%.

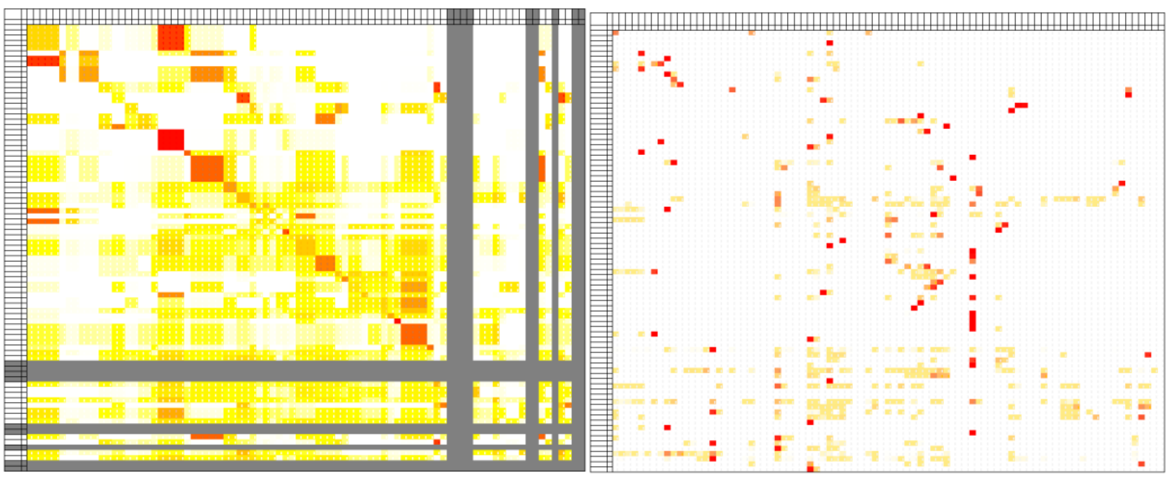


Figure 3-6: highlights of connections in IO table (left) and US LCI database (right). Values between the lowest and highest were highlighted in 3 color scales: white (lowest), yellow (0.01% of the highest), and red (highest). Grey area were processes in the US LCI database that have no accurate matches in the IO table, such as “coal, combusted in industrial boiler” process.

The US LCI database has less interconnections than the IO table, this result was also observed in the previous sections. However, the comparisons between industries and products could be arbitrary for two reasons. First, the sectors in the IO table count both the material flows and the other economic activities. The purchase of goods are not necessarily the material inputs for producing the products. For example, a steel company may purchase fruit from a farm for company events; this may result in a connection between the steel manufacturing sector and the fruit farming sector. However, fruit for company events is not a physical input used to produce steel, and given the scope of typical process-based inventories, as such will not be listed in the inventory of steel production process in the US LCI database. Second, the IO table and the US LCI database have different system boundaries. In the US LCI database, the connections between processes are limited to only products and materials. The scope of the processes generally excluded other activities in the inputs, such as the use of tools and machineries. Therefore, when comparing to equivalent industries in the IO table, it is more appropriate to use specific products that can represent whole industries from US LCI.

3.5.4 Comparison with the IO table based on individual processes

To better understand the differences between the connections in the IO table and the US LCI database, several specific processes were chosen to be compared with equivalent industrial sectors in the IO table.

Table 3-7 shows the top 5 inputs regarding economic purchase value for cement manufacturing sectors in the IO table; for contrast, I also list the top 5 inputs sorted by their mass values from the US LCI database. The results showed that the energy and the transportation were important attributes for cement manufacturing. However, transportation of any type was not included in the equivalent processes in the US LCI database ('Portland cement, at plant').

Table 3-8 compares the total fossil CO_2 emissions, for producing one metric ton of cement, calculated from the EIO-LCA model and the US LCI database. The CO_2 emissions from the EIO-LCA model were calculated assuming the price for US cement was $77.5/ton in 2002 (USGS 2002). The total CO_2 emissions include both direct and indirect emissions; they are the sum of the emissions of the sectors or processes listed in the tables. The results show that the emissions from each US LCI process are generally higher, with a few exceptions, such as truck and pipeline transportation. These higher values are possibly caused by the parameter uncertainties in the US inventories. For example, the direct emissions from the US cement process are 70% higher compared to those from the EIO-LCA model, possibly due to parameter uncertainty. On the other hand, the US LCI truck transportation process has smaller emissions, because it is outside the system boundary of the cement process. The emissions from the truck process are only composed from upstream productions. The US LCI database includes more than 100 truck transportation processes, these transportation processes are inputs of some processes in the database. As discussed previously, whether or not to include transportation inputs in the inventories should be consistent across all the processes. Therefore, the cement manufacturing industry should consider including truck transportation in its inventory. The exclusion of transportation from cement manufacturing processes in the US LCI database might be an issue of using inconsistent system boundaries across processes in the database, as discussed in section 3.4. Because IO-LCA has a clear system boundary for all the sectors in the system, it can be used as a reference to reinforce the inclusions or exclusions of certain processes in the inventories.

Table 3-7: top 5 inputs for Cement manufacturing, sorted by direct economic values in the IO table, and mass values in the US LCI database, respectively.

IO table	**US LCI**
Top 5 inputs for Cement manufacturing sector	
Power generation and supply	Limestone
Natural gas distribution	Water
Ground or treated minerals and earths manufacturing	Gypsum
Lime and gypsum product manufacturing	Clay, unspecified

Truck transportation	Shale

Table 3-8: Fossil CO_2 emissions to produce 1 metric ton of Portland cement, calculated from EIO-LCA model (left) and the US LCI database (right). The shaded rows show the total CO_2 emissions, including both direct and indirect emissions. The remaining rows show the top 10 emissions from different sectors or processes.

IO sectors	Fossil CO_2 emissions (kg)
Total	413.9
Cement manufacturing	334.0
Power generation and supply	62.5
Lime and gypsum product manufacturing	1.9
Truck transportation	1.7
Oil and gas extraction	1.4
Ground or treated minerals and earths manufacturing	1.4

US LCI processes	Fossil CO_2 emissions (kg)
Total	963.5
Portland cement	553.0
Coal	282.0
Electricity	105.7
Natural gas	13.5
Fossil fuel	5.2
Transport, train	2.8

Petroleum refineries	1.3
Rail transportation	1.2
Pipeline transportation	1.0
Clay and non-clay refractory manufacturing	0.5
Remaining sectors	6.8

Transport, barge	0.5
Transport, ocean freighter	0.33
Transport, truck	0.32
Transport, pipeline	0.002
Remaining processes	0.003

3.6 Scenario uncertainty estimation in the US LCI database

In the previous chapter, a range method was used to analyze the parameter uncertainty in IO matrix-based LCA models. This chapter introduces a method to estimate the scenario uncertainty in the models. Scenario uncertainty reflects the uncertainty in the results caused by different choices in the LCA studies, such as allocation methods selections and system boundary drawings (Huijbregts et al. 2003). In this study, simultaneously choosing different inventories is considered as one type of choice in LCA studies; the uncertainty caused by such different choices is evaluated to represent on type of scenario uncertainty in the matrix-based LCA models.

In the current US LCI database, various processes have overly specific inputs. For example, "Transport, combination truck, diesel powered", is the only truck transportation input for the "Lime, agricultural, corn production" process. This suggests that only diesel powered combination trucks are used in the production of lime, excluding the possibility of using gasoline or other powered trucks. These overly specific processes can cause scenario uncertainty in traditional LCA studies, because the processes fail to provide other possible choices as inputs. Typically, this is also a problem in the matrix-based LCA models where the processes are connected, and potentially contribute to each other's environmental effects. Moreover, in matrix-based LCA models, the results only show the aggregated effects from each process. Without a profound knowledge of all inventories in the database, the users are unable to realize about the existence of overly specific processes. Thus, the scenario uncertainties caused by these processes are likely to be ignored. This introduces methods to consider scenario uncertainties in the matrix-based LCA model, using the US LCI database as a case study. Because the results calculated from a matrix-based LCA model are based on the connections between processes within the boundary of the model, the scenario uncertainty caused by different choices of inputs should be within the same boundary. Before new processes are introduced, the scenario uncertainties can be estimated using existing information in the model. As such, in this study, the scenarios are based on processes that are already part of the US LCI database, no new inventories are constructed. The scenario uncertainties are separately evaluated for US LCI processes and industrial categories.

3.6.1 Scenario uncertainty in US LCI processes

The scenario uncertainties for US LCI processes were evaluated by creating a range of alternative scenarios while treating each environmental effect separately. Each possible scenario is built by replacing alternative inputs to a process. The alternative inputs are similar US LCI processes that serve the same function. As an example, all 99 electricity processes (including 78 grid electricity processes and 21 fuel electricity processes) in the database are considered as similar processes and used as alternatives. All the alternatives were used to create different scenarios, the range of alternative scenarios represents the scenario uncertainty. The scenario uncertainty caused by using direct and indirect alternative inputs are estimated separately. Fossil $\mathrm{CO_2}$ emissions are used as an example to demonstrate the results.

First, I estimated scenario uncertainties caused by using different direct electricity inputs as alternatives. For a process, its specified inputs from electricity were replaced by all alternative electricity processes in the database; new results were calculated based on these alternatives and used to form a range. When there were multiple electricity inputs for a process in the original inventory, the values of the common category inputs were summed for a single input value. For example, the "Polyethylene terephthalate, resin, at plant" (PET) process mentioned above has two upstream electricity inputs (0.051 kWh "Electricity, at cogen, for natural gas turbine", and .0.056 kWh "Electricity, at grid, US, 2008") for each kg production in the original inventory. Thus, the total electricity input value was the sum (0.107 kWh). Then, I fit the new inventory into a new $\boldsymbol{A}$ matrix ($\boldsymbol{A}^{\boldsymbol{new}}$). In $\boldsymbol{A}^{\boldsymbol{new}}$, the 0.107 kWh electricity input for the PET resin process was iteratively replaced as a scenario by each of the 99 electricity processes in the database. Replacing the electricity input by all available alternatives resulted in 99 different technology matrices ($\boldsymbol{A_i}^{\boldsymbol{new}}, i = 1,2, \dots ,99$). While all other values in the inventory remain unchanged, the difference between these 99 $\boldsymbol{A_i}^{\boldsymbol{new}}$ matrices was only due to the different electricity processes used for the

PET process. Throughout this analysis, the $\boldsymbol{B}$ matrix and $\boldsymbol{f}$ vector in Equation 3 remained unchanged. I calculated 99 different g vectors (g vector has one value, fossil CO_2, in this study) from the 99 different $\boldsymbol{A_i}^{\boldsymbol{new}}$ matrices; the range of fossil CO_2 generated was the final result for producing 1 kg of PET resin in the US LCI database.

Next, the electricity inputs for all processes were replaced by alternatives to represent the scenario uncertainties caused by indirect electricity consumption. The method is similar to the one mentioned above, with a slight difference in building the new alternative matrices. Instead of replacing the electricity input for only one process, one of the 99 electricity processes was used as an alternative for all of the processes in the database. Thus, in the $\boldsymbol{A_i}^{\boldsymbol{new}}$, the electricity input for all the processes changed from the default to alternative i. For example, when "Electricity, at grid, US, 2008" is chosen as the scenario, all processes use this process as their only electricity inputs. The results calculated from this method represent the scenario uncertainties caused by using both direct and indirect electricity alternative inputs, and are compared with the scenario uncertainties caused by using only direct electricity alternative inputs.

The overall uncertainties across all US LCI processes caused by choosing different direct electricity inputs are shown in Figure 3-7. For each process, I calculated the fossil CO_2 emissions based on different scenarios. Grid electricity processes (78) and fuel electricity processes (21) are separately listed, because the fuel electricity alternatives represent the most extreme cases. It is unlikely for a process to use only one type of fuel electricity as input; most of the electricity used is from one region's grid electricity mix. The percentage values in Figure 3-7 were calculated based on the differences between each alternative and the default scenarios, which was assumed as the emission calculated from using the default electricity (the electricity input in the original inventory) as input. Thus, each row in the figure has 99 results, representing the differences between 99 alternatives and the default scenario. Note that processes 148 to 246 on the y-axis have no results, because they are the electricity processes, using alternative electricity inputs as different scenarios do not affect the results of these processes.

Figure 3-7 shows two important results. First, there is one outlier for each process. In all cases, the outliers can be traced to using a specific electricity process, namely "Electricity, onsite boiler, hardwood mill, average, NE-NC" as the electricity input. This electricity process is a byproduct of producing hardwood in a hardwood mill; the large environmental effect values are possibly due to the allocation of the effects from the production. For better visualization, values calculated from using "Electricity, onsite boiler, hardwood mill, average, NE-NC" as the electricity inputs are excluded from the results.

Second, not surprisingly, the fuel electricity scenarios have larger ranges compared with grid electricity scenarios. The grid electricity processes are different mixes of the fuel electricity processes in the database; the most fossil CO_2 intense electricity generation methods are mixed with the least intense methods, thus resulting in moderated CO_2 emissions.

The results from scenario uncertainty caused by using both direct and indirect (total) alternatives show similar results (Figure 3-8): the outliers are caused by "Electricity, onsite boiler, hardwood mill, average, NE-NC" process; fuel electricity scenarios result in larger ranges. To compare the differences between the cases of using only direct alternatives and using both direct and indirect alternatives, I compared the maximum CO_2 emissions values calculated from these two cases for a process. For each process, I used the ratio of the two maximum values to represent the difference; the results are shown in Figure 3-9. Using both direct and indirect scenario alternatives can result in as large as 33 times more CO_2 emissions for some processes; in general, the differences are around 5 times. The results indicate the importance of the indirect emissions, certain electricity processes can cause large scenario uncertainty in the model. In addition, the results show the importance of including more similar processes for the users to choose in the database. If only one electricity process is available to choose, any process that uses electricity would inevitably use the single electricity as input, ignoring both the direct and indirect scenario uncertainty.

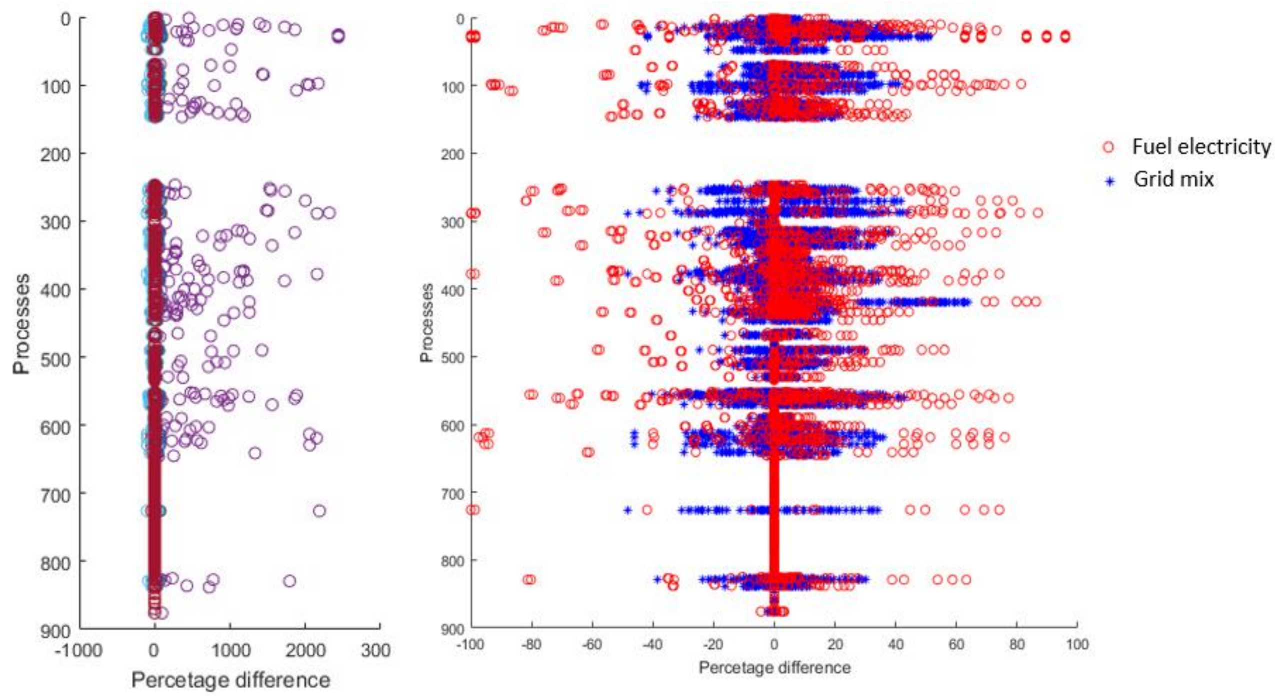


Figure 3-7: Overall scenario uncertainty caused by using direct alternative electricity inputs. The default electricity input for each process was the electricity input from the original inventory. Left: fossil CO_2 emissions, as percentage difference from the default, for 876 gate-to-gate processes (without cutoff processes). Right: the emissions for each process were calculated by using 78 grid electricity and 21 fuel electricity scenarios, without the outliers caused by using "Electricity, onsite boiler, hardwood mill, average, NE-NC". Each scenario used one of the 99 electricity generation processes as electricity input.

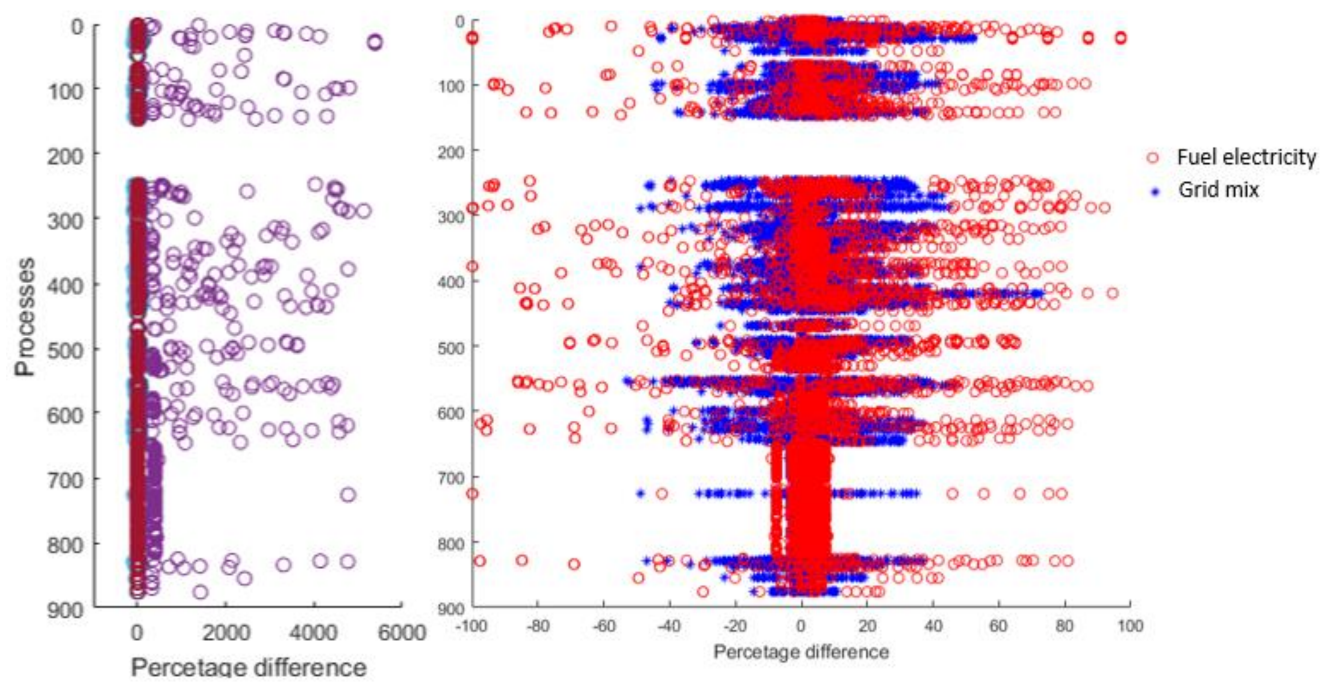


Figure 3-8: Overall scenario uncertainty caused by using both direct and indirect alternative electricity inputs. The default electricity input for each process was the electricity input from the original inventory. Left: fossil CO2 emissions, as percentage difference from the default, for 876 gate-to-gate processes (without cutoff processes). Right: the emissions for each process were calculated by using 78 grid electricity and 21 fuel electricity scenarios, without the outliers caused by using "Electricity, onsite boiler, hardwood mill, average, NE-NC". Each scenario used one of the 99 electricity generation processes as electricity input.

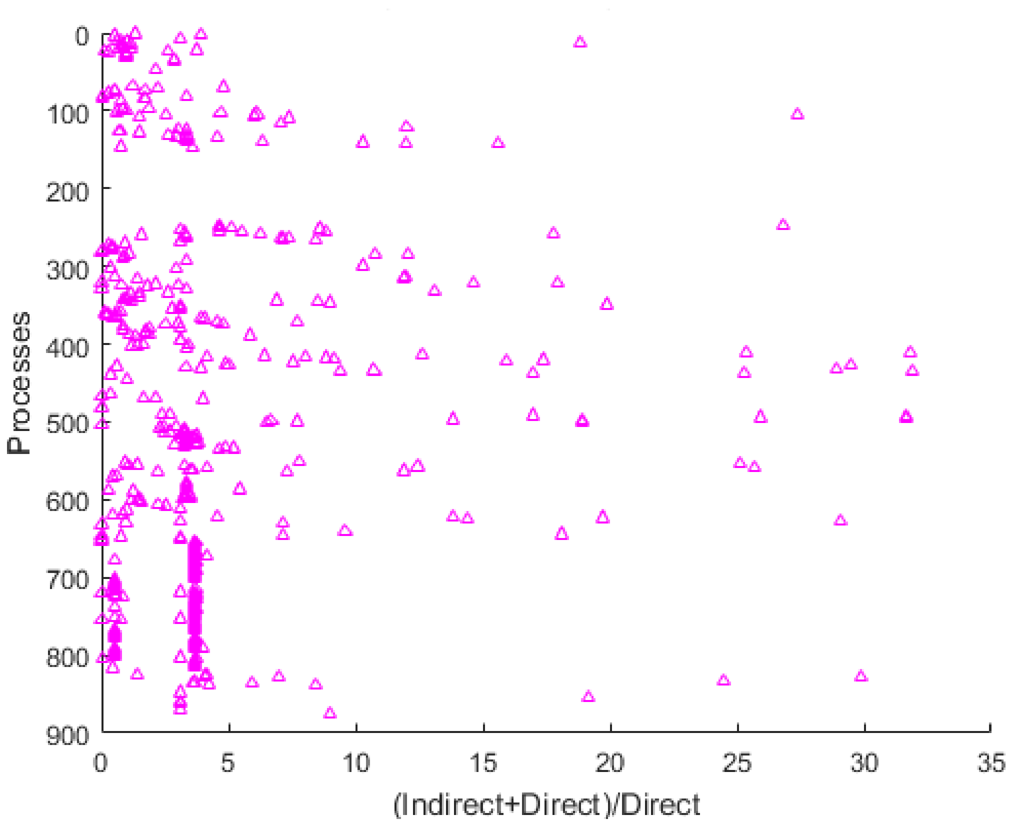


Figure 3-9: Overall scenario uncertainty caused by using alternative electricity inputs. Y-axis represents 876 gate-to-gate processes (without cutoff processes) in the US LCI database. Values on the x-axis are the ratios of total to direct fossil CO_2 emissions.

The minimum and maximum values from these scenarios were used to calculate the range uncertainty for each process. Excluding outliers and processes without electricity inputs, the results show that for grid electricity alternatives, the average (across all US LCI processes) of the minimum and maximum scenario uncertainties is within -10% and 10%, respectively (Table 3-9). The corresponding standard deviation are 13% and 12%, respectively, indicating similar variabilities from the negative and positive sides. The results from fuel electricity are larger than the grid electricity; however, the general scenario uncertainty for all the processes is within 20%.

Table 3-9: Mean and standard deviation of the minimum or maximum values for all 876 processes, based on four different cases

	Mean (%)		Standard deviation (%)	
	Minimum	Maximum	Minimum	Maximum
Fuel electricity, direct	-12.6	10.9	23.9	20.6
Fuel electricity, total	-22.2	20.3	27.0	24.2
Grid electricity, direct	-5.6	5.5	11.0	10.6
Grid electricity, total	-10.1	9.8	12.8	12.0

An example process is used to demonstrate how upstream inputs contribute to the scenario uncertainty. "Iron, sand casted" process is chosen as the example because 1) it has various products as inputs, including electricity; and 2) it is potential input for many other products, such as machinery. For the process, the default scenario provided in the original US LCI inventory resulted in 1120 kg of total fossil CO_2 emissions, using "Electricity, grid US, 2000" as the electricity input. Figure 3-10 shows the fossil CO_2 emissions for 1 metric ton of "Iron, sand casted" process, which resulted from all 99 electricity scenarios, and distinguishes results from grid and fuel electricity scenarios. Each distinct marker represents the result calculated from one scenario used. The top sections of the figure show that the total CO_2 emissions vary between 240 and 1770 kg; the ranges formed by using grid electricity alternatives are smaller than the ranges from the fuel electricity alternatives. There is an outlier again at 19MT (not shown) which was caused by using "Electricity, onsite boiler, hardwood mill, average, NE-NC".

Similar to the results in chapter 2, the figure lists the top ten processes by the maximum values that contribute to the total emission of "Iron, sand casted" process. In the bottom graphs, the rows show the CO_2 emissions results from different product contributors sorted by their maximum value in descending order. Similar to the top graph, each of the ten product contributor has 78 distinct markers from the grid electricity and 21 from the fuel electricity. It can be seen that Bituminous coal electricity process is the most important contributor to the uncertainty in producing sand casted iron. On the other hand, some processes only contribute to the total emission, not the uncertainty. For example, “Bituminous coal, combusted in industrial boiler” process has a consistent emission value. The process contributes the same amount of emission regardless of the scenario chosen is because that it is only an input to sand casted iron process, not an input to any electricity process.Figure 3-11 includes four different cases to compare the differences between using direct alternatives and total alternatives as well as using fuel electricity and grid electricity alternatives. . Similar to the results for all processes, fuel electricity has larger ranges compared with grid electricity; the emissions are larger considering both direct and indirect alternatives than using only direct alternatives. The differences between using total alternatives and direct alternatives are small (less than 100 kg), indicating small indirect electricity use in the supply chain for the process.

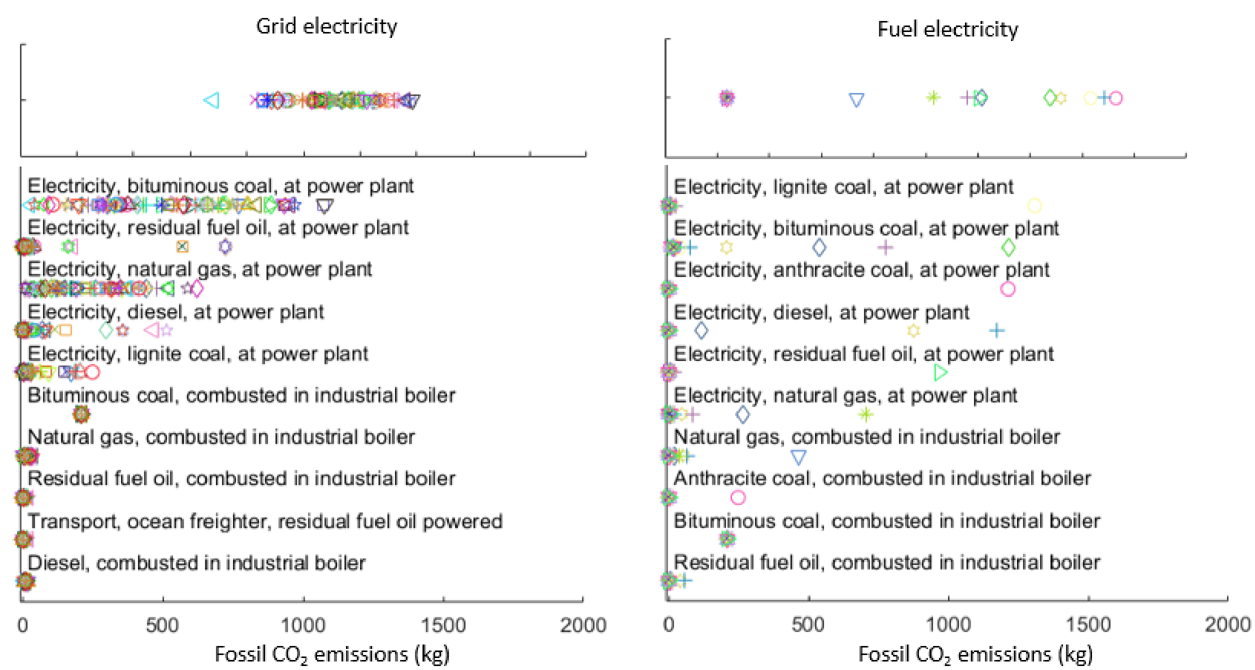


Figure 3-10: Fossil CO_2 emissions for one metric ton of “Iron, sand casted”. Left: scenario uncertainty caused by using grid electricity. Right: scenario uncertainty caused by using fuel electricity. The top

graphs show the total emissions. The bottom graph shows the results from the top ten product contributors under alternative scenarios (markers).

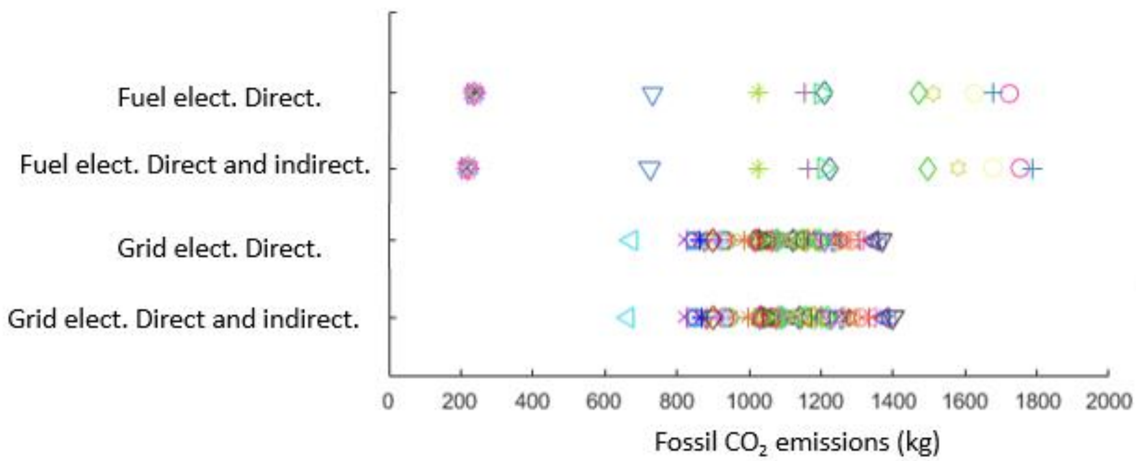


Figure 3-11: Total fossil CO_2 emissions for one metric ton of "Iron, sand casted", considering four different cases.

Apart from electricity, in the US LCI database, other similar processes can also be used as alternatives. As discussed earlier in the chapter, there are several categories of the database where there are data for many similar processes; here, these categories are chosen to demonstrate further scenario uncertainty case studies. The same method used for electricity scenarios was used for transportation and fossil fuel alternatives. Because the "Iron, sand casted" process excluded transportation as input, I choose another example to show the uncertainty due to using alternative transportation inputs; only direct alternatives are considered.

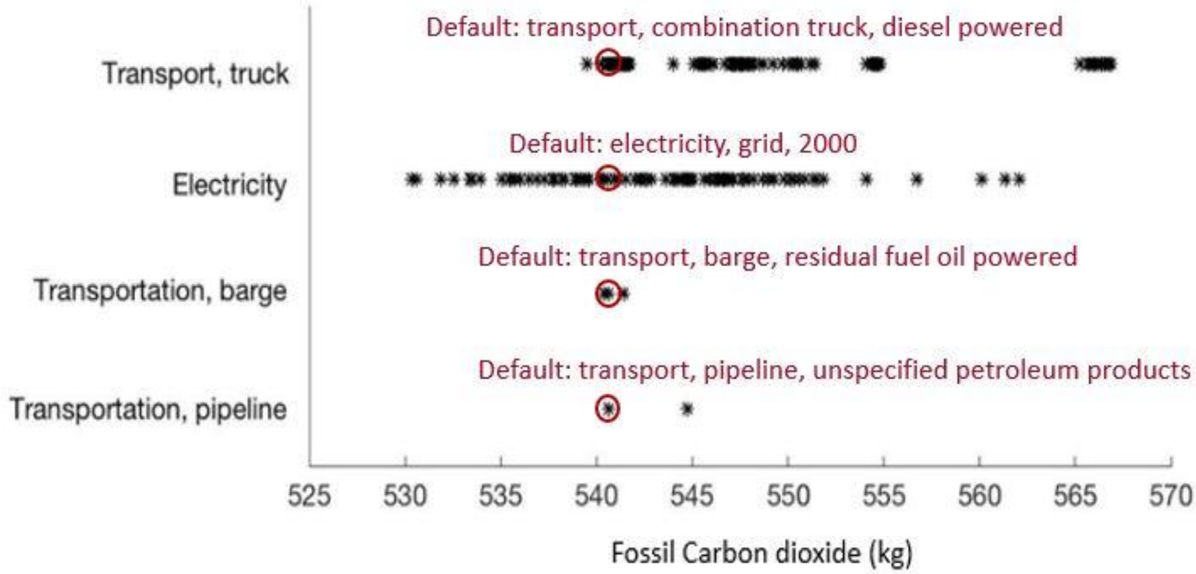


Figure 3-12 shows the total fossil CO_2 emissions for producing one metric ton of “Benzene, at plant”. The default scenario used the processes specified in the current US LCI database as inputs. The markers indicate the results from alternative scenarios in four electricity (99) and transportation (151) industries. The number of scenarios is different in each industry. As in Figure 3-10, I excluded the outlier results from “Electricity, onsite boiler, hardwood mill, average, NE-NC”. The results from different scenarios ranged from 540 to 567 kg in truck transportation, and from 530 to 563 kg in electricity; in both industries, the scenario uncertainties are similar. Jointly, truck transportation and electricity form a range (530 to 567 kg) that is only -2 to 5% different from the results in the default scenario (540.6 kg). The range of results from alternative scenarios in transportation barge and pipeline was much narrower; however, these industries only had a few alternative scenarios (less than three each). If the database provide more processes in the same category, the variability can become more precise.

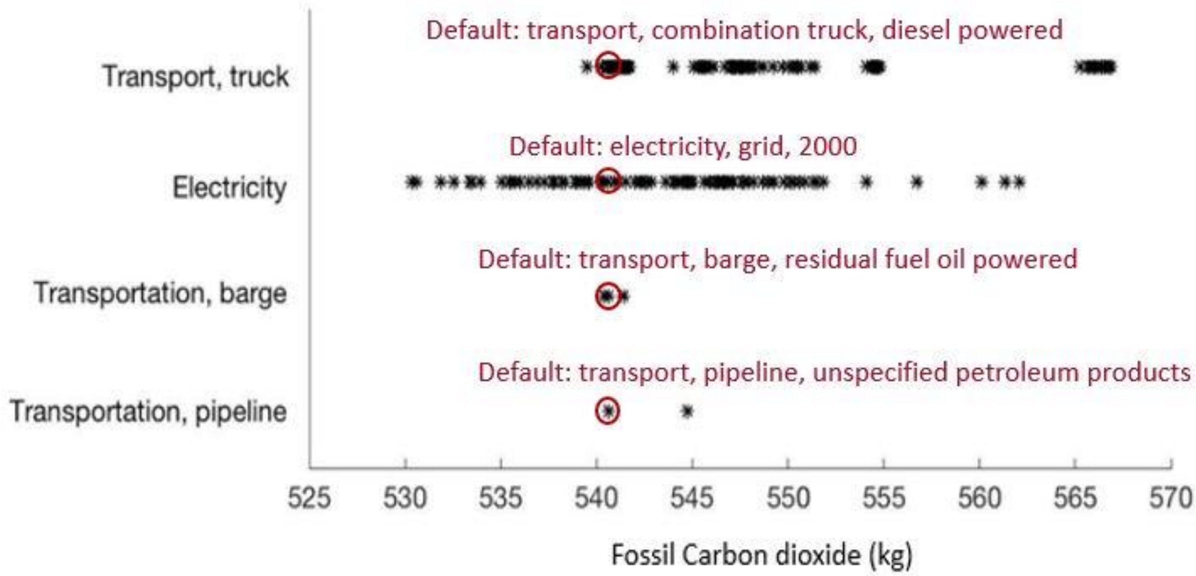


Figure 3-12: total fossil CO_2 emissions, in kg, for 1 ton of "Benzene, at plant" by using alternative scenarios in electricity and transportation industries. The default values are circled and the default inputs are listed.

3.6.2 Scenario uncertainties in US LCI industries

The method and the results shown in the previous section provide the scenario uncertainties for individual processes. To estimate the uncertainties on the industrial level, I needed to develop a second method, because the first method cannot be applied to all alternative inputs. When multiple similar inputs are available, the alternatives are easy to find, thus the scenario uncertainty can be estimated. However, as discussed previously, the processes in the US LCI are not well-connected, the numbers of inputs/outputs in most processes are not large enough for analysis using the first method. Therefore, I developed the second method to analyze uncertainties at industrial levels.

The second method involved a few more steps. First, to classify similar processes, the processes in the US LCI database were categorized according to the ISIC classes explained in section 3.5.2 Classification based on ISIC code. The 1471 processes were categorized into 83 industrial categories, detailed results are shown in Table S3 and S4. Second, new alternative matrices $\boldsymbol{A_i}^{newII}$ were found based on industries rather than processes. Third, total fossil CO_2 results were calculated from the alternative $\boldsymbol{A_i}^{\boldsymbol{newII}}$ matrices via Equation 3; the results show the total fossil CO_2 emissions to produce 1 kg of product in one selected final demand industry.

Then, I found a new $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrix with 83 columns and 83 rows based on industries, instead of the original $\boldsymbol{A}$ matrix with 1471 columns and 1471 rows based on processes. The 83 columns in the new A matrix represented 83 industries in the US LCI database; the 83 rows were the inputs to the 83 industries, same as in the original A matrix. The 83x83 $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrix differed from the 1471x1471 $\boldsymbol{A}$ matrix in that the columns and rows were industries but not product flows. In this way, each industry (column) had 83 inputs from 83 input industries (rows). The industries in the 83 columns were estimated first, then the values for the 83 input industries were calculated.

I took the average input values across all processes in each product industry as the new input value in each column of the new matrix, thus the inputs to each of the 83 product industries were the averages of the inputs from each product industry, resulting in a default matrix with average input values for all 83 product industries. This step resulted in a 1471 x 83 matrix; the 1471 rows were the input processes from the original $\boldsymbol{A}$ matrix, while the 83 columns represented the 83 product industries. Then, each product industry's input from each input industry was calculated by adding all inputs within the input industry, resulting in a single input value. For example, the input from the manufacturing of plastic products industry to the manufacture of engines and turbines industry was the sum of inputs values of all processes in the manufacturing of plastic products industry.

Third, each product industry (column) in the 83 x 83 $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrix was replaced by a representative process in the industry, thus in the new 83 x 83 $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrix, one product industry had inputs from a representative process while the rest 82 product industries had the mean input values as mentioned previously. This new $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrix represents one scenario. Thus, all processes in the same industry provide the same number of scenarios. This set of scenarios together with the other 82 sets are used to estimate the range of emissions in Equation 3. For example, there were 25 processes in the plastic products manufacturing industry, the representative processes resulted in 25 83x83 alternative technology matrices. In each of the 25 alternative matrices, the plastic product manufacturing industry (column 42) had inventory of one selected process in the category (for example, ‘Composite scrap, from composites compression molding, at plant’); the remaining 82 columns had mean values as default. As there were 1471 processes in the 83 industries, I had 1471 83x83 alternative $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrices in total, all these $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrices were used for estimating the range result for total fossil CO_2 emissions.

For each alternative $\boldsymbol{A_i}^{\boldsymbol{n83}}$, there was a corresponding environment vector ($\boldsymbol{B}$ matrix in Equation 3). Each alternative environmental matrix was generated with the same method: the mean emission values were taken as the default 83x1 vector, and each emission value for one industry was replaced by a representative value from the emission values of each process.

Finally, total fossil CO_2 emissions were calculated from Equation 3, with a defined final demand value from an industry. As there were 1471 alternative 83x83 $\boldsymbol{A_i}^{\boldsymbol{n83}}$ matrices and 1471 corresponding $\boldsymbol{B}$ matrices, the range of total fossil CO_2 emissions was formed by a set of 1471 values and included all possible emission values from the method.

Figure 3-13 shows the ranges of fossil CO_2 emissions calculated for one metric ton of product in: “Grow of cereals” category. The legend for the markers is shown in Figure 3-14. Each distinct marker represents an industry in which its default representative process is replaced by an alternative process. For example, the yellow cross markers represent the values resulting from using alternatives in the Road Transportation industry while keeping the others as the mean values. Alternative processes in the Road Transportation industry resulted in at least two different fossil CO_2 emissions values in the growth of cereals. Overall, the results in Figure 3-13 suggest that the majority of the discrepancies were caused by using processes in certain industries as the replacement, namely Energy, Electricity power generation, and Transportation.

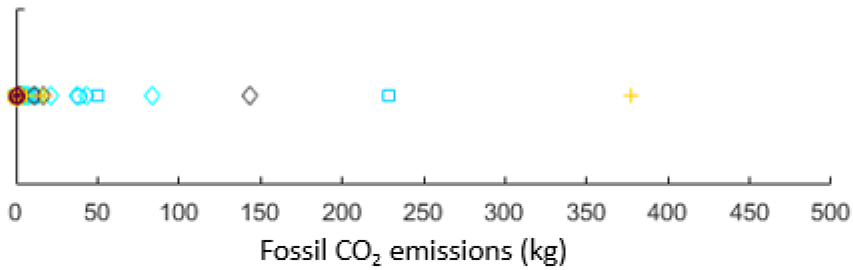


Figure 3-13: fossil CO_2 emissions, in kg, for 1 metric ton of Manufacture of basic iron and steel category (top), and Manufacture of basic chemicals (bottom)

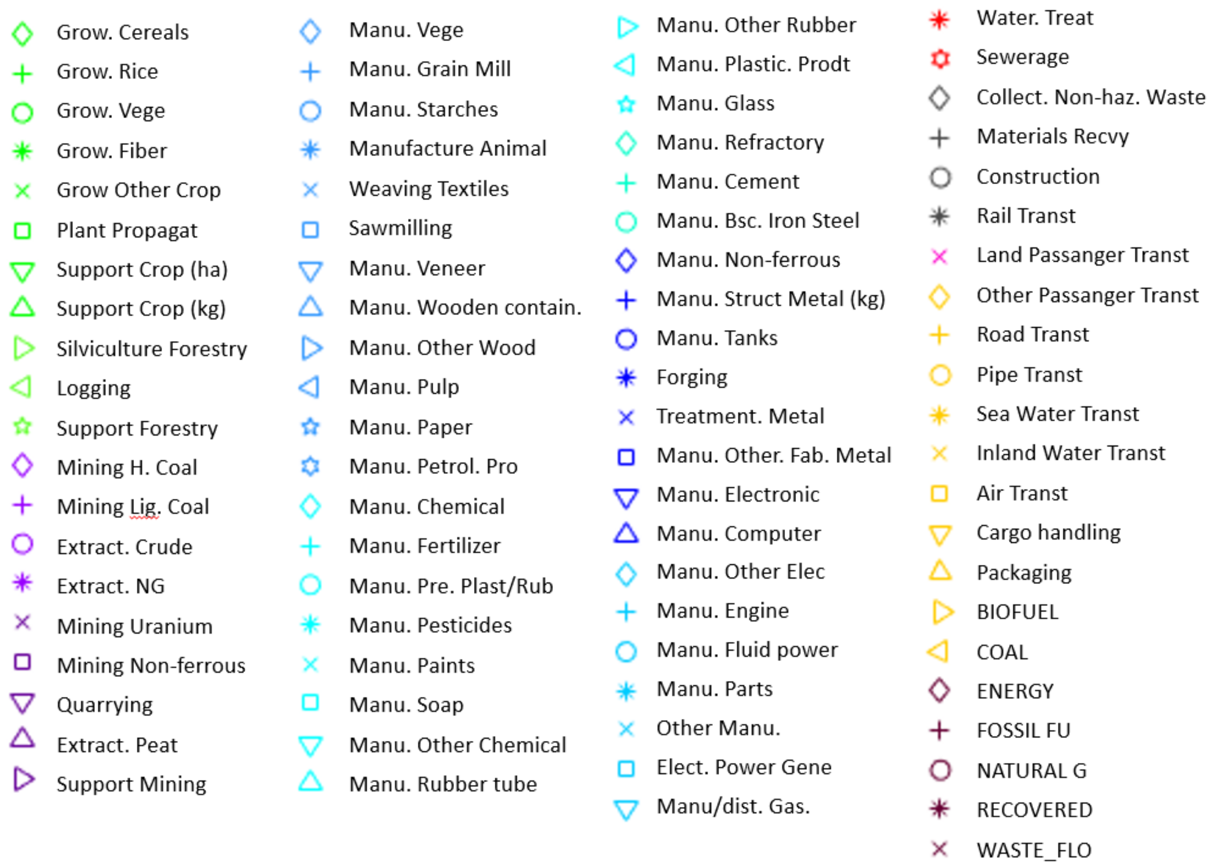


Figure 3-14: legend for Figure 3-13.

The large discrepancies observed are possibly due to differences in product industries; the inputs and outputs can vary significantly due to the use of alternative processes. Using a process in the category to represent the other processes is not reasonable in these cases. This is also confirmed by another observation from the uncertainty estimation method: using particular processes as the representatives in the technology matrix generates unreasonable results (large negative total fossil CO_2 emissions), possibly due to the double-counting of inputs, especially from fuel consumption. The results show that without altering the processes in the Road Transportation category, the differences were still large. This observation confirms the importance of providing all possible inventories to the users, as the ranges were simply caused by using different representative processes within one industrial category.

3.7 Conclusions for the chapter

This chapter provides analyses of the processes in the US LCI database and the scenario uncertainty caused by using different alternative inputs in the inventories.

The analysis of the processes in the US LCI database show that the processes have potential problems, especially when incorporated into matrix-based LCA models. First, inconsistent system boundaries and missing inputs to processes can cause neglects of environmental effects. Second, the processes in the database are not well-connected, only one fourth of the processes have at least one upstream or downstream connection, indicating that the database is not fully taking advantage of matrix-based LCA models. Therefore, to overcome these two issues, the US LCI database can focus on: 1) defining a consistent system boundary for all processes, and 2) update the inventories of some processes. To minimize the time and effort in the updates, processes without energy inputs should be updated first to avoid the neglects of environmental effects from the consumption of energy. Then the cutoff processes should be updated with full inventories. The cut-off processes that do not have any similar alternative in the database should be given priority. The cut-off inputs can be replaced by other alternatives in the database. For example, the processes that use “CUTOFF Electricity, fossil, unspecified, at power plant” as the electricity input should use another non-cutoff electricity input as replacement before the cutoff electricity process can be updated with a full inventory.

In this study, the EIO-LCA model is used to show the differences between the connections in the US LCI database and the connections in the IO table. The results showed that the US LCI database has much less connections. One advantage of IO-LCA models is that the models have a clear system boundary for all the sectors; thus, the results calculated from the models are consistent and easy to interpret. The US LCI database as well as other process based LCI databases can use

IO-LCA models as a reference to identify the potential missing inventories and reduce part of the neglects in the environmental effects.

In this chapter, I also used two methods to evaluate the scenario uncertainties in the US LCI database. The first method focused on the uncertainties due to choices of alternative electricity and transportation in the inventory. The second method evaluated the scenario uncertainties caused by choosing different processes in each industrial category. The results from the first method indicate that scenario uncertainties are generally within -20% and 20% from the default choice, and may show some outliers. The second method results in bigger scenario uncertainties: an example shows that by choosing different processes within the same industrial category, the CO_2 emissions for 1 kg of industrial product can vary between 0 and 400 kg. Both methods show that the scenario uncertainties in matrix-based LCA models can be large. The results calculated based on the current US LCI database are only preliminary as the connections between processes are rather sparse. However, this method can provide better results on future database versions, which ideally will include more well-connected inventories.

4. Chapter. LCIA uncertainty in a process-based LCI database

The previous chapter analyzed the processes in the US LCI database. By considering the contributions to the indirect effects, I analyzed different types of processes in the database and their potential impacts on the uncertainty in matrix-based LCA models. Additionally, I computed scenario uncertainties in the process-based matrix LCA model by considering the scenario uncertainty in the inventories. In this chapter, I present an analysis of the uncertainty in the environmental impacts for the processes in the US LCI database. Here, the uncertainty analysis is based on 1) the variability in the characterized environmental effects for each inventory, 2) the differences in the coverages of substances, and 3) the characterization of factor values from different impact assessment models.

4.1 Introduction to LCIA and the comparison between LCIA methods

4.1.1 Life cycle impact assessment

As regulated by ISO 14040 standard, Life Cycle Impact Assessment (LCIA) is a phase of Life Cycle Assessment (LCA) (ISO 2006b). This phase seeks to evaluate the environmental impacts from a product system (Owens 1997). To achieve this evaluation, Life cycle inventory (LCI) data are associated with environmental impact categories (ISO 2006b).

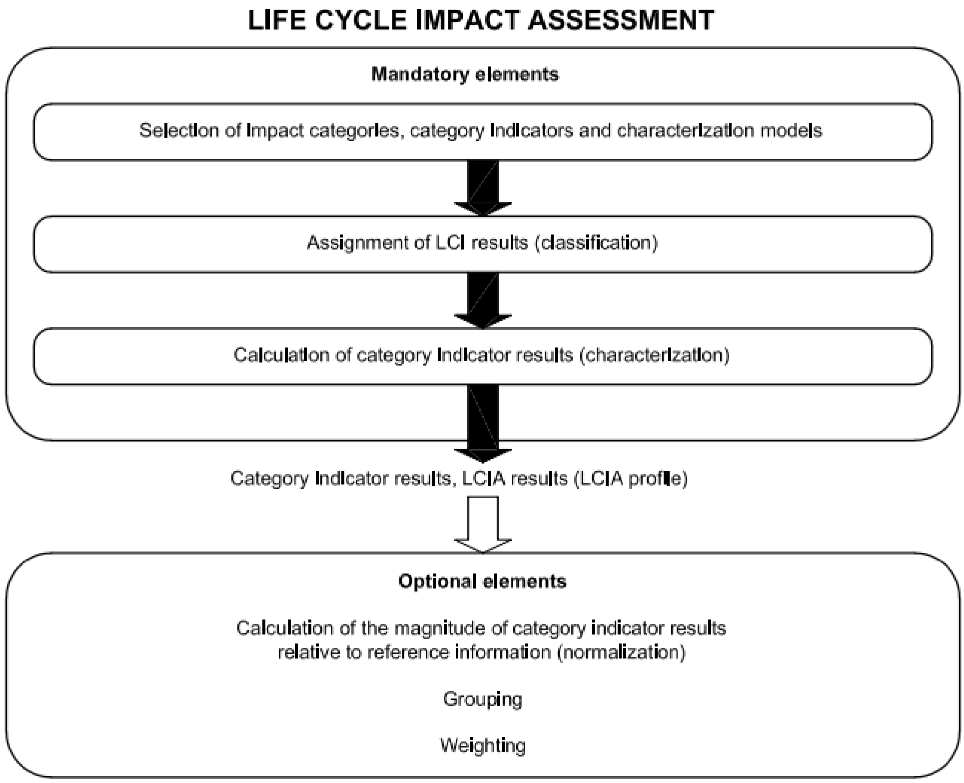


Figure 4-1: Elements of the LCIA phase provided in ISO 10040 (ISO 2006b)

According to the ISO 14040 standard, LCIA has three mandatory elements: selection, classification, and characterization (Figure 4-1) (ISO 2006b). The first element is the selection of impact categories. An impact category is a class that represents environmental issues (ISO 2006b), such as global warming or cumulative energy demand. The selection of impact categories should be related to the goal and scope of the LCA study. For example, appropriate geographic locations should be considered (Matthews et al. 2014). The second element is classification, which maps the inventory flows that are considered to contribute to an impact category. These flows are referred to as substances in previous LCIA studies. The third element provides an assessment of impacts via characterization indicators for each substance. The indicators are also referred to as "equivalency factors"; but in this study, I will consistently use the term "characterization factors". Characterization factors are used to transform environmental effects to quantified environmental impacts. There are three more elements in LCIA studies, but they are optional. In this chapter, I focus on discussing the uncertainties generated from the first three mandatory elements.

Based on the goal and scope of the study, the impact categories can be divided into two major types: midpoint and endpoint impacts. Midpoint impacts are intermediate damages that increase the impact concentration, and thus change the local environment. Examples of midpoint impacts are global warming, ozone depletion, acidification, and eutrophication (Bare et al. 2000). Endpoint impacts are final effects or damages to the ecosystem, humans, and resources (Udo de Haes et al. 1999). Examples of endpoint impacts include global atmospheric temperature rising due to greenhouse gas emissions (Lashof and Ahuja 1990), or increasing cardiovascular events due to toxic air emissions (Brook et al. 2004). Midpoint and/or endpoint impact categories are included in various methods. In some cases, a few traditional midpoint categories can be modeled as endpoint categories. For example, in the impact assessment method "ReCiPe-Endpoint", ozone depletion is modeled as an endpoint category, indicating the damage caused by thinning the stratospheric ozone layer, such as increasing occurrences of skin cancer.

Multiple impact assessment methods have been developed for different purposes in LCA studies over time. Early impact assessments were generally developed according to the only available reference - ISO standard (Baumann and Rydberg 1994). Then in 1999, the SETAC-Europe working group provided guidelines for improving impact assessment methods (Udo de Haes et al. 1999). Since then, the concepts of impact assessment framework, and principles of characterization factor modeling have become widely accepted and implemented in LCIA. Currently, many LCIA methods exist and some are regularly updated. As more choices of impact methods for the same geographical area become available, the choice of an appropriate method for a given LCIA study is an important challenge. As a result, the differences between the methods is an interesting topic in the field of LCIA research (Owsianiak et al. 2014; Dreyer et al. 2003).

4.1.2 Differences in LCIA methods

The comparison between different LCIA methods can be traced to the 1990's. Baumann and Rydberg (1994) compared three early LCIA methods: ecological scarcity (ECO), environmental theme (ET), and environmental priority strategies in product design (EPS). The main difference between ECO, ET, and EPS was in the estimation of the characterization factors with respect to different goals and scopes. For example, the ECO method assumed that the pollutants were emitted to the local area, whereas the EPS method focused on emissions to the whole atmosphere. Pennington et al. (2004) systematically reviewed 12 impact categories, examining the differences between multiple impact assessment methods in relation to their models and methodologies. The available LCIA methods for each category were listed and the spatial and temporal differences between methods were summarized. Both Baumann and Rydberg, and Pennington emphasized the importance of choosing the appropriate impact assessment method according to the goal and scope of each individual study, such as the impact area. However, these pioneering studies focused mostly on qualitative differences, and did not elaborate a quantitative comparison between LCIA methods.

More recently, some LCA studies have considered the variability of results caused by choosing different impact methods. Both Bovea and Gallardo (2006) and Dreyer et al. (2003) compared the LCIA results for particular materials using three methods: CML, Ecoinciator95, and EDIP. Bovea and Gallardo (2006) compared the impact results of three different plastic materials (PVC, PP and PE). Their study showed that for the same plastic product, the differences between the minimum and maximum values in the impact results varied between 0 to more than 800 times; the higher values occurred in the photochemical oxidation category. Dreyer et al. (2003) examined the differences in impact results for the lacquer product system due to characterization factor values by calculating the contribution of impacts from each substance. In the Dreyer and colleauges' study, the results were between 0 to 8200 times; aquatic ecotoxicity category had the largest range. Additionally, Owsianiak et al. (2014) compared the results of plastic materials from three impact assessment methods (ILCD 2009, ReCiPe 2008, and IMPACT 2002+), and concluded that the variability in the LCIA results was between 5% and more than 1,000,000%. Similar comparisons based on particular materials or products can be found in other LCA studies: Martinez et al. 2015; Cavalett et al. 2013; Xue and Landis 2010; Brent and Hietkamp 2003; de Vries and de Boer 2010. All of these studies demonstrate that for a product, different impact methods can lead to different LCIA results. LCA is supposed to be for decision support and strategic thinking. The presence of different results means there is potential for different decisions. However, some issues have not been addressed yet. First, all existing comparisons used only a few impact methods. Systematic quantitative comparisons across more than three impact methods has not been addressed. Second, though these studies provided variabilities from using different impact assessment methods; they did not quantify the causes of variability. The variances could be caused by the differences in the coverages of substances or by discrepancies in the characterization values. Third, existing studies used specific LCA case studies. Here, I aim to study the variability in the impacts of many different products using an LCI dataset with inventories for many processes.

4.1.3 Matrix-based LCA model and LCIA

Matrix-based LCA methods are used to scale the inventory and provide direct and indirect LCA effects. A given LCI dataset can be mapped to matrices in order to evaluate the total impact results for its processes. As discussed in Chapter 3, Equation 3 is used to calculate environmental effects. The vector $\boldsymbol{g}$ in equation 1 includes the results from all types of environmental effects provided in the system boundary of the matrix-based model. In LCIA, the entrywise (Hadamard) product in Equation 4 is used to calculate the impacts for each category in a method. In Equation 5, $\boldsymbol{q_i^k}$ is the characterization row vector for the impact method $\boldsymbol{k}$ and category $\boldsymbol{i}$; each entry value in $\boldsymbol{q_i^k}$ is the characterization factor corresponding to the respective elementary flows. Only elementary flows that are substances in the category have characterization factor values. The $\boldsymbol{q_i^k}$ entries corresponding to elementary flows that are not substances in the category are set to zero; in LCA software, this is generally intended as a default placeholder for the elementary flows whose potential impacts are currently unknown. For an impact method $\boldsymbol{k}$ and category $\boldsymbol{i}$, the result $\boldsymbol{h_i^k}$ is a vector that represents the impact values of all elementary flows. For example, suppose that in a LCA study, $\boldsymbol{g}$ includes the results from two global warming substances: carbon dioxide, and methane emitted to air. The corresponding global warming characterization factors in $\boldsymbol{q_i^k}$ are multiplied by the respective emission values from $\boldsymbol{g}$, resulting in two impact values in the $\boldsymbol{h_i^k}$ vector. The sum of all values in the $\boldsymbol{h_i^k}$ vector is the total global warming impact results.

Equation 5: $\boldsymbol{h_i^k} = \boldsymbol{q_i^k} \circ \boldsymbol{g}$

LCA practitioners often select one impact assessment method and at least one impact category. For example, developed by the US EPA, the TRACI method is a common choice for LCA studies of products produced in the US (Bare et al. 2003). TRACI stands for “Tool for Reduction and Assessment of Chemicals and Other Environmental Impacts”. Within TRACI, the global warming

(GW) category is often selected, as it is the impact category for the evaluation of climate change impacts. LCA software includes features that allow easy and fast selections from these methods and categories to provide straightforward impact results using Equation 2. For example, the SimaPro software (version 8.3) contains information on characterization factors for around 50 impact assessment methods for the users to choose. However, it fails to show the differences in the LCIA methods as well as the possible different results when other methods are chosen.

4.1.4 Inventories reporting regarding environmental impacts

Criteria have been developed to determine the inventories that should be included in the system boundary (Suh et al. 2004); they are based on ratios of the mass, and energy or economic values of one functional unit of the process under study. These criteria, often referred to as cutoff criteria, can be problematic. When excluded, these processes might result in large impact values, as the characterization factor values for the excluded processes can be large. For example, " Dichlorodifluoromethane, CFC-12" has a large GW characterization factor (around 10,000 $\mathrm{kg\ CO_2eq}$). Thus, emissions as small as 0.001 mg can result in an GW impact of 0.1 $kg\ CO_2eq$. However, under total-mass-based cutoff criteria, the small emissions are likely to be excluded from the inventory. The exclusion of small emissions can result in ignoring large LCIA results. Yet, no LCA study has focused on understanding the potentially neglected impact results due to the selection of criteria.

In this study, I performed a comprehensive comparison of uncertainties arising from the selection and use of different LCIA methods. Processes from the US LCI database are used to demonstrate the results. Our work considers three key sources of variability in LCIA results: 1) differences in the environmental effects from the US LCI process inventories, 2) differences in coverage of substances in the methods, and 3) differences in the characterization factor values for all commonly used impact assessment methods. Finally, the impact assessment results are used to develop a new criteria for drawing system boundaries in LCA studies.

4.2 Summary of impact categories and substances

While there are many LCIA methods available, I use a practitioner's perspective in this analysis. As such, I obtained characteristics of the 50 impact methods and categories provided in the

SimaPro software (version 8.3). The number of substances for the 19 most widely used impact categories in 45 selected methods are listed in Table 4-1. The 5 remaining methods only provided one or a few impact categories - such as cumulative energy demand methods - and are not listed in Table 4-1.

The results show that on average, each method provides approximately 10 impact categories, with a few exceptions that cover only one or two. These exceptions are customized methods that were developed for a specific purpose. For example, IPCC methods only provide information on GW categories. Some categories are used in most of the methods, such as global warming and acidification; while others are given in only a few methods, such as abiotic depletion. For each category, different methods provide connections to significantly different numbers of characterized substances. For example, the number of substances for the Freshwater Ecotoxicity category vary from 46 in CML 1992 to 22,706 in TRACI 2.1.

Some of the methods are simply different versions of the same methods, e.g., there are three different TRACI methods: TRACI, TRACI 2, and TRACI 2.1. As a result, I only focus on distinct methods from the latest versions. Five impact categories (Global warming (GW), Acidification, Eutrophication, Ozone depletion, and Ecotoxicity) were chosen based on their widespread use, acceptance, and variation, for three reasons. First, these categories are available in most of the impact assessment methods. This is not the case for every category, for instance, “Smog” was available only in a few methods. Second, GW, Acidification, Eutrophication and Ozone depletion have relatively widely accepted coverages of substances. Third, the number of characterized substances vary significantly in these five categories: from as few as 18 substances in Acidification to as many as 30,514 substances in Ecotoxicity. Overall, the selected methods robustly represent the coverages of substances in all other categories. Under this selection of example categories, the study only focuses on comparing the methods that include these five categories (red italics in Table 4-1).

Table 4-1: Numbers of characterized substances in major impact categories (columns) for 45 impact assessment methods (rows). The displayed methods are embedded in the SimaPro software (version 8.3). Highlighted rows with red and Italic font are the methods chosen for demonstration in this study.

	Global warming	Acidifi-cation	Eutrophi-cation	Ozone depletion	Freshwater ecotoxicity	Marine ecotoxicity	Terrestrial ecotoxicity	HH cancer	HH non-cancer	HH criteria air pollutants	Human toxicity	Photo-chemical oxidation	Smog	Land comp e-	Water intake	Natural resource depletion	Abiotic depletion	Solid waste	Ionizing radiation
BEES V4.02	17	10	18	6	245			93	224	10			132		19	23			
BEES+ V4.03	*17*	*10*	*20*	*6*	*244*			*88*	*223*	*10*			*132*		*1094*	*23*			
Boulay et al 2011 V1.00									770						995				
CML 2 baseline 2000 V2.05	54	6	42	23	864	866	858				885	131					209		
CML 2001 V2.05	*Vary*	*25*	*42*	*23*	*220*	*866*	*220*				*885*	*131*		*37*			*209*		*49*
CML 1992 V2.06	32	14	43		46													93	
CML-IA non-baseline V3.00	Vary	24	4		852	851	836							37					49
CML-IA baseline V3.00	65	8	40	23	853	851	845				865	131					97		
CML_2_baseline_2000	54	6	42	23	864	866	858				885	131					209		
Eco-indicator 99 (E) V2.09	51	9	9	25	196			174		179				142		76			64
Eco-indicator 99 (H) V2.09	51	9	9	25	196			132		177				142		72			63
Eco-indicator 99 (I) V2.09	102	18		46	296			60		354				142		47			99
Eco-indicator 95 V2.06	*32*	*14*	*43*	*25*				*13*					*71*			*78*		*93*	
Ecological footprint V1.01	3													42		824		4	
Ecological Scarcity 2006															824	757			
Ecopoints 97 (CH) V2.07	35			19															
Ecosystem Damage Potential														125					
EDIP 2003 V1.04	*94*	*11*	*23*	*21*	*277*		*277*				*753*		*165*			*118*		*78*	*3*
EDIP/UMIP 97 V2.05	111	16	60	26	217		221				316	133				102		75	3
EPD 2007	54	5	41									134							
EPD (2008) V1.04	*94*	*5*	*45*									*134*							
EPS 2000 V2.07		16			216										4	41			
Greenhouse Gas Protocol	*Vary*															*182*			
Hoekstra et a 2012 water	715	7																	
ILCD 2011 Midpoint V1.02	*100*	*7*	*26*		*15626*			*4734*	*3434*			*133*		*125*	*842*	*166*			*62*
IPCC 2007 GWP 20a	*94*																		
IPCC 2007 GWP 100a	*94*																		
IPCC 2007 GWP 500a	*94*																		
Motoshita et all 2010										840									
Pfister el al 2009					930					930					930	930			
Pfister el al 2010					930					930						930			
ReCiPe Endpoint(E)	95	6	20	25	11863		26572				26572	137	12						54
ReCiPe Endpoint(H)	95	6	20	25	11862		26572				26572	137	12						54
ReCiPe Endpoint(I)	95	6	20	25	14920	14920	14920				14920	137	12	75		101			54
ReCiPe Midpoint(E)	*95*	*6*	*27*	*25*	*11988*		*26572*				*26572*	*137*	*12*						
ReCiPe Midpoint(H)	*95*	*6*	*27*	*25*	*11985*		*26572*				*26572*	*137*	*12*						
ReCiPe Midpoint(I)	*95*	*6*	*27*	*25*	*14920*	*14920*	*14920*				*26572*	*137*	*12*		*15*				
Selected LCI results														57					
TRACI	97	8	12	89	298			294	580				510						
TRACI 2	69	13	28	96	22706			5506	4048	5			1172						

TRACI 2.1	*94*	*14*	*30*	*96*	*22706*			*5506*	*4048*	*5*			*1173*			*25*			
USEtox default					*6923*			*3836*	*468*										
USEtox recommended					*7902*			*3816*	*3024*										
USEtox recommended_int					*22545*			*5427*	*3915*										
USEtox sensitivity					*19743*			*5428*	*3925*										
Total numbers of methods	**33**	**28**	**25**	**22**	**30**	**7**	**13**	**14**	**11**	**10**	**12**	**14**	**13**	**10**	**8**	**17**	**4**	**5**	**11**

Table 4-2: characterization factor values (in kg CO_2 eq) for all 110 global warming (GW) substances generalized from 14 popularly used impact methods.

	BEES+ V4.03	CML 2001 V2.05	Eco-indicator 95 V2.06	EDIP 2003 V1.04	EPD (2008) V1.04	Greenhouse Gas Protocol V1.01	ILCD 2011 Midpoint V1.02	IPCC 2007 GWP 20a V1.02	IPCC 2007 GWP 100a V1.02	IPCC 2007 GWP 500a V1.02	ReCiPe Midpoint (I) V1.08	ReCiPe Midpoint (H) V1.08	ReCiPe Midpoint (E) V1.08	TRACI 2.1 V1.01	Ranges
1-Propanol, 3,3,3-trifluoro-2,2-bis(trifluoromethyl)-, HFE-7100				297	297	297	297	1040	297	297	90	297	1040	297	90 - 1040
Butane, 1,1,1,3,3-pentafluoro-, HFC-365mfc				794	794	794	794	2520	794	794	241	794	2520	794	241 - 2520
Butane, perfluoro-				8860	8860	8860	8860	6330	8860	8860	12500	8860	6330	8860	6330 - 12500
Butane, perfluorocyclo-, PFC-318				10300	10300	10300	10300	7310	10300	10300	14700	10300	7310	10300	7310 - 14700
Carbon dioxide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon dioxide, biogenic						1									1 - 1
Carbon dioxide, fossil	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon dioxide, in air						1									1 - 1
Carbon dioxide, land transformation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon monoxide		1.57				1.57									1.57 - 1.57
Carbon monoxide, biogenic						1.57									1.57 - 1.57
Carbon monoxide, fossil		1.57													1.57 - 1.57
Chlorinated fluorocarbons, hard			7100												7100 - 7100
Chlorinated fluorocarbons, soft			1600												1600 - 1600
Chloroform	30	100	25	31	31	31	31	108	31	31	9.3	31	108	31	9.3 - 108
Cis-perfluorodecalin				7500	7500	7500	7500	5500	7500	7500					5500 - 7500
Dimethyl ether				1	1	1	1	1	1	1	1	1	1	1	1 - 1
Dinitrogen monoxide	296	275	270	298	298	298	298	289	298	298	153	298	289	298	153 - 298
Ethane, 1,1,1,2-tetrafluoro-, HFC-134a		3300	1200	1430	1430	1430	1430	3830	1430	1430	435	1430	3830	1430	435 - 3830
Ethane, 1,1,1-trichloro-, HCFC-140	140	450	100	146	146	146	146	506	146	146	45	146	506	146	45 - 506
Ethane, 1,1,1-trifluoro-, HFC-143a		5500	3800	4470	4470	4470	4470	5890	4470	4470	1590	4470	5890	4470	1590 - 5890
Ethane, 1,1,2,2-tetrafluoro-, HFC-134				1100	1100	1100	1100	3400	1100	1100	335	1100	3400	1100	335 - 3400
Ethane, 1,1,2-trichloro-1,2,2-trifluoro-, CFC-113		6100	4500	6130	6130	6130	6130	6540	6130	6130	2700	6130	6540	6130	2700 - 6540
Ethane, 1,1,2-trifluoro-, HFC-143				353	353	353	353	1240	353	353	107	353	1240	353	107 - 1240
Ethane, 1,1-dichloro-1-fluoro-, HCFC-141b		2100	580	725	725	725	725	2250	725	725	220	725	2250	725	220 - 2250
Ethane, 1,1-difluoro-, HFC-152a		410	150	124	124	124	124	437	124	124	38	124	437	124	38 - 437
Ethane, 1,2-dibromotetrafluoro-, Halon 2402				1640	1640	1640	1640	3680	1640	1640	503	1640	3680	1640	503 - 3680
Ethane, 1,2-dichloro-1,1,2,2-tetrafluoro-, CFC-114		7500	7000	10000	10000	10000	10000	8040	10000	10000	8730	10000	8040	10000	7000 - 10000
Ethane, 1,2-difluoro-, HFC-152				53	53	53	53	187	53	53	16	53	187	53	16 - 187
Ethane, 1-chloro-1,1-difluoro-, HCFC-142b		5200	1800	2310	2310	2310	2310	5490	2310	2310	705	2310	5490	2310	705 - 5490
Ethane, 1-chloro-2,2,2-trifluoro-(difluoromethoxy)-, HCFE-235da2				350	350	350	350	1230	350	350	106	350	1230	350	106 - 1230
Ethane, 2,2-dichloro-1,1,1-trifluoro-, HCFC-123		390	90	77	77	77	77	273	77	77	24	77	273	77	24 - 390

Ethane, 2-chloro-1,1,1,2-tetrafluoro-, HCFC-124		2000	440	609	609	609	609	2070	609	609	185	609	2070	609	185 - 2070
Ethane, chloropentafluoro-, CFC-115		4900	7000	7370	7370	7370	7370	5310	7370	7370	9990	7370	5310	7370	4900 - 9990
Ethane, fluoro-, HFC-161				12	12	12	12	43	12	12	3.7	12	43	12	3.7 - 43
Ethane, hexafluoro-, HFC-116			6200	12200	12200	12200	12200	8630	12200	12200	18200	12200	8630	12200	6200 - 18200
Ethane, pentafluoro-, HFC-125		5900	3400	3500	3500	3500	3500	6350	3500	3500	1100	3500	6350	3500	1100 - 6350
Ether, 1,1,1-trifluoromethyl methyl-, HFE-143a				756	756	756	756	2630	756	756	230	756	2630	756	230 - 2630
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347mcc3				575	575	575	575	1980	575	575	175	575	1980	575	175 - 1980
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347mcf2				374	374	374	374	1310	374	374	114	374	1310	374	114 - 1310
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347pcf2				580	580	580	580	1900	580	580	175	580	1900	580	175 - 1900
Ether, 1,1,2,2-Tetrafluoroethyl methyl-, HFE-254cb2				359	359	359	359	1260	359	359	109	359	1260	359	109 - 1260
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356mec3				101	101	101	101	355	101	101	31	101	355	101	31 - 355
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcc3				110	110	110	110	386	110	110	33	110	386	110	33 - 386
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcf2				265	265	265	265	931	265	265	80	265	931	265	80 - 931
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcf3				502	502	502	502	1760	502	502	153	502	1760	502	153 - 1760
Ether, 1,2,2-trifluoroethyl trifluoromethyl-, HFE-236ea2				989	989	989	989	3370	989	989	301	989	3370	989	301 - 3370
Ether, 1,2,2-trifluoroethyl trifluoromethyl-, HFE-236fa				487	487	487	487	1710	487	487	148	487	1710	487	148 - 1710
Ether, 2,2,3,3,3-Pentafluoropropyl methyl-, HFE-365mcf3				11	11	11	11	41	11	11	4	11	41	11	4 - 41
Ether, di(difluoromethyl), HFE-134				6320	6320	6320	6320	12200	6320	6320	1960	6320	12200	6320	1960 - 12200
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245cb2				708	708	708	708	2440	708	708	215	708	2440	708	215 - 2440
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245fa1				286	286	286	286	1010	286	286	87	286	1010	286	87 - 1010
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245fa2				659	659	659	659	2280	659	659	200	659	2280	659	200 - 2280
Ether, ethyl 1,1,2,2-tetrafluoroethyl-, HFE-374pc2				557	557	557	557	1930	557	557	169	557	1930	557	169 - 1930
Ether, nonafluorobutane ethyl-, HFE569sf2 (HFE-7200)				59	59	59	59	207	59	59	18	59	207	59	18 - 207
Ether, pentafluoromethyl-, HFE-125				14900	14900	14900	14900	13800	14900	14900	8490	14900	13800	14900	8490 - 14900
Hexane, perfluoro-				9300	9300	9300	9300	6600	9300	9300	13300	9300	6600	9300	6600 - 13300
HFE-227EA				1540	1540	1540	1540	4540	1540	1540	468	1540	4540	1540	468 - 4540
HFE-236ca12 (HG-10)				2800	2800	2800	2800	8000	2800	2800	860	2800	8000	2800	860 - 8000
HFE-263fb2				11	11	11	11	38	11	11	3	11	38	11	3 - 38
HFE-329mcc2				919	919	919	919	3060	919	919	279	919	3060	919	279 - 3060
HFE-338mcf2				552	552	552	552	1920	552	552	168	552	1920	552	168 - 1920
HFE-338pcc13 (HG-01)				1500	1500	1500	1500	5100	1500	1500	460	1500	5100	1500	460 - 5100
HFE-43-10pccc124 (H-Galden1040x)				1870	1870	1870	1870	6320	1870	1870	569	1870	6320	1870	569 - 6320
Hydrocarbons, chlorinated											3.29	10.6	28		3.29 - 28
Methane	23	62	11	25	25	25	25	72	25	25	7.6	25	72	25	7.6 - 72
Methane, biogenic	20	59	8	22.25	22.25	25	22.3	69.25	22.25	22.25	4.85	22.3	69.25	22.25	4.85 - 69.25
Methane, bromo-, Halon 1001	5	16		5	5	5	5	17	5	5	1	5	17	5	1 - 17

Methane, bromochlorodifluoro-, Halon 1211		3600	4900	1890	1890	1890	1890	4750	1890	1890	575	1890	4750	1890	575 - 4900
Methane, bromodifluoro-, Halon 1201				404	404	404	404	1380	404	404	123	404	1380	404	123 - 1380
Methane, bromotrifluoro-, Halon 1301	6900	7900	4900	7140	7140	7140	7140	8480	7140	7140	2760	7140	8480	7140	2760 - 8480
Methane, chlorodifluoro-, HCFC-22	1700	4800	1600	1810	1810	1810	1810	5160	1810	1810	549	1810	5160	1810	549 - 5160
Methane, chlorotrifluoro-, CFC-13		10000	13000	14400	14400	14400	14400	10800	14400	14400	16400	14400	10800	14400	10000 - 16400
Methane, dibromo-				1.54	1.54	1.54	1.54	5.4	1.54	1.54	0.47	1.54	5.4	1.54	0.47 - 5.4
Methane, dichloro-, HCC-30	10	35	15	8.7	8.7	8.7	8.7	31	8.7	8.7	2.7	8.7	31	8.7	2.7 - 35
Methane, dichlorodifluoro-, CFC-12	10600	10200	7100	10900	10900	10900	10900	11000	10900	10900	5200	10900	11000	10900	5200 - 11000
Methane, dichlorofluoro-, HCFC-21				151	151	151	151	530	151	151	46	151	530	151	46 - 530
Methane, difluoro-, HFC-32		1800		675	675	675	675	2330	675	675	205	675	2330	675	205 - 2330
Methane, fluoro-, HFC-41				92	92	92	92	323	92	92	28	92	323	92	28 - 323
Methane, fossil	23	62	11	25	25	25	25	72	25	25	7.6	25	72	25	7.6 - 72
Methane, iodotrifluoro-				0.4	0.4	0.4	0.4	1	0.4	0.4	0.1	0.4	1	0.4	0.1 - 1
Methane, monochloro-, R-40	16	55		13	13	13	13	45	13	13	4	13	45	13	4 - 55
Methane, tetrachloro-, CFC-10	1800	2700	1300	1400	1400	1400	1400	2700	1400	1400	435	1400	2700	1400	435 - 2700
Methane, tetrafluoro-, CFC-14	5700	3900	4500	7390	7390	7390	7390	5210	7390	7390	11200	7390	5210	7390	3900 - 11200
Methane, trichlorofluoro-, CFC-11		6300	3400	4750	4750	4750	4750	6730	4750	4750	1620	4750	6730	4750	1620 - 6730
Methane, trifluoro-, HFC-23		9400		14800	14800	14800	14800	12000	14800	14800	12200	14800	12000	14800	9400 - 14800
Nitrogen fluoride				17200	17200	17200	17200	12300	17200	17200	20700	17200	12300	17200	12300 - 20700
Pentane, 2,3-dihydroperfluoro-, HFC-4310mee				1640	1640	1640	1640	4140	1640	1640	500	1640	4140	1640	500 - 4140
Pentane, dodecafluoro-, PFC-4-1-12											13300	9160	6510		6510 - 13300
Pentane, perfluoro-				9160	9160	9160	9160	6510	9160	9160	13300	9160	6510	9160	6510 - 13300
PFC-9-1-18											9500	7500	5500	7500	5500 - 9500
PFPMIE				10300	10300	10300	10300	7620	10300	10300	12400	10300	7620	10300	7620 - 12400
Propane, 1,1,1,2,2,3-hexafluoro-, HFC-236cb				1340	1340	1340	1340	3630	1340	1340	407	1340	3630	1340	407 - 3630
Propane, 1,1,1,2,3,3,3-heptafluoro-, HFC-227ea				3220	3220	3220	3220	5310	3220	3220	1040	3220	5310	3220	1040 - 5310
Propane, 1,1,1,2,3,3-hexafluoro-, HFC-236ea				1370	1370	1370	1370	4090	1370	1370	418	1370	4090	1370	418 - 4090
Propane, 1,1,1,3,3,3-hexafluoro-, HCFC-236fa				9810	9810	9810	9810	8100	9810	9810	7660	9810	8100	9810	7660 - 9810
Propane, 1,1,1,3,3-pentafluoro-, HFC-245fa				1030	1030	1030	1030	3380	1030	1030	314	1030	3380	1030	314 - 3380
Propane, 1,1,2,2,3-pentafluoro-, HFC-245ca				693	693	693	693	2340	693	693	211	693	2340	693	211 - 2340
Propane, 1,3-dichloro-1,1,2,2,3-pentafluoro-, HCFC-225cb				595	595	595	595	2030	595	595	181	595	2030	595	181 - 2030
Propane, 3,3-dichloro-1,1,1,2,2-pentafluoro-, HCFC-225ca				122	122	122	122	429	122	122	37	122	429	122	37 - 429
Propane, perfluoro-				8830	8830	8830	8830	6310	8830	8830	12500	8830	6310	8830	6310 - 12500
Propane, perfluorocyclo-				17340	17340	17340		12700	17340	17340				17340	12700 - 17340
Sulfur hexafluoride		15100		22800	22800	22800	22800	16300	22800	22800	32600	22800	16300	22800	15100 - 32600
Trifluoromethylsulfur pentafluoride				17700	17700	17700	17700	13200	17700	17700	21200	17700	13200	17700	13200 - 21200

The observed high variability in the GW characterization factor values is somewhat unexpected because compared to other impact categories, the GW category is considered to be a relatively well-developed category. The estimation method for the GW category was assumed to be developed from one research agency, the Intergovernmental Panel on Climate Change (IPCC), and accepted by most of the methods. Thus, the coverages of substances were expected to be identical or at least similar between different methods. However, the results show that some methods have much smaller numbers of substances, such as BEES, CML2001, and Eco-indicator (which I stipulate are relatively older, but are still widely available in LCA software tools). No method includes all substances listed in Table 4-2. The ILCD method, for example, includes six substances that are not included in any other methods; yet it does not include "Perfluorocyclopropane", a substance that is included in most of the other methods.

Apart from the differences in the coverages of substances, the characterization factors also vary significantly across methods. This variability is beyond the variability expected from using different specific global warming timeframes. For example, there are six different values for Chloroform from 14 methods while the GW metric is defined at 20, 100, and 500 years.

4.3 Variability in the impact assessment results in the US LCI database

Differences in the coverages from substances, and differences in the characterization factors are two sources for the variability in the LCIA results. A third source of variability is from differences in inventories that are connected to LCIA methods. The number of included substances in the inventory affects the LCIA result. This section evaluates the effects from the coverages of these GW substances in life cycle inventories.

The 2701 elementary flows in the US LCI database include potential substances in each impact category. The purpose of this section is to identify these substances by matching their information with the elementary flows and substances provided in each category. The information includes the names of the materials or emissions in the elementary flows, as well as two other restrictive elements: compartments such as air, water and soil, and by impact regions such as lake, and river. As an example, Table 4-3 shows all elementary flows for Mercury in the US LCI database, specified to compartments and impact regions. Matlab software was used for the matching between the information in the elementary flows and the substances in each category (code available in the Appendix), by the names and other restricted information.

In some cases, the substances provided in impact categories are not specified by impact regions and compartments. Current practice is to apply the substances and their characterization factors in an impact method to all possible regions and compartments in the elementary flows. For instance, in the Ecoindicator 95 method, "Mercury emissions to air" is not regionally specified in the "heavy metals" impact category. The substance and its characterization factor are applied to all US LCI mercury flows to air (No. 1398, 1403, 1404, 1405 and 1411 in Table 4-3). On the other hand, when a substance provided by an impact method is regionally specified, an elementary flow in a LCI database should have the same impact region considered as a match. For example, in the ReCiPe Midpoint method, one impact region for Mercury to soil is "forestry". As shown in Table 4-3, in the US LCI database, Mercury does not have forestry as one of its impact regions, indicating that the substance from the ReCiPe Midpoint method does not match any US LCI elementary flow.

Table 4-4 shows the all GW substances in the US LCI database. Thirty five out of the 110 GW substances shown in Table 4-4 were identified as elementary flows. These GW substances were not regionally specified in the methods and applied to all elementary flows with the same chemical names. Thus, 94 US LCI elementary flows specified by impact regions were identified as matches.

Table 4-3: Elementary flows for Mercury with different impact regions and compartments in the US LCI database

Flow No. in USLCI	Name	Impact region	Compartment	Unit
1398	Mercury	unspecified	air	kg
1399	Mercury	unspecified	water	kg
1400	Mercury	industrial	soil	kg
1401	Mercury	ocean	water	kg
1402	Mercury	agricultural	soil	kg
1403	Mercury	high population density	air	kg
1404	Mercury	low population density	air	kg
1405	Mercury	stratosphere	air	kg
1406	Mercury	ground-	water	kg
1407	Mercury	ground-, long-term	water	kg
1408	Mercury	lake	water	kg
1409	Mercury	river	water	kg
1410	Mercury	unspecified	soil	kg
1411	Mercury	low. pop.	air	kg

Table 4-4: GW substances in the US LCI database and their characterization factors in different methods.

	BEES+ V4.03	CML 2001 V2.05	Eco-indi-cator 95 V2.06	EDIP 2003 V1.04	EPD (2008) V1.04	Green-house Gas Pro-tocol V1.01	ILCD 2011 Mid-point V1.02	IPCC 2007 GWP 20a V1.02	IPCC 2007 GWP 100a V1.02	IPCC 2007 GWP 500a V1.02	ReCiPe Mid-point (I) V1.08	ReCiPe Mid-point (H) V1.08	ReCiPe Mid-point (E) V1.08	TRACI 2.1 V1.01	Ranges
Carbon dioxide	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon dioxide, biogenic						1									1 - 1
Carbon dioxide, fossil	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon dioxide, land transformation	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Carbon monoxide		1.57				1.57									1.57 - 1.57
Carbon monoxide, biogenic						1.57									1.57 - 1.57
Carbon monoxide, fossil		1.57													1.57 - 1.57
Chloroform	30	100	25	31	31	31	31	108	31	31	9.3	31	108	31	9.3 - 108
Dimethyl ether				1	1	1	1	1	1	1	1	1	1	1	1 - 1
Dinitrogen monoxide	296	275	270	298	298	298	298	289	298	298	153	298	289	298	153 - 298
Ethane, 1,1,1,2-tetrafluoro-, HFC-134a		3300	1200	1430	1430	1430	1430	3830	1430	1430	435	1430	3830	1430	435 - 3830
Ethane, 1,1,1-trichloro-, HCFC-140	140	450	100	146	146	146	146	506	146	146	45	146	506	146	45 - 506
Ethane, 1,1,2-trichloro-1,2,2-trifluoro-, CFC-113		6100	4500	6130	6130	6130	6130	6540	6130	6130	2700	6130	6540	6130	2700 - 6540
Ethane, 1,1-difluoro-, HFC-152a		410	150	124	124	124	124	437	124	124	38	124	437	124	38 - 437
Ethane, 1,2-dichloro-1,1,2,2-tetrafluoro-, CFC-114		7500	7000	10000	10000	10000	10000	8040	10000	10000	8730	10000	8040	10000	7000 - 10000
Ethane, hexafluoro-, HFC-116			6200	12200	12200	12200	12200	8630	12200	12200	18200	12200	8630	12200	6200 - 18200
Ethane, pentafluoro-, HFC-125		5900	3400	3500	3500	3500	3500	6350	3500	3500	1100	3500	6350	3500	1100 - 6350
Hydrocarbons, chlorinated											3.29	10.6	28		3.29 - 28
Methane	23	62	11	25	25	25	25	72	25	25	7.6	25	72	25	7.6 - 72

Methane, biogenic	20	59	8	22.25	22.25	25	22.3	69.25	22.25	22.25	4.85	22.3	69.25	22.25	4.85 - 69.25
Methane, bromo-, Halon 1001	5	16		5	5	5	5	17	5	5	1	5	17	5	1 - 17
Methane, bromochlorodifluoro-, Halon 1211		3600	4900	1890	1890	1890	1890	4750	1890	1890	575	1890	4750	1890	575 - 4900
Methane, bromotrifluoro-, Halon 1301	6900	7900	4900	7140	7140	7140	7140	8480	7140	7140	2760	7140	8480	7140	2760 - 8480
Methane, chlorodifluoro-, HCFC-22	1700	4800	1600	1810	1810	1810	1810	5160	1810	1810	549	1810	5160	1810	549 - 5160
Methane, chlorotrifluoro-, CFC-13		10000	13000	14400	14400	14400	14400	10800	14400	14400	16400	14400	10800	14400	10000 - 16400
Methane, dichloro-, HCC-30	10	35	15	8.7	8.7	8.7	8.7	31	8.7	8.7	2.7	8.7	31	8.7	2.7 - 35
Methane, dichlorodifluoro-, CFC-12	10600	10200	7100	10900	10900	10900	10900	11000	10900	10900	5200	10900	11000	10900	5200 - 11000
Methane, dichlorofluoro-, HCFC-21				151	151	151	151	530	151	151	46	151	530	151	46 - 530
Methane, difluoro-, HFC-32		1800		675	675	675	675	2330	675	675	205	675	2330	675	205 - 2330
Methane, fossil	23	62	11	25	25	25	25	72	25	25	7.6	25	72	25	7.6 - 72
Methane, monochloro-, R-40	16	55		13	13	13	13	45	13	13	4	13	45	13	4 - 55
Methane, tetrachloro-, CFC-10	1800	2700	1300	1400	1400	1400	1400	2700	1400	1400	435	1400	2700	1400	435 - 2700
Methane, tetrafluoro-, CFC-14	5700	3900	4500	7390	7390	7390	7390	5210	7390	7390	11200	7390	5210	7390	3900 - 11200
Methane, trichlorofluoro-, CFC-11		6300	3400	4750	4750	4750	4750	6730	4750	4750	1620	4750	6730	4750	1620 - 6730
Methane, trifluoro-, HFC-23		9400		14800	14800	14800	14800	12000	14800	14800	12200	14800	12000	14800	9400 - 14800
Nitrogen fluoride				17200	17200	17200	17200	12300	17200	17200	20700	17200	12300	17200	12300 - 20700
Sulfur hexafluoride		15100		22800	22800	22800	22800	16300	22800	22800	32600	22800	16300	22800	15100 - 32600

The number of substances for the five chosen impact categories are shown in Table 4-5. The first row in Table 4-5 shows the numbers of substances summarized from all impact methods for each category and the corresponding compartments (e.g., as described above there are a total of 110 distinct global warming substances across all methods considered). The third row represents the numbers of chemicals in each category that are included in the USLCI elementary flows. The forth row shows the number of elementary flows that have the same name with the substances in each category. Finally, the last row shows the total number of US LCI elementary flows classified by the compartments in the second row. The US LCI database classified 1030 elementary flows with compartment air, 237 with soil, and 924 as water. The results show that considering all five impact categories (the last column), around 60% (938 out of 2191) of the US LCI elementary flows are not substances in any of these categories, resulting in zero impacts. In addition, for each impact category, different methods provide different numbers of substances, resulting a range of number of substances covered (row 3). The ranges are generally large. For example, ozone depletion method has a number of matched substances vary between 6 and 25, indicating using one method can result in the neglect of 75% substances provided in another method.

Table 4-5: Summary of the number of substances and matching elementary flows in five selected impact categories for the US LCI database.

	GW	Acicifi-cation	Eutrophi-cation	Ozone Depletion	Eco-toxicity	All five categories
Number of substances from all methods	110	19	93	108	30514	30514
Compartments for the substances	Air	Air	Air, water, soil	Air	Air, water, soil	Air, water, soil
Matched substances (compartment specified)	17 - 35	6-14	14 - 26	6 - 25	244 - 830	
Maximum number of matched elementary flows considering all impact regions	94	48	71	39	830	938
Number of elementary flows	1030	1030	2191	1030	2191	2191

The approximate 60% of exclusion of substances can be due to different reasons. First, possible cutoff criteria can cause neglects of emissions; the emissions that are smaller than the cutoff value are not reported in the inventory. Second, some particular substances are simply not emissions in the production. To better understand the reasons of the exclusions, based on individual industries and processes, I applied other data sources as reference to identify whether there are data gaps in the inventories.

4.4 Validating substances coverages and variability in the impact assessment results based on individual processes

In the previous section, I listed the differences between the number of substances in the impact methods and in the US LCI database. The results showed that the differences can be large, in that the database may currently lack information on a large number of substances with known impacts. It is reasonable that there are more substances included in impact assessment methods than the numbers of substances emitted from production since data comes from many individual processes, each of which could in fact not have emissions of such substances. However, if results from another data source shows that the emissions likely exist but are not covered in the US LCI process, it means that there is a data gap and the inventory should be updated to include the emissions. To demonstrate the idea of using these references to determine whether there are data gaps, in this study, I used the global warming impact category as an example, because the data for this category are currently available. The methods can be applied to other impact categories as more third-party data can be acquired.

The US EPA's Greenhouse Gas Reporting Program (GHGRP)[2] provides annual Greenhouse Gas emissions data from large emitting industries. In 2009, the US EPA published a mandatory reporting rule for greenhouse gas emissions. It regulated that facilities in the US should report any emissions that are more than 25,000 metric tons carbon dioxide eq per year. Since then, the US EPA collects reported emissions from these facilities and provides the data to the public. The latest data are from 2015, for 32 industry types. These data were used in this study to identify greenhouse gas emissions from different industries and as a reference to identify possible data gaps in the US LCI database.

[2] US EPA Greenhouse Gas Reporting Program. https://www.epa.gov/ghgreporting/ghg-reporting-program-data-sets, accessed 05-01-2017

Based on the data provided by GHGRP, the greenhouse gas emissions reported by each industry under the mandatory reporting rule are summarized in Table 4-6, cells with "EPA" indicate that there were more than 25,000 metric tons of carbon dioxide equivalent greenhouse gas emissions from various industries (EPA provides 32 industries, for simplicity, only industries covered in the US LCI database are listed in the table). The summarized results from the EPA reports show that carbon dioxide, methane and dinitrogen oxide are reported in the emissions from all industries, while the other six greenhouse gases are reported in only in metal, chemical, and electronic manufacturing industries. The table, lists the inclusion or exclusion of the greenhouse gases in the US LCI database; the red cells indicate the EPA reported emissions that are excluded from any US LCI process within the same industry. The result shows that there are data gaps for some industries in the database, especially in ethanol production and electronics manufacturing industries; the non-zero values are reported to EPA from these industries, but the substance are not included in the processes' inventories. For example, EPA requires metal production industries to report perfluorocarbons; however, among the 22 US LCI metal processes, none have perfluorocarbons as outputs. The exclusion of these substances could be caused by the time differences between the inventories reported and the release of the mandatory reporting rule; some of the inventories were reported before 2005, thus the emissions reporting were not regulated by the rule. These old inventories can be improved referencing the rule. However, the exclusions of global warming substances indicate possible exclusion of substances from other impact categories, and currently no reference can be found to identify possible gaps. Future studies can aim to solve these problems by identifying impact substances from industrial emissions.

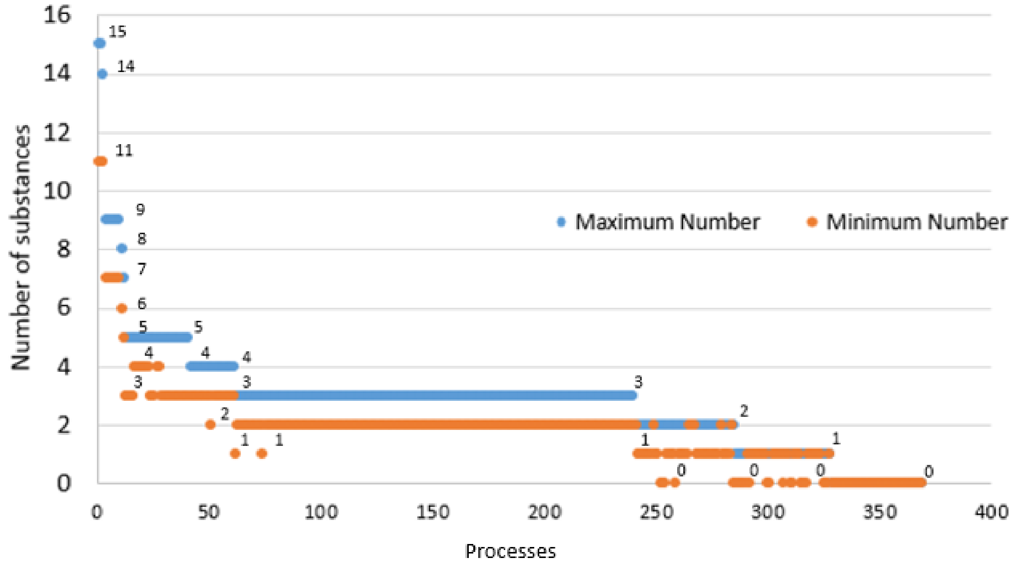
Table 4-6: Mandatory Greenhouse gases reported to the US EPA GHGRP for each industry. Cell listed as "EPA" are emissions reported under the mandatory reporting rule. Cells highlighted with red color are emissions that are not included in any of the US LCI process within each industry.

	Greenhouse gas substances								
Industry	CO_2	CH_4	N_2O	Fluorinated GHGs	Hydrofluorocarbons (HFCs)	Perfluorocarbons (PFCs)	Sulfur hexafluoride (SF_6)	Nitrogen trifluoride (NF3)	Other Fully Fluorinated GHGs
Power plants	EPA	EPA	EPA						
Petroleum and NG systems	EPA	EPA	EPA						
Refineries	EPA	EPA	EPA						
Chemicals	EPA	EPA	EPA	EPA					
Metals	EPA	EPA	EPA		EPA	EPA	EPA		
Pulp and paper	EPA	EPA	EPA						
Ethanol Production	EPA	EPA	EPA						
Underground coal mines	EPA	EPA	EPA						
Electronics manufacturing	EPA	EPA	EPA		EPA	EPA	EPA	EPA	EPA

The evaluation on the industrial level provides a high level summary of the inclusion of global warming substances. A detailed level analysis was also performed to understand the inclusion of US LCI processes. For simplicity, the matrix method is applied. Considering all substances summarized from the 14 different impact methods, the values in the $\boldsymbol{B}$ matrix were used to identify whether a process had certain substances in the direct emission. Each row in the $\boldsymbol{B}$ matrix, found in Equation 3, represents an elementary flow, which is a direct input or output for the processes in the columns. For each column, non-zero values in the rows represent direct emissions from identified substances in each process. Thus, identifying the non-zero values in the substance rows efficiently leads to the substances from each process. The zero values were assumed to have zero effects, thus resulting in no corresponding impacts.

Figure 4-2 shows the ranges in number of GW substances for the US LCI gate-to-gate processes. Using their maximum values, these ranges are sorted by the process having the largest number of GW substances (left) to the smallest (right). The two values for each process are the maximum and minimum number of substances summarized from 14 impact assessment methods (shown in Figure 4-2). For example, in Figure 4-2, process number one had a range of identified substances between 11 and 15; this range resulted from using different impact methods. The "cut-off" processes do not have any output component; thus, they were not shown in Figure 4-2. Cradle-to-gate processes were also excluded in Figure 4-2, because their emissions are not exclusively direct emissions. Figure 4-2 also omits processes without GW substances. The results show that the discrepancies between the maximum and minimum numbers can be large. Only 314 or 25% of the 876 cradle-to-gate processes had more than one GW substance, and 523 processes do not include any GW in their inventories. As show in Figure 4-2, the processes with the largest numbers of GW substances are fuel combustion processes.

There were some instances in which the number of substances was small or even zero. This lack of substances induces a small or zero value for the direct GW impact results in most of the processes (i.e., it would report that the process has no global warming impact). The reason for the lack of substances can be traced to the inventories of the processes. Most processes do not include GW substances in their inventories. It is possible that the processes do not have GW emissions. For example, the "electricity, US, grid mix" process is a mix of electricity generated by different types of fuels. In this case, generating grid electricity does not involve any real production (no emission is produced from the process). However, these special cases only apply to a small part of the processes, not to all the 523 processes. GW substance emissions may also be excluded from the inventory when they are outside the system boundary of the LCA studies. This exclusion can result in ignoring impact values in the results. When the system boundary is set, the inclusion/exclusion of certain emissions is often based on benchmarks referred to as cutoff criteria. The cutoff criteria specify a boundary using mass, energy or economic value, rather than impact results. Thus, small emissions from substances are more susceptible to being excluded from the inventory. I will discuss cutoff issues more in the next section.

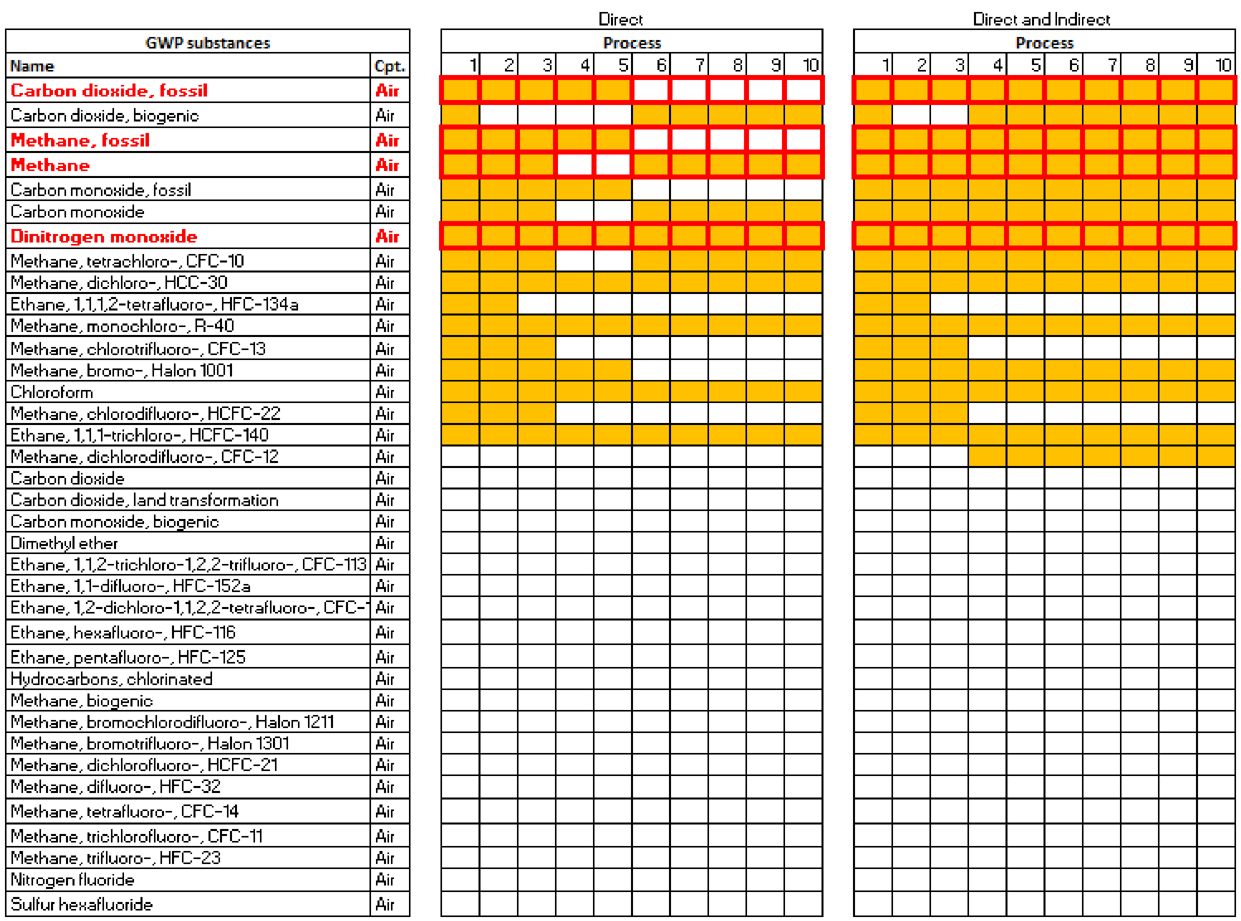


No.	US LCI Process Index No.	Process Name
1	481	Recovered energy, for Polyol ether, for flexible foam polyurethane production, at plant, CTR
2	482	Recovered energy, for Polyol ether, for rigid foam polyurethane production, at plant, CTR
3	483	Recovered energy, for Polypropylene, resin, at plant, CTR
4	74	Bituminous coal, combusted in industrial boiler
5	75	Bituminous coal, combusted in industrial boiler, at pulp and paper mill (EXCL.)
6	274	Fuels, burned at coated freesheet, average production, at mill
7	275	Fuels, burned at coated mechanical paper, average production, at mill
8	276	Fuels, burned at unbleached kraft bag sack paper, average production, at mill
9	277	Fuels, burned at uncoated freesheet, average production, at mill
10	278	Fuels, burned at uncoated mechanical paper, average production, at mill

Figure 4-2: Numbers of Global warming (GW) substances in the gate-to-gate process from the US LCI database. The processes were sorted from the largest number of substances (left) to the smallest (right). The two values for each process are the maximum and minimum number of substances in 14 popular impact assessment methods (see Table 4-2). The "cut-off" processes in the US LCI database are not shown in this figure, as these processes do not have any output component. Also omitted are the processes without GW substances after No. 360. The first 10 processes' names are shown in the table.

So far, I have identified the *direct emission* substances from each process in the US LCI database. Now I focus on the indirect/upstream emission substances and their impacts from each process. The indirect emissions for each process were obtained from the $\boldsymbol{g}$ vector. After identifying the substances, the final ranges of impact results were computed from their corresponding characterization factors. The differences observed in the impact results were due to the variabilities in the characterization factors, and the number of substances covered in each method.

In the direct analysis, I found 548 processes with no GW substances (from any GW methods) in their direct emissions (i.e. in the $\boldsymbol{B}$ matrix). In the direct and indirect analysis, 268 out of these 548 processes include GW substances in their upstream (i.e., in their $\boldsymbol{g}$ vectors). As an example, Figure 4-3 summarizes the occurrence GW substances for the processes with the top ten highest number of GW substances in their direct inventories (i.e., the first ten processes listed in Figure 4-3). The non-zero substances corresponding to direct and indirect emissions are displayed separately and highlighted in orange; red border cells are reported as non-zero values by the EPA GHGRP. The results indicate that 1) more substances are found in the total emissions; 2) some substances are widely included, such as fossil carbon dioxide; 3) some GW substances reported in EPA GHGRP are not included in some of the processes' inventories.

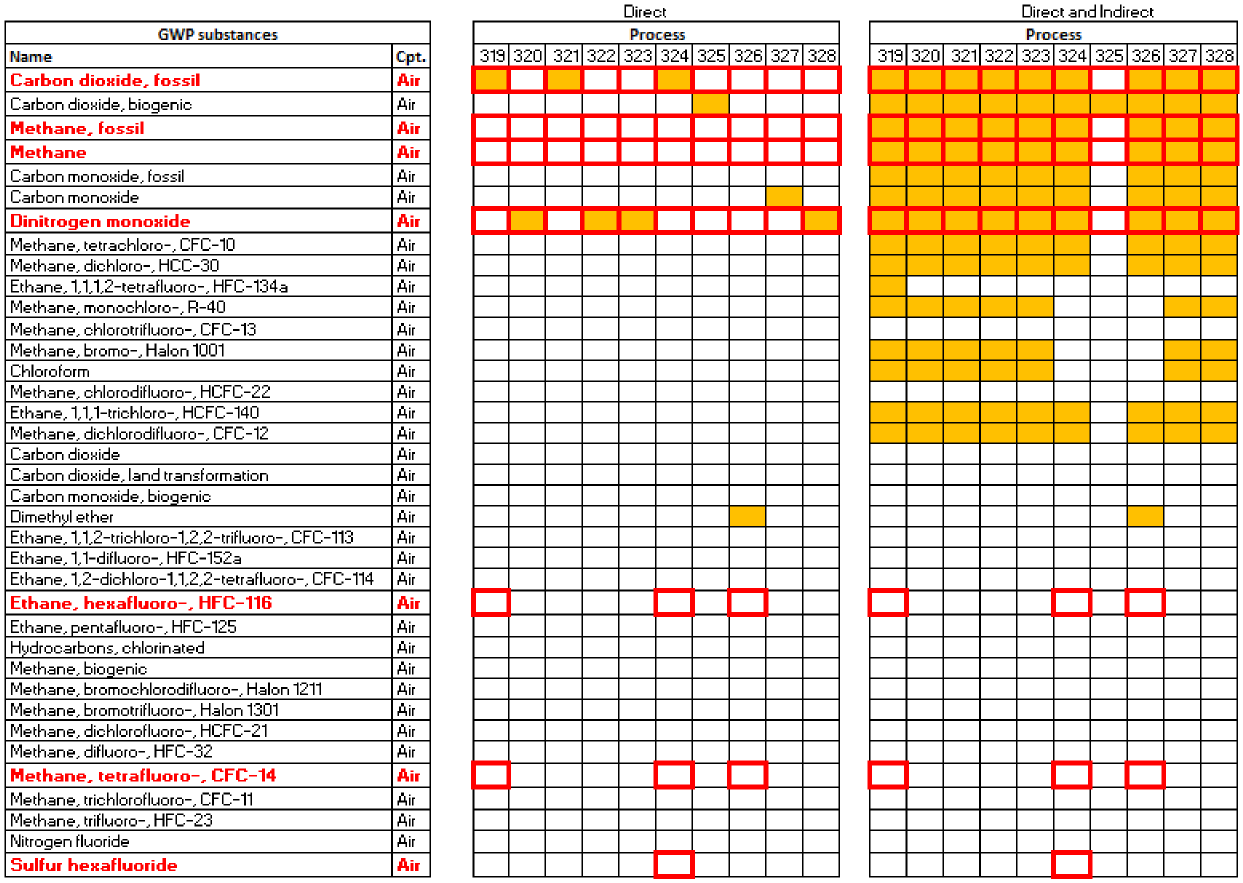


No.	US LCI Process Index No.	Process Name
1	481	Recovered energy, for Polyol ether, for flexible foam polyurethane production, at plant, CTR
2	482	Recovered energy, for Polyol ether, for rigid foam polyurethane production, at plant, CTR
3	483	Recovered energy, for Polypropylene, resin, at plant, CTR
4	74	Bituminous coal, combusted in industrial boiler
5	75	Bituminous coal, combusted in industrial boiler, at pulp and paper mill (EXCL.)
6	274	Fuels, burned at coated freesheet, average production, at mill
7	275	Fuels, burned at coated mechanical paper, average production, at mill
8	276	Fuels, burned at unbleached kraft bag sack paper, average production, at mill
9	277	Fuels, burned at uncoated freesheet, average production, at mill
10	278	Fuels, burned at uncoated mechanical paper, average production, at mill

Figure 4-3: Non-zero values for the US LCI processes that have the largest numbers of global warming (GW) substances. The marked cells in the tables represent non-zero values. Cells with red borders are reported as non-zero values by the EPA GHGRP. The direct and indirect tables were obtained from the $\mathbf{B}$ matrix, and $\mathbf{g}$ vector for each process respectively (the non-zero values are highlighted in orange).

Ten example processes with only one direct GW substance in the $\boldsymbol{B}$ matrix columns are shown in Figure 4-4. Perhaps contrary to expectation, when a process has only one GW substance, it is not necessarily “carbon dioxide”, but can also be “dinitrogen monoxide (N_2O)”.The results also show that the numbers of substances in the $\boldsymbol{g}$ vector for the same process are larger, further indicating that indirect emissions are important to the impact results.

Figure 4-3 and Figure 4-4 highlight the substances included in the process inventories. For processes with either the top 10 highest or lowest numbers of GW substances, when EPA’s GHGRP is used as a reference, potential data gaps are found in in the processes’ inventories. Though the total effects cover more substances, the missing substances are still excluded from the inventories, indicating the missing substances are not included in the inventory of any upstream inputs. Excluding these substances results in missing impact values; this is an issue in LCI databases, especially for the processes that have small numbers of GW substances. Addressing this issue can improve the quality of databases and facilitate better LCA results.

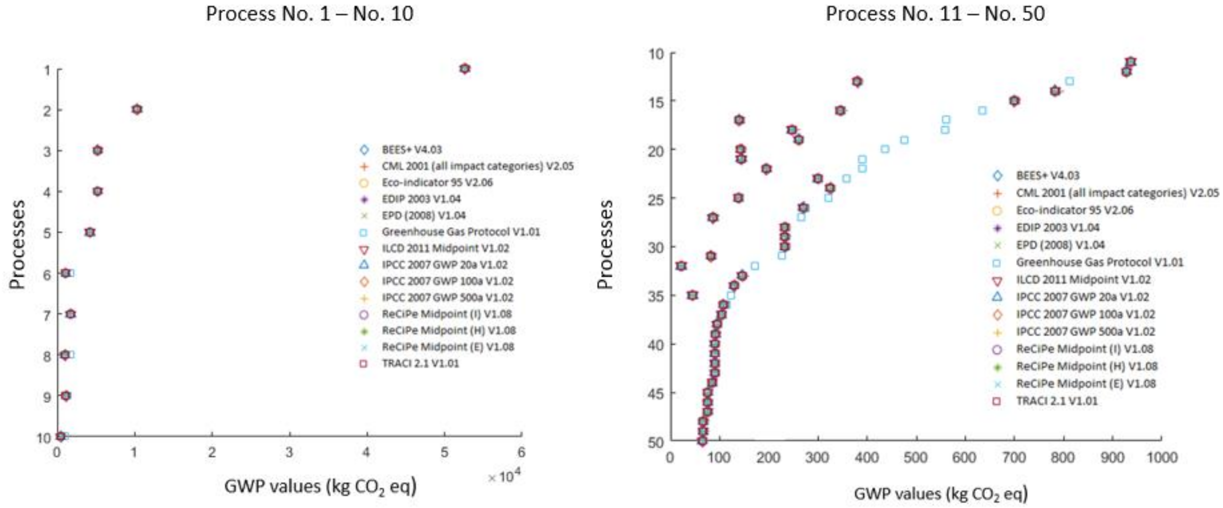


No.	US LCI Process Index No.	Process Name
319	438	Propylene oxide, at plant
320	471	Rapeseed residues, at field
321	589	Soda powder, at plant
322	607	Soybean residues, at field
323	608	Soybean residues, at field, 1998-2001
324	619	Steel, cold-formed studs and track, at plant
325	630	Switchgrass, harvested, wet
326	826	Urea formaldehyde resin, neat, 65% solids
327	828	Veneer, hardwood, dry, at veneer mill, E
328	835	Wheat straw, at field

Figure 4-4: Non-zero values for the US LCI processes that have only one global warming (GW) substance. The highlighted cells in the tables represent non-zero values. Cells with red borders are reported as non-zero values by the EPA GHGRP. The process number corresponds to the x-axis in Figure 4-2.

Next, using Equation 3 and Equation 5, I calculated the total impact assessment results per functional unit for each of the 876 gate-to-gate processes in the US LCI database. All 14 methods were used in the estimation. Again, Matlab software was used to match substances. Among the 876 gate-to-gate processes, 608 have non-zero GW impact results which are graphed below. Of these 608 processes, Figure 4-5 shows results for the 50 processes with the largest total GW impact values per functional unit. The total impact values for each process were calculated based on 14 different GW methods, as shown in the legend. Each row in the figure represents the 14 total emissions from one functional unit production of a process. The displayed processes were sorted by the maximum GW impact value calculated from all methods. Figure 4-6 shows the results for the remaining 558 non-zero-impact processes. The processes with the 10 largest total GW impact values are different than the processes with the 10 largest numbers of GW substances in Figure 4-3, because the GW impact values are affected by the characterization factor values for the substances, whose values can differ by three orders of magnitudes between different substances.

In general, the GW results are similar across different methods. Among the 608 processes, 517 have less than 5% absolute departure from the average value (i.e., the difference between the maximum or minimum value and the average is less than 5%). There are some big outliers from two impact methods. No. 17 to No. 23 on the x-axis, for example, have larger values calculated from the Greenhouse gas protocol method (light blue squares) than using the other methods. On the other hand, processes No. 305 to No. 310 have larger values from the CML 2001 method compared to the other methods (Figure 4-6).



No.	US LCI Process Index No.	Name	Industrial category	Funct unit
1	896	Metal composite material (MCM) panel, at plant'	Architectural and Structural Metals Manufacturing	sq meter
2	898	Metal panel, insulated, at plant'	Architectural and Structural Metals Manufacturing	sq meter
3	620	Cladding, roll formed, at plant	Architectural and Structural Metals Manufacturing	sq meter
4	897	Metal composite material (MCM) sheet, at plant	Architectural and Structural Metals Manufacturing	sq meter
5	815	Fuel grade uranium, at regional storage	Uranium-Radium-Vanadium Ore Mining	kg
6	1007	Prefinished engineered wood flooring, at engineered wood flooring plant, E	Engineered Wood Member (ex. Truss) Manufacturing	kg
7	1073	Reforesting, high intensity site, US SE	Forest Nurseries, Gathering Forest Prod.	ha
8	787	Engineered flooring, hardwood, unfinished, E	Engineered Wood Member (ex. Truss) Manufacturing	kg
9	1045	Railroad ties, hardwood, creosote treated, SE	Wood Preservation	kg
10	1182	Solid strip and plank flooring, hardwood, E	Sawmills	kg

Figure 4-5: GW values in kg CO_2 eq per functional unit, from 14 impact methods, marked by the different symbols described in the legend. Processes No.1 to No.10 are shown on the left, and processes No. 11 to No. 50 are shown on the right. The processes are sorted by total impact results including direct and indirect impacts. The first 10 processes' names, industrial categories, functional units, and original index numbers from the US LCI database are listed in the table.

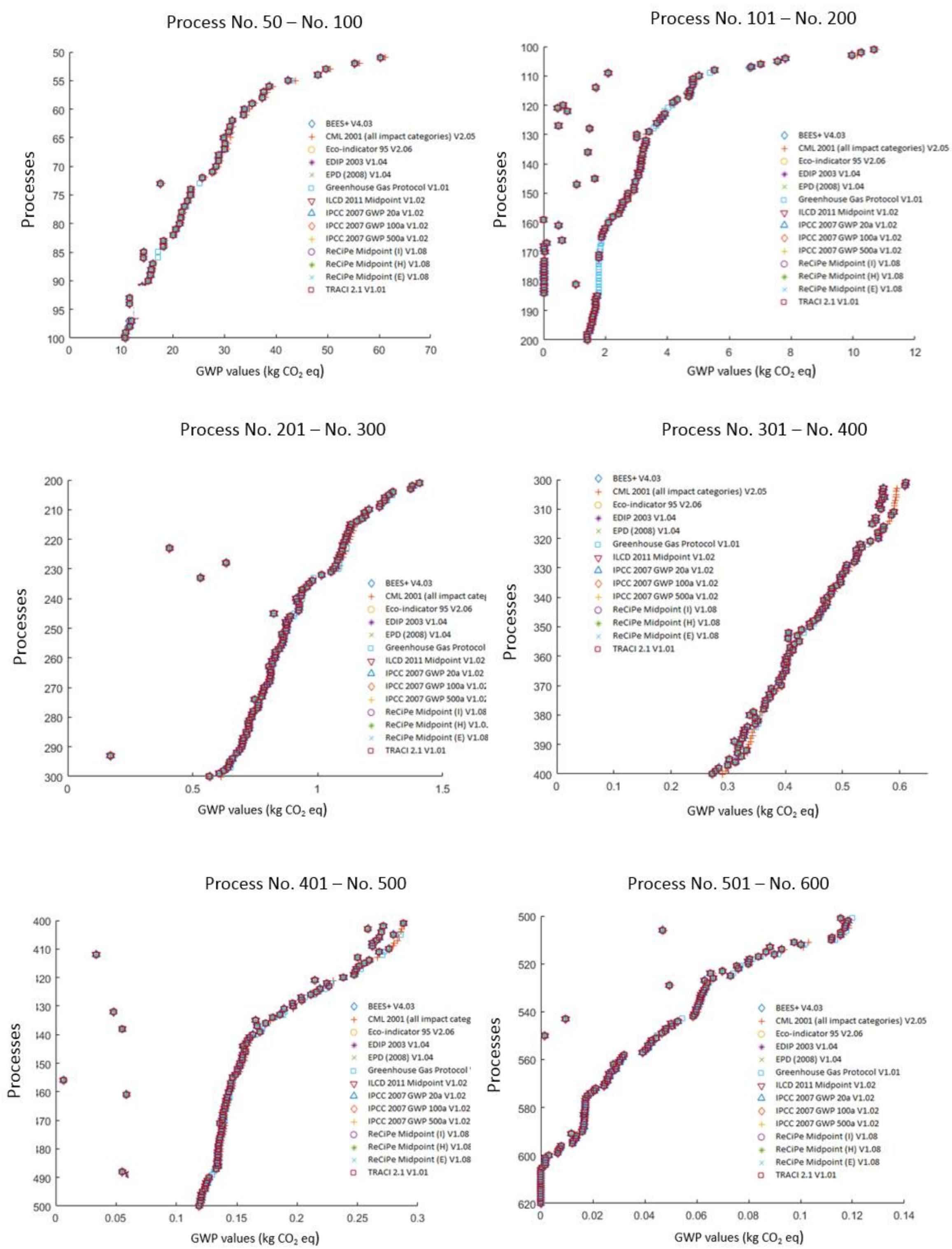


Figure 4-6: GW values in kg CO_2 eq per functional unit from 14 impact methods for processes No. 50 to No. 620. The processes are sorted from high to low by the total impact results including direct and indirect impacts. Other processes with zero GW impact from any of the methods are not shown.

The processes provided in Figure 4-5 and Figure 4-6 were sorted to visualize the uncertainties in all processes; however, the functional units of these processes are different, making comparisons of uncertainties between processes impossible. In addition, the processes from the same industry could have similar impacts. Thus, I also grouped the processes from the same industries together to enhance the interpretation of results. Figure 4-7, Figure 4-8 and Figure 4-9 provide GW impact results for three example categories: transportation, electricity, and plastic material. These three categories are chosen as examples because their processes have relatively similar attributes, such as upstream flows and downstream uses. The results show that within the three categories, the maximum and minimum impact values are generally from the same impact methods. IPCC 2007 20a often provides the largest GW impact, while ReCiPe Midpoint (I) results in the minimum impact value. These two methods cover the same numbers of substances, thus, the differences in the impact values were due to the differences in the characterization factor values.

For the GW impact category, different time intervals is one of the reasons for the discrepancies in the impact results. As shown in Figure 4-7, Figure 4-8 and Figure 4-9, for most of the processes, clearly there are three sets of GW impacts. They are the results from three GW time intervals: short (20 years), medium (100 years), and long term (500 years). The differences in the characterization factors are the sources of the variances in these three sets: for some of the substances, such as methane, the short term characterization factors are larger than the long term ones. This difference regarding the time span is due to the lifetime of a substance: if the substance can be removed from the atmosphere in a fairly short amount of time (less than 500 years), its characterization factor value decreases over years. Therefore, the impact results calculated from impact methods using different GW time intervals are different, they should be separately and clearly listed when provided to the users. In this study, I believe showing all results together with clearly listed legends can help the users to understand the differences caused by choosing different impact methods; listing all impact results together can also provide the differences caused by using different time intervals. When the methods are incorporated into LCA software, the results can be improved by introducing user interface features. In short, the software should aim to provide all possible impact results from different impact methods and clearly separate the results from different time intervals

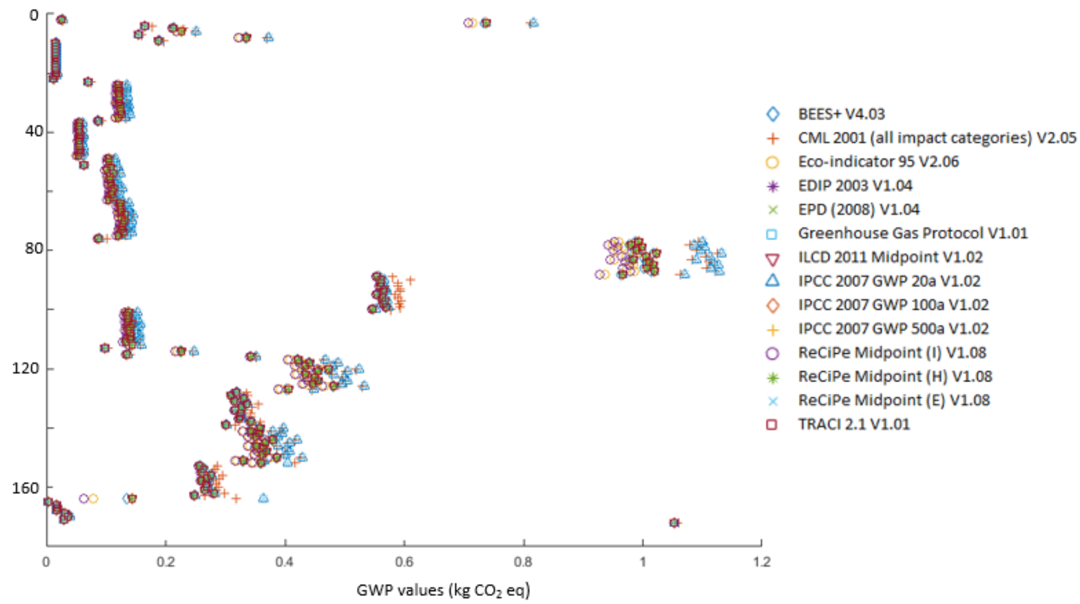


Figure 4-7: GW impact values in kg CO_2 eq per ton-km for 190 transportation processes in the US LCI database.

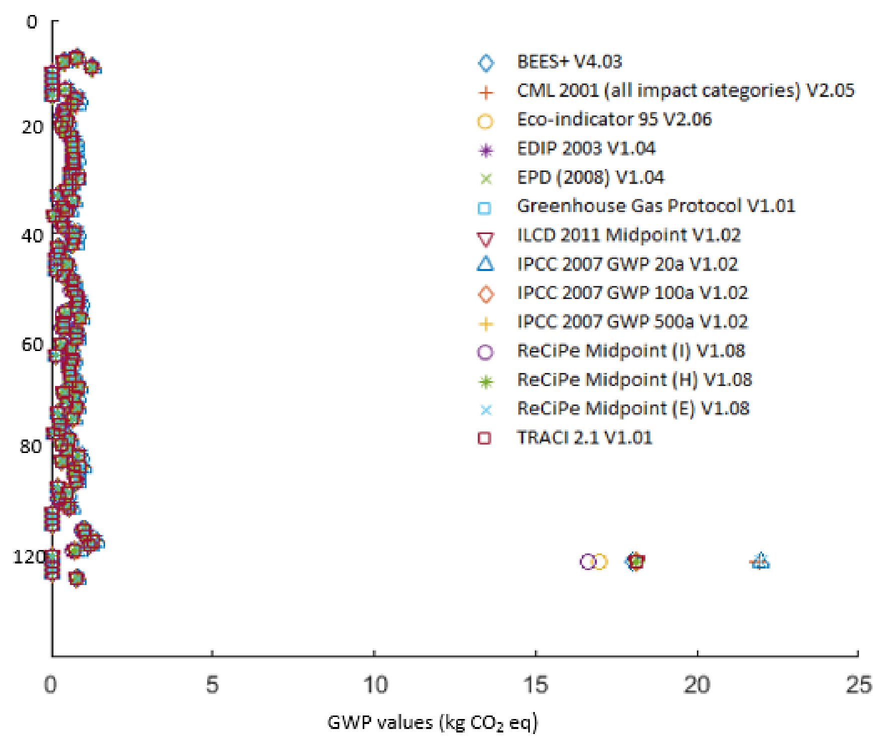


Figure 4-8: GW impact values in kg CO_2 eq per kWh for 98 electricity processes in the US LCI database.

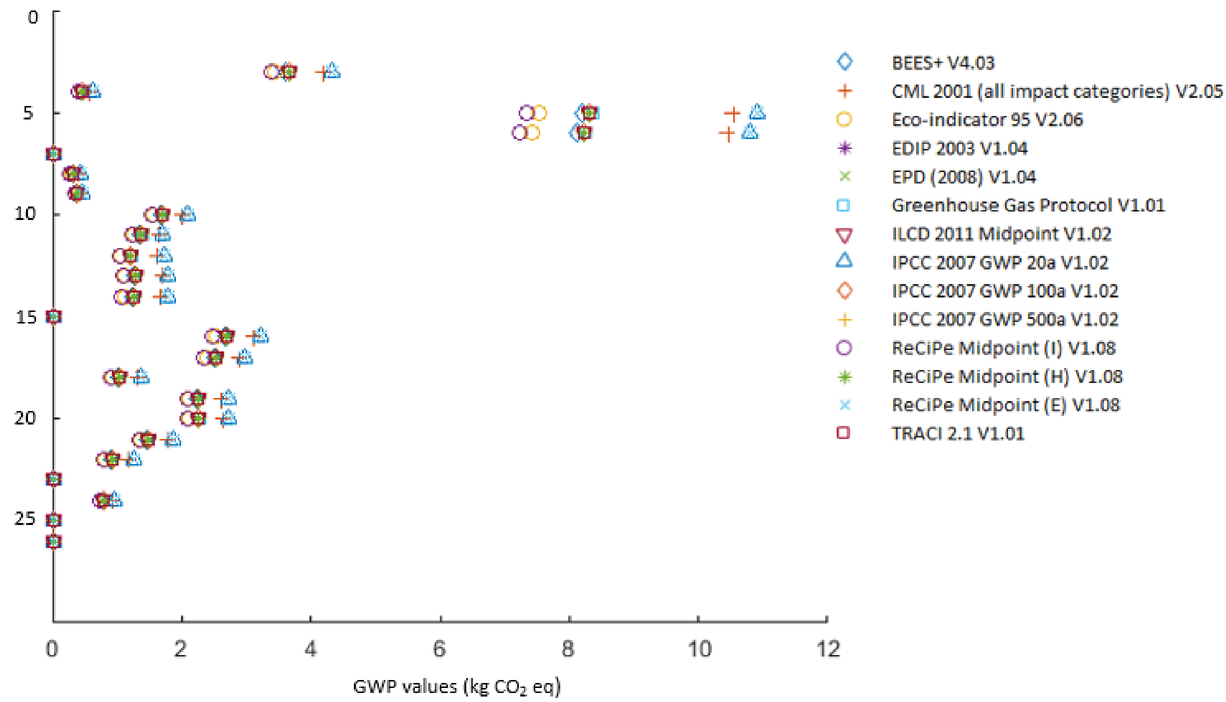


Figure 4-9: GW impact values in kg CO_2 eq per kg for 23 plastic material processes in the US LCI database

The results above were high-level summaries across all US LCI processes to demonstrate the variability in results from various GW methods. Showing the detailed results calculated from LCIA methods can help LCA practitioners to understand the uncertainties caused by selecting different impact methods, which is more easily understood when considering a single process (which is the type of decision a practitioner would make when putting together a study). As such, Figure 4-10 shows the GW impacts calculated from 14 different methods for an example process, "Crude palm kernel oil, at plant". The process was chosen because compared to most of the processes, it has a larger range of GW impact values. Among the 14 methods, two methods (CML2001, and GHG Protocol) cover different substances (see Table 4-6).

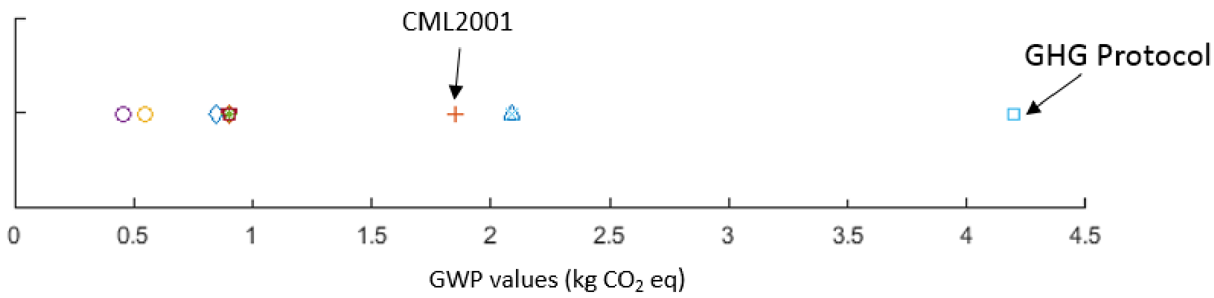


Figure 4-10: Total GW impacts for the "Crude palm kernel oil, at plant" process calculated from 14 different methods. Two of the 14 methods listed in the figure have different covered substances (The markers are the same as in Figure 4-5).

Table 4-7: GW substances for the "Crude palm kernel oil, at plant" process, and impacts for the substances calculated from 14 impact methods. The cells with larger values are highlighted with darker background.

Substances for "Crude palm kernel oil, at plant" process	BEES+ V4.03	CML 2001 V2.05	Eco-indicator 95 V2.06	EDIP 2003 V1.04	EPD (2008) V1.04	Greenhouse Gas Protocol V1.01	ILCD 2011 Midpoint V1.02	IPCC 2007 GWP 20a V1.02	IPCC 2007 GWP 100a V1.02	IPCC 2007 GWP 500a V1.02	ReCiPe Midpoint (I) V1.08	ReCiPe Midpoint (H) V1.08	ReCiPe Midpoint (E) V1.08	TRACI 2.1 V1.01
Carbon dioxide, biogenic						3.287								
Carbon dioxide, fossil	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266	0.266
Carbon monoxide		0.013				0.013								
Carbon monoxide, fossil		0.003												
Dinitrogen monoxide	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	9E-04	0.002	0.002	0.002
Ethane, 1,1,1-trichloro-, HCFC-140	1E-09	3E-09	7E-10	1E-09	1E-09	1E-09	1E-09	4E-09	1E-09	1E-09	3E-10	1E-09	4E-09	1E-09
Methane	0.577	1.554	0.276	0.627	0.627	0.627	0.627	1.805	0.627	0.627	0.191	0.627	1.805	0.627
Methane, dichloro-, HCC-30	4E-05	1E-04	6E-05	3E-05	3E-05	3E-05	3E-05	1E-04	3E-05	3E-05	1E-05	3E-05	1E-04	3E-05
Methane, dichlorodifluoro-, CFC-12	9E-08	9E-08	6E-08	9E-08	9E-08	9E-08	9E-08	1E-07	9E-08	9E-08	5E-08	9E-08	1E-07	9E-08
Methane, fossil	0.005	0.013	0.002	0.005	0.005	0.005	0.005	0.015	0.005	0.005	0.002	0.005	0.015	0.005
Methane, tetrachloro-, CFC-10	0.001	0.002	8E-04	8E-04	8E-04	8E-04	8E-04	0.002	8E-04	8E-04	3E-04	8E-04	0.002	8E-04
Total	**0.851**	**1.852**	**0.547**	**0.901**	**0.901**	**4.201**	**0.901**	**2.09**	**0.901**	**0.901**	**0.46**	**0.901**	**2.09**	**0.901**

Thus, the discrepancies between the remaining 12 methods are caused entirely by the differences in their characterization factors. As shown in Table 4-6, the larger value from the GHG Protocol method was caused by "Carbon dioxide, biogenic", a substance that was not included in any other methods. Because the impact value for this substance is 3.3 kg CO_2 eq, larger than the total GW impact calculated from all other methods, it causes an outlier in the total GW impact values. If this substance was not included, the GW impacts calculated from the GHG Protocol method would be 0.914 kg CO_2eq, which falls in the lower end of the impact range. On the other hand, the CML2001 method included two substances ("carbon monoxide" and "carbon monoxide, fossil") that were generally excluded from other methods. Here, by saying excluded, I mean that the chemicals were not shown in the list of substances of the method. However, because the impact values from these two substances were not large, the total impact results from the CML2001 method were within the range of other methods. It can be concluded that for this process, the discrepancies of the total impact results are caused by differences in: 1) the total emission values for the characterized substances in the $\boldsymbol{g}$ vector; 2) the coverages of substances in methods; and 3) the differences in the characterization factor values of the substances. From the example in Figure 4-10 and the results from all US LCI processes (Figure 4-6), I can generally conclude that the outliers of the impact results are often caused by the inclusion of certain unusual substances in a particular method. The ranges in the impact results can be attributed to the differences in the characterization factors.

It would be useful to incorporate visualizations, like those in Figure 4-10 and Table 4-6, as readily available tools in LCA software. These visualizations improve the understanding of the LCIA results by showing the main sources of discrepancies. I believe that these visualizations would enable LCIA users to make more robust decisions.

To better understand the correlation between the numbers of substances covered and the total impact results, I performed a regression analysis to test the relation between the numbers of characterized substances and the impact results.

In matrix-based models, the resulting emissions are calculated from a dot product between a vector of substances and a vector of processes (Equation 3). Suppose both vectors have p elements, where p is the number of substances from an environmental impact. To evaluate the scenario uncertainty, I considered alternatives for the vector of substances. However, sometimes the vector of substances has several missing entries; this number often changes with different scenarios. The proportion of completeness is defined as 1-(number of missing substances divided by p). Algebraically, the dot product is a sum of entry-wise products in two vectors; all things equal, this sum will be smaller if some entries are zeros. I decided to test the extent to which the results are affected by the proportion of substance completeness in our analysis. See Figure 4-11 for the case of Global Warming, three other environmental impacts are considered in Figure S1 of the Appendix. I first computed the proportion of substance completeness for multiple scenarios (denoted by marker color). Then I evaluated the resulting emissions under different processes (608 in this case). Because different process result in distinct magnitudes, I standardized the results of each process, i.e. I subtracted the average and divided by the standard deviation. The null hypothesis I tested is that a constant model is better than a linear model. A constant model (zero slope) represents the absence of a linear relationship between the results and the proportion of completeness. Using weighted least squares regression, I rejected the null hypothesis in favor of a non-zero slope (F statistic=479, df=8510, pValue<0.001). The regression weights were inversely proportional to the variance of repeated results within the domain of substance completeness proportion.

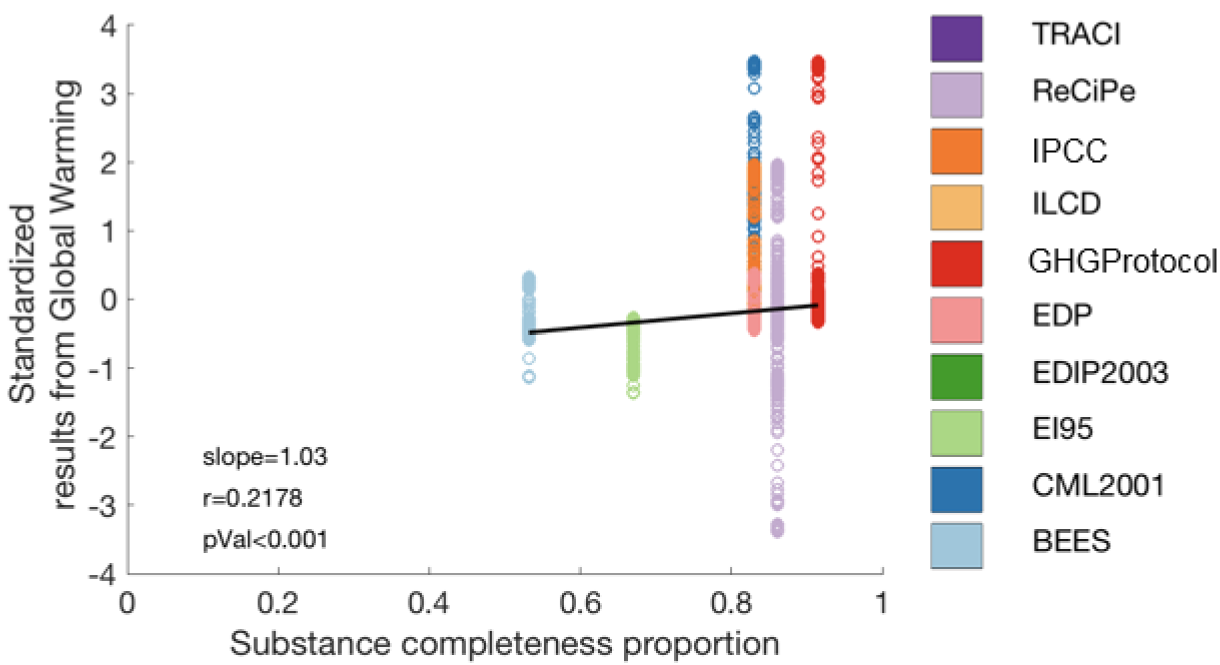


Figure 4-11: Testing the relation between the results from Global Warming and substance completeness proportions. The marker color indicates different alternative scenarios. The black line is the fit obtained from a linear weighted least squares regression.

Results from the regression analysis reject the null hypothesis in favor of a correlation between the numbers of substances with the impact results. Similar results are shown for other three impact categories (Eutrophication, Acidification, and Ozone depletion). From the regression figure, it can be seen that CML2001 and GHGProtocol methods result in higher GW impacts. Considering the results in Table 4-6, it could be possible that the larger values are caused by a few substances that are excluded from all other methods, such as the biogenetic carbon dioxide. It will be helpful to quantitatively identify the uncertainty from the coverage of substances and the differences in the characterization factors. However, the number of substances covered in the US LCI inventories are not large enough to include most of the substances provided by each impact method; most processes cover similar substances. Thus, the results of regression test (and other potential methods) are determined by only a few exceptions, such as the substances shown in Table 4-6. The conclusion made based on these results can be arbitrary. Future studies can focus on improving the estimation with more completed inventories.

4.5 Impact based inventory reporting criteria

As discussed previously, most inventories in the US LCI database do not have characterized substances in each impact category, and some of the exclusions can be confirmed as data gaps by introducing other data sources, such as EPA GHGRP. This lack of information results in potential neglects of impact values in the LCA results. Here, I introduce a new inventory reporting criterion. The criteria are developed with respect to the potential environmental impacts and informed by the analysis above. I believe this new impact based criteria can help LCA studies to build more robust inventories.

The proposed criteria are estimated based on the characterization factors of a substance and the knowledge of existing impacts from processes. Similar to the traditional cutoff criteria estimation, a certain ratio is used to regulate the minimum report impact value. The ratio can be defined according to the purpose of the studies, such as 5% (less strict), 1%, or 0.5% (stricter). Then, using the corresponding characterization factor, the minimum report impact value is converted to physical units of emissions. The estimation method is described in Equation 6. The criterion was the result of the impact values and the substance's characterization factor value. In Equation 6, $\mathbf{T}_{\boldsymbol{i}}$ is the new impact based criterion for a certain substance $\boldsymbol{i}$, $\mathbf{r}$ is a constant ratio, $\mathbf{P}$ is the environmental impact result for the process under study, and $\boldsymbol{CF_i}$ is the characterization factor.

Equation 6: $\mathbf{T}_{\boldsymbol{i}} = \frac{\mathbf{r} \times \mathbf{P}}{\boldsymbol{CF_i}}$

In this study, I determine $\mathbf{P}$ based on the impact values from existing LCA studies. For instance, the GW impact from the "Electricity, bituminous coal, at power plant" process is currently around $1\ \mathrm{kg\ CO_2eq}$ per kWh generation. Our new criteria rules that any substances with more than 0.05, 0.01, or 0.005 $\mathrm{kg\ CO_2eq}$ (5%, 1%, or 0.01% of the $1\ \mathrm{kg\ CO_2eq}$, respectively) GW impact should be ensured to be included in the inventory.

Table 4-7 shows the criteria estimation for the "Electricity, bituminous coal, at power plant" process. The criteria for all GW values were calculated referencing the current impact values in the bituminous coal electricity generation. In the current US LCI database, producing 1 kWh of electricity generated from bituminous coal results in 0.99 $\mathrm{kg\ CO_2eq}$ GW impacts, this value is used for $\mathbf{P}$ in Equation 6. To evaluate the results in two different situations, the ratio $\mathbf{r}$ was defined as 1% and 5%.

Because the maximum across all $\boldsymbol{CF_i's}$ results in the most extreme case of impact result, the maximum GW characterization factor ($\boldsymbol{CF}$) values from 14 methods were used to estimate the strict criteria. The average characterization factor values were used for general criteria estimation.

Table 4-8: Maximum characterization factor value and new cut-off criteria for each substance. Cut-off criteria were based on 5% and 1% of total GW for 1kWh "Electricity, bituminous coal, at power plant" The first 34 GW substances are shown as examples.

Substance name	Average CF value (kgCO2eq)	Max CF value (kgCO2eq)	General criteria, 5% of total impact (kg)	Strict criteria, 5% of total impact (kg)	General criteria, 1% of total impact (kg)	Strict criteria, 1% of total impact (kg)	Current values in the US LCI (kg)
1-Propanol, 3,3,3-trifluoro-2,2-bis(trifluoromethyl)-, HFE-7100	325	1040	2E-04	5E-05	3E-05	1E-05	
Butane, 1,1,1,3,3-pentafluoro-, HFC-365mfc	831	2520	6E-05	2E-05	4E-06	4E-06	
Butane, perfluoro-	6860	12500	7E-06	4E-06	8E-07	8E-07	
Butane, perfluorocyclo-, PFC-318	7980	14700	6E-06	3E-06	7E-07	7E-07	
Carbon dioxide	1	1	5E-02	5E-02	1E-02	1E-02	
Carbon dioxide, biogenic	0	1	7E-01	5E-02	1E-02	1E-02	
Carbon dioxide, fossil	1	1	5E-02	5E-02	1E-02	1E-02	9.9E-01
Carbon dioxide, in air	0	1	7E-01	5E-02	1E-02	1E-02	
Carbon dioxide, land transformation	1	1	5E-02	5E-02	1E-02	1E-02	
Carbon monoxide	0	2	2E-01	3E-02	6E-03	6E-03	
Carbon monoxide, biogenic	0	2	4E-01	3E-02	6E-03	6E-03	
Carbon monoxide, fossil	0	2	4E-01	3E-02	6E-03	6E-03	1E-04
Chlorinated fluorocarbons, hard	507	7100	1E-04	7E-06	1E-06	1E-06	
Chlorinated fluorocarbons, soft	114	1600	4E-04	3E-05	6E-06	6E-06	
Chloroform	45	108	1E-03	5E-04	9E-05	9E-05	
Cis-perfluorodecalin	3607	7500	1E-05	7E-06	1E-06	1E-06	
Dimethyl ether	1	1	6E-02	5E-02	1E-02	1E-02	
Dinitrogen monoxide	283	298	2E-04	2E-04	3E-05	3E-05	
Ethane, 1,1,1,2-tetrafluoro-, HFC-134a	1717	3830	3E-05	1E-05	3E-06	3E-06	
Ethane, 1,1,1-trichloro-, HCFC-140	208	506	2E-04	1E-04	2E-05	2E-05	
Ethane, 1,1,1-trifluoro-, HFC-143a	4174	5890	1E-05	8E-06	2E-06	2E-06	
Ethane, 1,1,2,2-tetrafluoro-, HFC-134	1138	3400	4E-05	1E-05	3E-06	3E-06	
Ethane, 1,1,2-trichloro-1,2,2-trifluoro-, CFC-113	1	1	6E-02	5E-02	1E-02	1E-02	
Ethane, 1,1,2-trifluoro-, HFC-143	283	298	2E-04	2E-04	3E-05	3E-05	
Ethane, 1,1-dichloro-1-fluoro-, HCFC-141b	1717	3830	3E-05	1E-05	3E-06	3E-06	
Ethane, 1,1-difluoro-, HFC-152a	208	506	2E-04	1E-04	2E-05	2E-05	
Ethane, 1,2-dibromotetrafluoro-, Halon 2402	4174	5890	1E-05	8E-06	2E-06	2E-06	
Ethane, 1,2-dichloro-1,1,2,2-tetrafluoro-, CFC-114	1138	3400	4E-05	1E-05	3E-06	3E-06	
Ethane, 1,2-difluoro-, HFC-152	5387	6540	9E-06	8E-06	2E-06	2E-06	
Ethane, 1-chloro-1,1-difluoro-, HCFC-142b	387	1240	1E-04	4E-05	8E-06	8E-06	
Ethane, 1-chloro-2,2,2-trifluoro-(difluoromethoxy)-, HCFE-235da2	943	2250	5E-05	2E-05	4E-06	4E-06	
Ethane, 2,2-dichloro-1,1,1-trifluoro-, HCFC-123	176	437	3E-04	1E-04	2E-05	2E-05	

Ethane, 2-chloro-1,1,1,2-tetrafluoro-, HCFC-124	1499	3680	3E-05	1E-05	3E-06	3E-06	
Ethane, chloropentafluoro-, CFC-115	8522	10000	6E-06	5E-06	1E-06	1E-06	
Ethane, fluoro-, HFC-161	58	187	9E-04	3E-04	5E-05	5E-05	
Ethane, hexafluoro-, HFC-116	2655	5490	2E-05	9E-06	2E-06	2E-06	
Ethane, pentafluoro-, HFC-125	383	1230	1E-04	4E-05	8E-06	8E-06	
Ether, 1,1,1-trifluoromethyl methyl-, HFE-143a	119	390	4E-04	1E-04	3E-05	3E-05	
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347mcc3	831	2070	6E-05	2E-05	5E-06	5E-06	
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347mcf2	6534	9990	8E-06	5E-06	1E-06	1E-06	
Ether, 1,1,2,2-Tetrafluoroethyl 2,2,2-trifluoroethyl-, HFE-347pcf2	13	43	4E-03	1E-03	2E-04	2E-04	
Ether, 1,1,2,2-Tetrafluoroethyl methyl-, HFE-254cb2	9947	18200	5E-06	3E-06	5E-07	5E-07	
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356mec3	3650	6350	1E-05	8E-06	2E-06	2E-06	
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcc3	824	2630	6E-05	2E-05	4E-06	4E-06	
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcf2	624	1980	8E-05	3E-05	5E-06	5E-06	
Ether, 1,1,2,3,3,3-Hexafluoropropyl methyl-, HFE-356pcf3	409	1310	1E-04	4E-05	8E-06	8E-06	
Ether, 1,2,2-trifluoroethyl trifluoromethyl-, HFE-236ea2	615	1900	8E-05	3E-05	5E-06	5E-06	
Ether, 1,2,2-trifluoroethyl trifluoromethyl-, HFE-236fa	393	1260	1E-04	4E-05	8E-06	8E-06	
Ether, 2,2,3,3,3-Pentafluoropropyl methyl-, HFE-365mcf3	111	355	4E-04	1E-04	3E-05	3E-05	
Ether, di(difluoromethyl), HFE-134	120	386	4E-04	1E-04	3E-05	3E-05	
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245cb2	290	931	2E-04	5E-05	1E-05	1E-05	
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245fa1	549	1760	9E-05	3E-05	6E-06	6E-06	
Ether, difluoromethyl 2,2,2-trifluoroethyl-, HFE-245fa2	1068	3370	5E-05	1E-05	3E-06	3E-06	
Ether, ethyl 1,1,2,2-tetrafluoroethyl-, HFE-374pc2	533	1710	9E-05	3E-05	6E-06	6E-06	
Ether, nonafluorobutane ethyl-, HFE569sf2 (HFE-7200)	12	41	4E-03	1E-03	2E-04	2E-04	
Ether, pentafluoromethyl-, HFE-125	5494	12200	9E-06	4E-06	8E-07	8E-07	
Hexane, perfluoro-	769	2440	6E-05	2E-05	4E-06	4E-06	
HFE-227EA	314	1010	2E-04	5E-05	1E-05	1E-05	
HFE-236ca12 (HG-10)	717	2280	7E-05	2E-05	4E-06	4E-06	
HFE-263fb2	606	1930	8E-05	3E-05	5E-06	5E-06	
HFE-329mcc2	65	207	8E-04	2E-04	5E-05	5E-05	
HFE-338mcf2	11092	14900	4E-06	3E-06	7E-07	7E-07	
HFE-338pcc13 (HG-01)	7207	13300	7E-06	4E-06	7E-07	7E-07	
HFE-43-10pccc124 (H-Galden1040x)	1562	4540	3E-05	1E-05	2E-06	2E-06	
Hydrocarbons, chlorinated	2804	8000	2E-05	6E-06	1E-06	1E-06	
Methane	12	38	4E-03	1E-03	3E-04	3E-04	
Methane, biogenic	982	3060	5E-05	2E-05	3E-06	3E-06	
Methane, bromo-, Halon 1001	602	1920	8E-05	3E-05	5E-06	5E-06	

Methane, bromochlorodifluoro-, Halon 1211	1619	5100	3E-05	1E-05	2E-06	2E-06	
Methane, bromodifluoro-, Halon 1201	2012	6320	2E-05	8E-06	2E-06	2E-06	
Methane, bromotrifluoro-, Halon 1301	3	28	2E-02	2E-03	4E-04	4E-04	
Methane, chlorodifluoro-, HCFC-22	32	72	2E-03	7E-04	1E-04	1E-04	
Methane, chlorotrifluoro-, CFC-13	29	69	2E-03	7E-04	1E-04	1E-04	
Methane, dibromo-	7	17	7E-03	3E-03	6E-04	6E-04	
Methane, dichloro-, HCC-30	2407	4900	2E-05	1E-05	2E-06	2E-06	6E-08
Methane, dichlorodifluoro-, CFC-12	437	1380	1E-04	4E-05	7E-06	7E-06	
Methane, dichlorofluoro-, HCFC-21	6896	8480	7E-06	6E-06	1E-06	1E-06	
Methane, difluoro-, HFC-32	2389	5160	2E-05	1E-05	2E-06	2E-06	
Methane, fluoro-, HFC-41	12586	16400	4E-06	3E-06	6E-07	6E-07	
Methane, fossil	2	5	3E-02	9E-03	2E-03	2E-03	8E-06
Methane, iodotrifluoro-	14	35	4E-03	1E-03	3E-04	3E-04	
Methane, monochloro-, R-40	10164	11000	5E-06	5E-06	9E-07	9E-07	
Methane, tetrachloro-, CFC-10	165	530	3E-04	9E-05	2E-05	2E-05	
Methane, tetrafluoro-, CFC-14	862	2330	6E-05	2E-05	4E-06	4E-06	
Methane, trichlorofluoro-, CFC-11	101	323	5E-04	2E-04	3E-05	3E-05	
Methane, trifluoro-, HFC-23	32	72	2E-03	7E-04	1E-04	1E-04	
Nitrogen fluoride	0	1	1E-01	5E-02	1E-02	1E-02	
Pentane, 2,3-dihydroperfluoro-, HFC-4310mee	19	55	3E-03	9E-04	2E-04	2E-04	
Pentane, dodecafluoro-, PFC-4-1-12	1631	2700	3E-05	2E-05	4E-06	4E-06	
Pentane, perfluoro-	6774	11200	7E-06	4E-06	9E-07	9E-07	
PFC-9-1-18	4484	6730	1E-05	7E-06	1E-06	1E-06	
PFPMIE	11714	14800	4E-06	3E-06	7E-07	7E-07	
Propane, 1,1,1,2,2,3-hexafluoro-, HFC-236cb	13064	20700	4E-06	2E-06	5E-07	5E-07	
Propane, 1,1,1,2,3,3,3-heptafluoro-, HFC-227ea	1564	4140	3E-05	1E-05	2E-06	2E-06	
Propane, 1,1,1,2,3,3-hexafluoro-, HFC-236ea	2069	13300	2E-05	4E-06	7E-07	7E-07	
Propane, 1,1,1,3,3,3-hexafluoro-, HCFC-236fa	7114	13300	7E-06	4E-06	7E-07	7E-07	
Propane, 1,1,1,3,3-pentafluoro-, HFC-245fa	2143	9500	2E-05	5E-06	1E-06	1E-06	
Propane, 1,1,2,2,3-pentafluoro-, HFC-245ca	7860	12400	6E-06	4E-06	8E-07	8E-07	
Propane, 1,3-dichloro-1,1,2,2,3-pentafluoro-, HCFC-225cb	1313	3630	4E-05	1E-05	3E-06	3E-06	
Propane, 3,3-dichloro-1,1,1,2,2-pentafluoro-, HCFC-225ca	2673	5310	2E-05	9E-06	2E-06	2E-06	
Propane, perfluoro-	1397	4090	4E-05	1E-05	2E-06	2E-06	
Propane, perfluorocyclo-	7310	9810	7E-06	5E-06	1E-06	1E-06	
Sulfur hexafluoride	1094	3380	5E-05	1E-05	3E-06	3E-06	
Trifluoromethylsulfur pentafluoride	745	2340	7E-05	2E-05	4E-06	4E-06	

Under the impact based inventory reporting criteria, the data reporters of LCA studies can be motivated to provide more potential substances in the inventories. In this way, the inventories can be improved and larger impact results can be expected. However, it is possible that after including more emissions, the environmental impact rises significantly, making the 1% or 5% total impact criteria larger than the original value. The larger criteria can result in the exclusions of emissions that are currently included. As a result, the new impact based criteria needs to be improved. However, based on the inventories in the current US LCI database, I am not able to decide how many new substances are going to be included and how much they are going to contribute to the total impact. Thus, the impact based criteria requires continued development.

4.6 Discussion

This study compared different commonly used impact assessment methods along with their impact categories. The substances in the elementary flows were identified to show the coverages of substances in LCI databases and it was found that different impact methods provided different coverages of impact categories and substances, as well as different characterization factor values. Considering five impact categories, around 50% of the US LCI elementary flows are not substances in the impact methods. Based on each process, when another data sources is used as a reference, some GW substance are missing from the inventory. These results could help the LCA practitioners better understand current situations in LCIA analyses.

The substances in the indirect effects in some cases can be much larger than the ones in the direct effects. This shows the effectiveness of a matrix-based LCA model in estimating indirect effects and impacts. The total (direct and indirect) impact of a gate-to-gate process is approximately the same as the impact of cradle-to-gate processes for the same product. This suggests that cradle-to-gate processes are not necessary when using a matrix-based model because the matrix model can sufficiently provide all upstream effects and impacts.

To conduct an LCIA, the LCA practitioners often select one impact method and rarely compare results from different methods. Typically, there is no awareness of what the results might be under different methods. In LCA software, the choice of the method is left to the discretion of the user. Consequently, if the users do not understand the potential impacts of choosing one method over another for the particular analysis, then one could accidently choose an inappropriate method. For example, a method with inappropriate GW time interval might be chosen for a study with a particular time scope. . There is also a danger of confirmation bias. The users could choose a method that supports the preconception and fails to investigate other possible alternatives. The consequences can be problematic. The impact results calculated from different methods show that the discrepancies can be large. The sources of discrepancies can be traced to different coverages and characterization factors in the substances. The wrong choice of a method may result in wrong decisions. To overcome these issues, I recommend new visualization tools that provide a rich description of the LCIA methods and show results comparing different impact methods. By providing readily available visualization tools in LCA software like SimaPro, the users would be able to make more robust decisions based on the observed ranges.

I showed that substances with large characterization factors are not necessarily included in the inventory of a process. To understand the exclusions, I used EPA's GHGRP as a reference to identify possible data gaps in the US LCI inventories. The results show that some processes have missing GW substances; this issue should be addressed when updating the database. No other reference can be found to identify possible gaps in other impact categories; however, the database should focus on improving the inventories to avoid data gaps in the GW category. A more specific cutoff criteria with respect to impact assessment results should be encouraged to LCI data reporters.

5. Chapter 5. Conclusions and future work

In this chapter, I provide brief answers to the research questions listed in chapter 1. I also provide a general conclusion, discussion, and future work.

5.1 Research question and answers

Chapter 2. Parameter uncertainty in the EIO-LCA model

- *What are the uncertainty ranges of direct and indirect life cycle energy consumptions over the supply chain of the U.S. industries based on economic input-output models with public available data?*
  In chapter 1, the uncertainty of energy consumptions in the US industries were evaluated based on multiple data sources and range methods. The results show that the uncertainty of direct life cycle energy consumption in the US industries is generally around 50%, with some extreme cases that reach over 40 times the default value. Considering the indirect energy consumption, the overall uncertainty of each industry is smaller. The total energy consumption, considering all 428 industries, is generally within -40% to 40%, with a few extreme cases that have over 4 times more impact.

- *What is the impact of each individual industry's uncertainty on results of other industries?*
  Based on the uncertainty results from the first research question, the industries with large discrepancies in the direct energy consumption were identified. The impacts from these industries on the total energy consumption was estimated.
  The results show that the uncertainties from each industry affect the uncertainties in the model differently. The top five industries that have the strongest impacts are: power generation and supply, petroleum refineries, oil and gas extraction, iron and steel mills, and coal mining.

- *Which industries have the largest uncertainties in the model? How to reduce the uncertainties of these industries?*

The results show that Coal mining sector and Petroleum lubricating oil and grease manufacturing sectors have the largest uncertainties (over 500% larger compared with default) in the direct energy consumptions. The total energy consumption value for Coal mining varies from 5 to 70 TJ/M$, and Petroleum lubricating oil and grease manufacturing varies from 3 to 110 TJ/M$. The reasons for their large uncertainty in total consumption values can be traced to the large discrepancies in the direct consumption, which are caused by problematic documented data.

Chapter 3. Data analysis in the US LCI database and scenario uncertainty in matrix-based models

- *In the current US LCI database, how many processes flows contribute to the indirect environmental effects when applied to matrix-based LCA models?*
  In this chapter, I assume that the gate-to-gate processes restricted by two criteria can contribute to the indirect effects when incorporated to matrix-based LCA models. The two criteria are: 1) processes with at least one upstream or downstream connection; and 2) processes that include energy and transportation in their direct inputs. By evaluating each process individually, I found that there are only 61 processes that meet these criteria. This indicates that less than 5% of processes in the US LCI database contribute to the indirect effects in matrix-based LCA models.

- *What are the total CO_2 emissions ranges from US industrial processes by considering different scenarios from current process-based life cycle inventory databases?*
  The scenario uncertainties for the processes in the US LCI database were analyzed by using alternative inputs as different scenarios. The results show that by using different utility inputs as alternatives, the scenario uncertainties are generally within -20% and 20%, with some outliers.

- *What are the ranges of total CO_2 emissions ranges from aggregated US industrial processes calculated from current process-based life cycle inventory databases?*

Bigger scenario uncertainties are observed by using different processes as alternatives within the same industrial category. One example industry shows that the CO_2 emissions for 1 kg of industrial product can vary between 0 and 400 kg.

Chapter 4. LCIA uncertainty in a process-based LCI database

- *In current LCIA methods, how many substances are covered? How many of these substances are included in elementary flows in the US LCI database? Does the US LCI database have enough flows that are characterized in impact assessment methods to build a robust inventory?*

  I examined the 50 LCIA methods summarized in the SimaPro software. The results show that the numbers of substances across impact categories vary significantly: from as few as 18 substances to as many as 30,514 substances. Within the same impact category, the numbers of substances covered by each method are generally similar, with a few exceptions. For each of the five categories used in this study, less than 50% of its characterized substances were included in the US LCI database. This result indicates that the US LCI database does not have a robust inventory for LCIA studies.

- *For processes in current process-based LCA databases, what are the uncertainties of direct and indirect environmental impacts caused by different impact characterization factors used in LCIA?*

  The results generally show that 80% of the gate-to-gate processes have less than 5% uncertainties, with respect to choosing different impact assessment methods. However, these small uncertainties are estimated based on insufficient US LCI inventories, the uncertainty results do not justify small uncertainties in the model.

- *What are the contributions of different characterization factor values and coverages of substances from different methods to the LCA result?*

  The results show that based on individual cases, the different coverage of substances does not have strong impacts on the total results. However, a statistical study rejected the possibility of independency in favor of a linear relationship between the number of substances and the total impact values.

- *What should be the new reported value in LCI for different substances considering impact assessment results?*

  I propose a new minimum data report criteria based on LCIA results. The proposed criteria regulates that all emissions from substances should be taken into consideration and measured before reporting an LCI database. An example result show that considering global warming impacts, the minimum reported value (by mass) can be as small as 5E-7 kg for 1kg electricity production. However, this value is larger than the minimum reported value for the same process in the current US LCI database.

5.2 Conclusion

This dissertation examines the uncertainties in the matrix-based LCA models. Three types of uncertainties (parameter, scenario, and model) are considered and evaluated based on two types of matrix-based LCA models: the input-output, and process-based LCA. With a range method, I estimated the uncertainties of two environmental effects (greenhouse gas emissions and energy consumptions) and five environmental impacts (global warming, ozone depletion, acidification, eutrophication and ecotoxicity) in matrix-based LCA models.

In chapter 2, I examine the parameter uncertainty and use the range method to propagate the uncertainty in the EIO-LCA model. Publicly available data sources and value-converting assumptions are used to estimate the parameter uncertainties in the direct industrial energy consumption. The total (including indirect) energy consumption ranges are estimated through the matrix-based LCA model. The results show that the parameter uncertainties can be large in IO based LCA models. The uncertainties can be traced to individual industries and reduced by improving the raw data.

In chapter 3, I estimate the scenario uncertainties in matrix-based LCA by using alternative inputs in the US LCI database. By examining the processes, I find the US LCI database fails to provide well-connected processes to take full advantage of matrix-based method. Based on our definition, less than 10% of the processes in the database are well-connected so that they contribute to the indirect environmental effects when incorporated to matrix-based LCA models. I also estimated the scenario uncertainty in the model with the range method. The results show that the scenario uncertainties of each process caused by using different electricity or transportation inputs are smaller compared to the parameter uncertainties estimated from chapter 1. However, the industrial level uncertainties are much larger, due to the incompleteness of the database.

The model uncertainty in matrix-based LCA models is addressed in chapter 4. Model uncertainty refers to the differences in LCIA methods. The same range method is used to estimate the variances in the environmental impact results for each US LCI process. In the LCIA methods selected for this study, I compare the differences in the coverages of substances and characterization factor values, and identified the number of substances in the US LCI elementary flows. The results show that the model uncertainty due to different choices of impact methods in the US LCI database is small, negligible in most of the processes. However, as the US LCI database does not have a robust inventory to support LCIA analysis, most of the processes do not include enough substances in their inventories. The impact values are the results from a few substances in the database, thus, I cannot conclude that the difference in impact methods has negligible effect on the total impact results. Aiming to improve the database, I propose new criteria to regulate minimum report inventory values. The criteria are estimated based on the impact results as well as the characterization factors for each substance.

The parameter, scenario, and model uncertainty together contribute to the uncertainty in matrix-based LCA models. The results in matrix-based LCA models generally show considerable uncertainties in the total energy consumption and GHG emission across most US industries. However, current LCA software fail to provide users with these uncertainties. The users often ignore the uncertainties in the data and model. LCA software is developed to assist LCA studies, which are in turn designed for making decisions based on quantitative results. When the uncertainties are ignored, LCA software can only provide deterministic results that lead to subjective decisions.

Furthermore, the analyses on the US LCI inventories indicate a potential problem in the LCI databases. The LCI database is widely applied to matrix-based LCA models for estimating total environmental effects and impacts. However, I find several problems in the current LCI database. These problems limit the advantages of matrix-based LCA models. The two biggest problems are inconsistencies in processes and incomplete inventories. Inconsistencies in processes are generally caused by including processes with different system boundaries in the same database. For example, cradle-to-gate processes and gate-to-gate processes are both included in the database. The incompleteness in the inventories can be found in both product flows and elementary flows. Processes are generally not connected in the database, resulting in the neglect of indirect effects. On the other hand, though the total number of elementary flows covered in the database is large, most of the substances that generate large environmental effects are excluded from the inventories. These types of incompleteness results in ignoring important effects and/or impacts; however, the LCA practitioners are often unaware of these problems when using the database.

In conclusion, the uncertainties in matrix-based LCA models can be large; however, they are easily ignored by LCA practitioners. Future LCI databases should focus on including better inventories as well as uncertainties in the inventories. LCA software should aim to provide better uncertainty estimation methods and results to the users.

5.3 Future work

5.3.1 Analyze the uncertainties of other environmental effects in the matrix-based LCA models

In this dissertation, the uncertainties in energy consumption and carbon dioxide emissions were analyzed for EIO-LCA model and the US LCI database, respectively. The same uncertainty estimation method introduced in this study can be applied to other environmental effects to both of the models as well as other matrix-based LCA models. For example, the uncertainty of carbon dioxide emissions in the EIO-LCA model can be evaluated next.

5.3.2 Quantify the relationship between the technology matrix and the environmental matrix

In this study, the uncertainties were separately evaluated for the technology matrix and environmental effect matrix. Due to the limitation of the database (only a few portion of the processes are connected), I have not traced the sources of the uncertainties to these two individual matrices. Future work can focus on quantitatively analyze the contributions from these two matrices to the overall uncertainty.

5.3.3 Estimate scenario uncertainty using other LCI databases

The US LCI database was used to demonstrate the methods and results in this dissertation. Future work can focus on identify the problems and estimate uncertainties with other LCI database, such as Ecoinvent. Ecoinvent has more than 10 thousand processes and elementary flows, if these processes are better connected, there can be more scenarios available. For example, except utility and transportation industry, similar processes within metal, plastic material production industries can be used as alternatives.

5.3.4 Test the correlation between number of substances covered and the total impact results

In this study, I tested the correlation between the numbers of substances and the impact results. The preliminary results were based on insufficient LCI data. Future work can repeat the same test on other LCI databases that include more substances. The conclusions from the regression tests could change. Furthermore, another parameter, the differences in the characterization factors can be used in the regression test. The results can provide quantitative conclusions on the effects of LCIA methods on a statistical perspective.

5.3.5 Improving the minimum report value criteria

The minimum report value criteria introduced in this study need to be improved. More inventory data that covers more substances should be used for estimating the criteria. With the real-life inventory data, control tests can be performed to test how the new criteria impact on the report of new inventories; on the other hand, sensitivity analysis can be applied for analyzing the impact from the new reported inventory to the future updates of the criteria.

Appendix

Table S1: IO industry code, name, and uncertainty ranges

Sector No.	IO No.	Name	Uncertainties	
1	1111A0	Oilseed farming	2%	-83%
2	1111B0	Grain farming	34%	-78%
3	111200	Vegetable and melon farming	20%	-54%
4	111335	Tree nut farming	14%	-54%
5	1113A0	Fruit farming	11%	-55%
6	111400	Greenhouse and nursery production	101%	-43%
7	111910	Tobacco farming	14%	-79%
8	111920	Cotton farming	13%	-73%
9	1119A0	Sugarcane and sugar beet farming	55%	-59%
10	1119B0	All other crop farming	102%	-55%
11	112120	Milk Production	18%	-62%
12	1121A0	Cattle ranching and farming	23%	-78%
13	112300	Poultry and egg production	152%	-55%
14	112A00	Animal production, except cattle and poultry and eggs	9%	-71%
15	113300	Logging	0%	-97%
16	113A00	Forest nurseries, forest products, and timber tracts	0%	-89%
17	114100	Fishing	0%	-100%
18	114200	Hunting and trapping	0%	-76%
19	115000	Agriculture and forestry support activities	0%	-69%
20	211000	Oil and gas extraction	13%	-76%
21	212100	Coal mining	1251%	-75%
22	212210	Iron ore mining	15%	-48%
23	212230	Copper, nickel, lead, and zinc mining	29%	-69%
24	2122A0	Gold, silver, and other metal ore mining	77%	-72%
25	212310	Stone mining and quarrying	92%	-69%
26	212320	Sand, gravel, clay, and refractory mining	70%	-48%
27	212390	Other nonmetallic mineral mining	75%	-44%
28	213111	Drilling oil and gas wells	139%	-94%
29	213112	Support activities for oil and gas operations	127%	-95%
30	21311A	Support activities for other mining	135%	-87%
31	221100	Power generation and supply	1%	-33%

32	221200	Natural gas distribution	0%	-16%
33	221300	Water, sewage and other systems	0%	-27%
34	230101	Nonresidential commercial and health care structures	18%	-87%
35	230102	Nonresidential manufacturing structures	2%	-87%
36	230103	Other nonresidential structures	33%	-89%
37	230201	Residential permanent site single- and multi-family structures	27%	-84%
38	230202	Other residential structures	28%	-84%
39	230301	Nonresidential maintenance and repair	35%	-89%
40	230302	Residential maintenance and repair	35%	-92%
41	311111	Dog and cat food manufacturing	77%	-10%
42	311119	Other animal food manufacturing	83%	-9%
43	311210	Flour milling and malt manufacturing	80%	-7%
44	311221	Wet corn milling	35%	-46%
45	311225	Fats and oils refining and blending	80%	-10%
46	31122A	Soybean and other oilseed processing	69%	-16%
47	311230	Breakfast cereal manufacturing	73%	-12%
48	311313	Beet sugar manufacturing	31%	-34%
49	31131A	Sugar cane mills and refining	27%	-28%
50	311320	Confectionery manufacturing from cacao beans	74%	-8%
51	311330	Confectionery manufacturing from purchased chocolate	79%	-8%
52	311340	Nonchocolate confectionery manufacturing	80%	-8%
53	311410	Frozen food manufacturing	73%	-10%
54	311420	Fruit and vegetable canning, pickling and drying	84%	-10%
55	311513	Cheese manufacturing	80%	-8%
56	311514	Dry, condensed, and evaporated dairy products	78%	-10%
57	31151A	Fluid milk and butter manufacturing	89%	-8%
58	311520	Ice cream and frozen dessert manufacturing	77%	-5%
59	311615	Poultry processing	61%	-15%
60	31161A	Animal (except poultry) slaughtering and processing	79%	-9%
61	311700	Seafood product preparation and packaging	91%	-9%
62	311810	Bread and bakery product manufacturing	90%	-9%
63	311820	Cookie, cracker and pasta manufacturing	79%	-8%
64	311830	Tortilla manufacturing	96%	-10%
65	311910	Snack food manufacturing	79%	-10%
66	311920	Coffee and tea manufacturing	80%	-9%
67	311930	Flavoring syrup and concentrate manufacturing	83%	-9%
68	311940	Seasoning and dressing manufacturing	74%	-9%
69	311990	All other food manufacturing	92%	-9%

70	312110	Soft drink and ice manufacturing	63%	-7%
71	312120	Breweries	58%	-12%
72	312130	Wineries	77%	-6%
73	312140	Distilleries	51%	-11%
74	3122A0	Tobacco product manufacturing	198%	-49%
75	313100	Fiber, yarn, and thread mills	19%	-20%
76	313210	Broadwoven fabric mills	21%	-25%
77	313220	Narrow fabric mills and schiffli embroidery	39%	-29%
78	313230	Nonwoven fabric mills	21%	-32%
79	313240	Knit fabric mills	33%	-28%
80	313310	Textile and fabric finishing mills	34%	-30%
81	313320	Fabric coating mills	39%	-32%
82	314110	Carpet and rug mills	29%	-34%
83	314120	Curtain and linen mills	37%	-30%
84	314910	Textile bag and canvas mills	41%	-31%
85	314990	All other miscellaneous textile product mills	23%	-34%
86	315100	Hosiery and sock mills	144%	-16%
87	315210	Cut and sew apparel contractors	219%	-13%
88	315220	Men's and boys' cut and sew apparel manufacturing	152%	-14%
89	315230	Women's and girls' cut and sew apparel manufacturing	264%	-18%
90	315290	Other cut and sew apparel manufacturing	119%	-7%
91	315900	Accessories and other apparel manufacturing	338%	-21%
92	316100	Leather and hide tanning and finishing	72%	-16%
93	316200	Footwear manufacturing	65%	-24%
94	316900	Other leather and allied product manufacturing	58%	-42%
95	321100	Sawmills and wood preservation	19%	-11%
96	321219	Reconstituted wood product manufacturing	27%	-12%
97	32121A	Veneer and plywood manufacturing	12%	-5%
98	32121B	Engineered wood member and truss manufacturing	9%	-5%
99	321910	Wood windows and doors and millwork	31%	-13%
100	321920	Wood container and pallet manufacturing	60%	-21%
101	321991	Manufactured home, mobile home, manufacturing	27%	-13%
102	321992	Prefabricated wood building manufacturing	30%	-13%
103	321999	Miscellaneous wood product manufacturing	38%	-13%
104	322110	Pulp mills	10%	-8%
105	322120	Paper mills	11%	-17%
106	322130	Paperboard Mills	10%	-11%
107	322210	Paperboard container manufacturing	88%	-8%

108	32222A	Coated and laminated paper, packaging materials, and plastic films manufacturing	48%	-3%
109	32222B	All other paper bag and coated and treated paper manufacturing	47%	-3%
110	322230	Stationery product manufacturing	53%	-2%
111	322291	Sanitary paper product manufacturing	35%	-10%
112	322299	All other converted paper product manufacturing	52%	-3%
113	323110	Printing	80%	-7%
114	323120	Support activities for printing	57%	-5%
115	324110	Petroleum refineries	82%	-66%
116	324121	Asphalt paving mixture and block manufacturing	1267%	-19%
117	324122	Asphalt shingle and coating materials manufacturing	2013%	-29%
118	324191	Petroleum lubricating oil and grease manufacturing	4233%	-54%
119	324199	All other petroleum and coal products manufacturing	466%	-86%
120	325110	Petrochemical manufacturing	30%	-40%
121	325120	Industrial gas manufacturing	51%	-30%
122	325130	Synthetic dye and pigment manufacturing	214%	-49%
123	325181	Alkalies and chlorine manufacturing	27%	-60%
124	325182	Carbon black manufacturing	110%	-72%
125	325188	All other basic inorganic chemical manufacturing	25%	-33%
126	325190	Other basic organic chemical manufacturing	64%	-31%
127	325211	Plastics material and resin manufacturing	39%	-61%
128	325212	Synthetic rubber manufacturing	60%	-32%
129	325220	Artificial and synthetic fibers and filaments manufacturing	125%	-50%
130	325310	Fertilizer Manufacturing	114%	-2%
131	325320	Pesticide and other agricultural chemical manufacturing	134%	-49%
132	325411	Medicinal and botanical manufacturing	208%	-46%
133	325412	Pharmaceutical preparation manufacturing	85%	-41%
134	325413	In-vitro diagnostic substance manufacturing	112%	-27%
135	325414	Biological product (except diagnostic) Manufacturing	65%	-39%
136	325510	Paint and coating manufacturing	127%	-42%
137	325520	Adhesive manufacturing	711%	-64%
138	325610	Soap and cleaning compound manufacturing	140%	-46%
139	325620	Toilet preparation manufacturing	129%	-43%
140	325910	Printing ink manufacturing	957%	-69%
141	3259A0	All other chemical product and preparation manufacturing	212%	-55%
142	326110	Plastics packaging materials, film and sheet	28%	-11%
143	326121	Unlaminated plastics profile shape manufacturing	34%	-7%
144	326122	Plastics Pipe and Pipe Fitting Manufacturing	20%	-8%
145	326130	Laminated plastics plate, sheet, and shapes	40%	-13%

146	326140	Polystyrene Foam Product Manufacturing	38%	-13%
147	326150	Urethane and Other Foam Product (except Polystyrene) Manufacturing	96%	-22%
148	326160	Plastics bottle manufacturing	21%	-5%
149	32619A	Other plastics product manufacturing	69%	-14%
150	326210	Tire manufacturing	27%	-22%
151	326220	Rubber and plastics hose and belting manufacturing	30%	-15%
152	326290	Other rubber product manufacturing	36%	-10%
153	32711A	Pottery, ceramics, and plumbing fixture manufacturing	16%	-19%
154	32712A	Brick, tile, and other structural clay product manufacturing	15%	-20%
155	32712B	Clay and non-clay refractory manufacturing	15%	-19%
156	327211	Flat glass manufacturing	35%	-24%
157	327212	Other pressed and blown glass and glassware manufacturing	48%	-6%
158	327213	Glass container manufacturing	42%	-9%
159	327215	Glass Product Manufacturing Made of Purchased Glass	38%	-3%
160	327310	Cement manufacturing	23%	-68%
161	327320	Ready-mix concrete manufacturing	18%	-21%
162	327330	Concrete pipe, brick and block manufacturing	20%	-19%
163	327390	Other concrete product manufacturing	21%	-20%
164	3274A0	Lime and gypsum product manufacturing	21%	-18%
165	327910	Abrasive product manufacturing	11%	-21%
166	327991	Cut stone and stone product manufacturing	23%	-22%
167	327992	Ground or treated minerals and earths manufacturing	14%	-19%
168	327993	Mineral wool manufacturing	34%	-8%
169	327999	Miscellaneous nonmetallic mineral products	17%	-21%
170	331110	Iron and steel mills	13%	-59%
171	331200	Iron, steel pipe and tube manufacturing from purchased steel	87%	-8%
172	331314	Secondary smelting and alloying of aluminum	43%	-24%
173	33131A	Alumina refining and primary aluminum production	12%	-45%
174	33131B	Aluminum product manufacturing from purchased aluminum	82%	-22%
175	331411	Primary smelting and refining of copper	14%	-30%
176	331419	Primary smelting and refining of nonferrous metal (except copper and aluminum)	12%	-27%
177	331420	Copper rolling, drawing, extruding and alloying	15%	-22%
178	331490	Nonferrous metal (except copper and aluminum) rolling, drawing, extruding and alloying	20%	-21%
179	331510	Ferrous metal foundaries	9%	-26%
180	331520	Nonferrous foundries	14%	-28%
181	332114	Custom roll forming	46%	-13%
182	33211A	All other forging, stamping , and sintering	49%	-13%

183	33211B	Crown, closure and metal stamping manufacturing	44%	-11%
184	33221A	Cutlery, utensils, pots, and pans manufacturing	42%	-13%
185	33221B	Handtool manufacturing	38%	-10%
186	332310	Plate work and fabricated structural product manufacturing	44%	-12%
187	332320	Ornamental and architectural metail products manufacturing	45%	-13%
188	332410	Power boiler and heat exchanger manufacturing	43%	-12%
189	332420	Metal tank, heavy gauge, manufacturing	44%	-12%
190	332430	Metal can, box, and other container manufacturing	36%	-13%
191	332500	Hardware manufacturing	42%	-12%
192	332600	Spring and wire product manufacturing	41%	-12%
193	332710	Machine shops	59%	-14%
194	332720	Turned product and screw, nut, and bolt manufacturing	46%	-10%
195	332800	Coating, engraving, heat treating and allied activities	59%	-18%
196	332913	Plumbing Fixture Fitting and Trim Manufacturing	27%	-23%
197	33291A	Valve and fittings other than plumbing	36%	-9%
198	332991	Ball and roller bearing manufacturing	24%	-17%
199	332996	Fabricated pipe and pipe fitting manufacturing	42%	-11%
200	33299A	Ammunition manufacturing	50%	-12%
201	33299B	Ordnance and accessories manufacturing	47%	-11%
202	33299C	Other fabricated metal manufacturing	56%	-16%
203	333111	Farm machinery and equipment manufacturing	32%	-13%
204	333112	Lawn and garden equipment manufacturing	35%	-10%
205	333120	Construction machinery manufacturing	156%	-24%
206	333130	Mining and oil and gas field machinery manufacturing	33%	-8%
207	333220	Plastics and rubber industry machinery	38%	-8%
208	333295	Semiconductor machinery manufacturing	54%	-7%
209	33329A	Other industrial machinery manufacturing	58%	-8%
210	333314	Optical instrument and lens manufacturing	53%	-6%
211	333315	Photographic and photocopying equipment manufacturing	48%	-6%
212	333319	Other commercial and service industry machinery manufacturing	294%	-31%
213	33331A	Vending, commerical, industrial, and office machinery manufacturing	187%	-22%
214	333414	Heating equipment (except warm air furnaces) manufacturing	44%	-8%
215	333415	Air conditioning, refrigeration, and warm air heating equipment manufacturing	29%	-12%
216	33341A	Air purification and ventilation equipment manufacturing	37%	-9%
217	333511	Industrial mold manufacturing	40%	-5%
218	333514	Special tool, die, jig, and fixture manufacturing	40%	-6%
219	333515	Cutting tool and machine tool accessory manufacturing	44%	-5%
220	33351A	Metal cutting and forming machine tool manufacturing	45%	-8%

221	33351B	Rolling mill and other metalworking machinery manufacturing	40%	-7%
222	333611	Turbine and turbine generator set units manufacturing	38%	-10%
223	333612	Speed Changer, Industrial High-Speed Drive, and Gear Manufacturing	29%	-12%
224	333613	Mechanical Power Transmission Equipment Manufacturing	27%	-12%
225	333618	Other engine equipment manufacturing	22%	-19%
226	333911	Pump and pumping equipment manufacturing	33%	-7%
227	333912	Air and gas compressor manufacturing	41%	-8%
228	333920	Material handling equipment manufacturing	39%	-9%
229	333991	Power-driven handtool manufacturing	25%	-14%
230	333993	Packaging machinery manufacturing	47%	-9%
231	333994	Industrial process furnace and oven manufacturing	45%	-9%
232	33399A	Fluid power process machinery	37%	-7%
233	33399B	Process and oven not fluid power machinery	33%	-6%
234	334111	Electronic computer manufacturing	52%	-22%
235	334112	Computer storage device manufacturing	56%	-2%
236	33411A	Computer terminals and other computer peripheral equipment manufacturing	136%	-25%
237	334210	Telephone apparatus manufacturing	88%	-10%
238	334220	Broadcast and wireless communications equipment	66%	-4%
239	334290	Other communications equipment manufacturing	97%	-7%
240	334300	Audio and video equipment manufacturing	38%	-14%
241	334411	Electron tube manufacturing	50%	-15%
242	334412	Bare printed circuit board manufacturing	83%	-5%
243	334413	Semiconductor and related device manufacturing	41%	-4%
244	334417	Electronic connector manufacturing	81%	-4%
245	334418	Printed circuit assembly (electronic assembly) manufacturing	59%	-3%
246	334419	Other electronic component manufacturing	72%	-4%
247	33441A	Electronic capacitor, resistor, coil, transformer, and other inductor manufacturing	59%	-4%
248	334510	Electromedical apparatus manufacturing	51%	-8%
249	334511	Search, detection, and navigation instruments	62%	-5%
250	334512	Automatic environmental control manufacturing	46%	-15%
251	334513	Industrial process variable instruments	67%	-6%
252	334514	Totalizing fluid meters and counting devices	47%	-15%
253	334515	Electricity and signal testing instruments	64%	-3%
254	334516	Analytical laboratory instrument manufacturing	77%	-6%
255	334517	Irradiation apparatus manufacturing	67%	-4%
256	33451A	Watch, clock, and other measuring and controlling device manufacturing	68%	-5%
257	334613	Magnetic and optical recording media manufacturing	83%	-6%

258	33461A	Software, audio and video reproduction	56%	-4%
259	335110	Electric lamp bulb and part manufacturing	7%	-16%
260	335120	Lighting fixture manufacturing	20%	-11%
261	335210	Small electrical appliance manufacturing	9%	-14%
262	335221	Household cooking appliance manufacturing	9%	-15%
263	335222	Household refrigerator and home freezer manufacturing	6%	-21%
264	335224	Household laundry equipment manufacturing	7%	-30%
265	335228	Other major household appliance manufacturing	8%	-17%
266	335311	Electric power and specialty transformer manufacturing	7%	-17%
267	335312	Motor and generator manufacturing	6%	-15%
268	335313	Switchgear and switchboard apparatus manufacturing	11%	-11%
269	335314	Relay and industrial control manufacturing	18%	-7%
270	335911	Storage battery manufacturing	5%	-17%
271	335912	Primary battery manufacturing	5%	-11%
272	335920	Communication and energy wire and cable manufacturing	5%	-15%
273	335930	Wiring device manufacturing	18%	-8%
274	335991	Carbon and graphite product manufacturing	7%	-18%
275	335999	Miscellaneous electrical equipment manufacturing	37%	-9%
276	336111	Automobile Manufacturing	31%	-16%
277	336112	Light Truck and Utility Vehicle Manufacturing	11%	-15%
278	336120	Heavy duty truck manufacturing	50%	-12%
279	336211	Motor vehicle body manufacturing	29%	-15%
280	336212	Truck trailer manufacturing	39%	-8%
281	336213	Motor home manufacturing	41%	-10%
282	336214	Travel trailer and camper manufacturing	44%	-10%
283	336300	Motor vehicle parts manufacturing	26%	-11%
284	336411	Aircraft manufacturing	31%	-10%
285	336412	Aircraft engine and engine parts manufacturing	33%	-13%
286	336413	Other aircraft parts and equipment	45%	-16%
287	336414	Guided missile and space vehicle manufacturing	55%	-9%
288	33641A	Other guided missile and space vehicle parts and auxiliary equipment manufacturing	31%	-6%
289	336500	Railroad rolling stock manufacturing	46%	-10%
290	336611	Ship building and repairing	30%	-9%
291	336612	Boat building	45%	-9%
292	336991	Motorcycle, bicycle, and parts manufacturing	35%	-10%
293	336992	Military armored vehicles and tank parts manufacturing	36%	-7%
294	336999	All other transportation equipment manufacturing	34%	-12%
295	337110	Wood kitchen cabinet and countertop manufacturing	49%	-18%

296	337121	Upholstered household furniture manufacturing	41%	-13%
297	337122	Nonupholstered wood household furniture manufacturing	37%	-19%
298	337127	Institutional furniture manufacturing	52%	-13%
299	33712A	Metal and other household nonupholsetered furniture	55%	-13%
300	337212	Custom architectural woodwork and millwork	98%	-15%
301	337215	Showcases, partitions, shelving, and lockers	53%	-14%
302	33721A	Office furniture manufacturing	2%	-91%
303	337910	Mattress manufacturing	51%	-14%
304	337920	Blind and shade manufacturing	46%	-13%
305	339111	Laboratory apparatus and furniture manufacturing	46%	-22%
306	339112	Surgical and medical instrument manufacturing	41%	-12%
307	339113	Surgical appliance and supplies manufacturing	41%	-13%
308	339114	Dental equipment and supplies manufacturing	50%	-7%
309	339115	Ophthalmic goods manufacturing	49%	-5%
310	339116	Dental laboratories	46%	-10%
311	339910	Jewelry and silverware manufacturing	58%	-12%
312	339920	Sporting and athletic goods manufacturing	46%	-12%
313	339930	Doll, toy, and game manufacturing	40%	-14%
314	339940	Office supplies (except paper) manufacturing	49%	-8%
315	339950	Sign manufacturing	50%	-10%
316	339991	Gasket, packing, and sealing device manufacturing	43%	-11%
317	339992	Musical instrument manufacturing	52%	-9%
318	339994	Broom, brush, and mop manufacturing	42%	-12%
319	33999A	All other miscellaneous manufacturing	43%	-12%
320	420000	Wholesale trade	6%	-67%
321	481000	Air transportation	11%	-91%
322	482000	Rail transportation	6%	-97%
323	483000	Water transportation	3%	-99%
324	484000	Truck transportation	1%	-99%
325	485000	Transit and ground passenger transportation	14%	-87%
326	486000	Pipeline transportation	70%	-97%
327	48A000	Scenic and sightseeing transportation and support activities for transportation	20%	-85%
328	491000	Postal service	8%	-66%
329	492000	Couriers and messengers	24%	-95%
330	493000	Warehousing and storage	31%	-32%
331	4A0000	Retail trade	5%	-40%
332	511110	Newspaper publishers	0%	-55%
333	511120	Periodical publishers	38%	-24%

334	511130	Book publishers	70%	-8%
335	5111A0	Directory, mailing list, and other publishers	111%	-2%
336	511200	Software publishers	113%	-52%
337	512100	Motion picture and video industries	9%	-29%
338	512200	Sound recording industries	309%	-1%
339	515100	Radio and television broadcasting	16%	-63%
340	515200	Cable and other subscription programming	66%	-31%
341	516110	Internet publishing and broadcasting	3220%	-1%
342	517000	Telecommunications	0%	-88%
343	518100	Internet service providers and web search portals	1407%	0%
344	518200	Data processing, hosting, and related services	230%	0%
345	519100	Other information services	824%	0%
346	522A00	Nondepository credit intermediation and related activities	12%	-42%
347	523000	Securities, commodity contracts, investments	28%	-18%
348	524100	Insurance carriers	781%	-1%
349	524200	Insurance agencies, brokerages, and related	10%	-41%
350	525000	Funds, trusts, and other financial vehicles	817%	0%
351	52A000	Monetary authorities and depository credit intermediation	74%	-60%
352	531000	Real estate	0%	-89%
353	532100	Automotive equipment rental and leasing	41%	-11%
354	532230	Video tape and disc rental	13%	-17%
355	532400	Commercial and industrial machinery and equipment rental and leasing	8%	-65%
356	532A00	General and consumer goods rental except video tapes and discs	4%	-52%
357	533000	Lessors of nonfinancial intangible assets	1%	-61%
358	541100	Legal services	4%	-91%
359	541200	Accounting and bookkeeping services	3%	-88%
360	541300	Architectural and engineering services	10%	-91%
361	541400	Specialized design services	2%	-40%
362	541511	Custom computer programming services	1%	-96%
363	541512	Computer systems design services	7%	-76%
364	54151A	Other computer related services, including facilities management	4%	-60%
365	541610	Management consulting services	7%	-80%
366	5416A0	Environmental and other technical consulting services	22%	-47%
367	541700	Scientific research and development services	4%	-72%
368	541800	Advertising and related services	3%	-85%
369	541920	Photographic services	3%	-38%
370	541940	Veterinary services	15%	-76%
371	5419A0	All other miscellaneous professional and technical services	2%	-80%

372	550000	Management of companies and enterprises	2%	-82%
373	561100	Office administrative services	2%	-60%
374	561200	Facilities support services	6%	-23%
375	561300	Employment services	6%	-84%
376	561400	Business support services	0%	-73%
377	561500	Travel arrangement and reservation services	7%	-88%
378	561600	Investigation and security services	0%	-50%
379	561700	Services to buildings and dwellings	11%	-94%
380	561900	Other support services	0%	-80%
381	562000	Waste management and remediation services	13%	-99%
382	611100	Elementary and secondary schools	263%	-12%
383	611A00	Colleges, universities, and junior colleges	2%	-60%
384	611B00	Other educational services	848%	-8%
385	621600	Home health care services	469%	-6%
386	621A00	Offices of physicians, dentists, and other health practitioners	3%	-63%
387	621B00	Healthcare and social assistance	15%	-19%
388	622000	Hospitals	67%	-24%
389	623000	Nursing and residential care facilities	24%	-19%
390	624200	Community food, housing, and other relief services, incl rehabilitation services	339%	0%
391	624400	Child day care services	207%	0%
392	624A00	Individual and family services	226%	0%
393	711100	Performing arts companies	132%	-2%
394	711200	Spectator sports	13%	-24%
395	711500	Independent artists, writers, and performers	345%	-2%
396	711A00	Promoters of performing arts and sports and agents for public figures	14%	-6%
397	712000	Museums, historical sites, zoos, and parks	120%	-2%
398	713940	Fitness and recreational sports centers	2%	-80%
399	713950	Bowling centers	19%	-12%
400	713A00	Amusement parks and arcades	2%	-87%
401	713B00	Other amusement, gambling, and recreation industries	4%	-83%
402	7211A0	Hotels and motels, including casino hotels	1%	-62%
403	721A00	Other accommodations	97%	-6%
404	722000	Food services and drinking places	2%	-41%
405	811192	Car washes	3%	-71%
406	8111A0	Automotive repair and maintenance, except car washes	2%	-93%
407	811200	Electronic equipment repair and maintenance	2%	-41%
408	811300	Commercial machinery repair and maintenance	3%	-64%
409	811400	Household goods repair and maintenance	2%	-61%

410	812100	Personal care services	10%	-69%
411	812200	Death care services	7%	-51%
412	812300	Drycleaning and laundry services	8%	-72%
413	812900	Other personal services	7%	-64%
414	813100	Religious organizations	188%	-1%
415	813A00	Grantmaking, giving and social advocacy organizations	427%	0%
416	813B00	Civic, social, professional and similar organizations	7%	-45%
417	814000	Private households	0%	0%
418	S00102	Other Federal government enterprises	0%	-100%
419	S00201	State and local government passenger transit	12%	-95%
420	S00203	Other state and local government enterprises	4%	-88%
421	S00300	Noncomparable Imports	0%	0%
422	S00401	Scrap	0%	0%
423	S00402	Used and Secondhand Goods	0%	0%
424	S00500	General Federal Defense	8%	-93%
425	S00600	General Federal non-defense government industry	6%	-83%
426	S00700	General state and local government services	6%	-99%
427	S00800	Owner-Occupied Dwellings	10%	-100%
428	S00900	ROW Adjustment	0%	0%

Table S2: List of cradle-to-gate processes in the US LCI database

Index No.	Name
2	Acrylonitrile, at plant
3	Acrylonitrile-butadiene-styrene copolymer, resin, at plant
15	Aluminum, cold rolling, at plant
16	Aluminum, extrusion, at plant
17	Aluminum, hot rolling, at plant
18	Aluminum, primary, ingot, at plant
22	Aluminum, secondary, ingot, at plant
28	Aluminum, sheet, coated, at plant
614	Carbon monoxide, at plant
625	Coil, coating, m2, at plant
626	Cold rolled sheet, steel, at plant
633	Composite wood I-joist, at plant, US PNW
634	Composite wood I-joist, at plant, US SE
643	Corn steep liquor
777	Electricity, biomass, at power plant
788	Enzyme, Alpha-amylase, Novozyme Liquozyme
789	Enzyme, Cellulase, Novozyme Celluclast
790	Enzyme, Glucoamylase, Novozyme Spirizyme
802	Ethylene glycol, at plant
814	Forest residue, processed and loaded, at landing system
824	Galvanized steel coil, coated, at plant
825	Galvanized steel sheet, at plant
829	Glue laminated beam processing, at plant, US PNW
830	Glue laminated beam processing, at plant, US SE
839	Gypsum wallboard product, regular, 0.5 inch (12.7 mm)
840	Gypsum wallboard product, type X, 0.625 inch (15.875 mm)
864	Hot rolled sheet, steel, at plant
865	Hydrochloric acid, at plant
893	Melamine urea formaldehyde hardener, at plant
894	Melamine urea formaldehyde resin, at plant
899	Metal panels, roof, at plant
900	Metal panels, wall, at plant
903	Methylene diphenyl diisocyanate resin, at plant, CTR
937	Packaging and information sheets, i2900 desktop scanner
938	Packaging, production scanners
963	Phenol formaldehyde, at plant
964	Phenol resorcinol formaldehyde hardener, at plant

965	Phenol resorcinol formaldehyde resin, at plant
980	Polyethylene terephthalate, resin, at plant, CTR
982	Polyethylene, high density, resin, at plant
984	Polyethylene, linear low density, resin, at plant, CTR
987	Polyethylene, low density, resin, at plant, CTR
988	Polylactide Biopolymer Resin, at plant
990	Polyol ether, for flexible foam polyurethane production, at plant, CTR
992	Polyol ether, for rigid foam polyurethane production, at plant, CTR
996	Polypropylene resin, at plant, CTR
998	Polystyrene, general purpose, at plant, CTR
1000	Polystyrene, high impact, resin, at plant, CTR
1002	Polyvinyl chloride, resin, at plant, CTR
1040	Quicklime, at plant
1139	Scanner, department, i3200, i3400
1140	Scanner, department, i4200, i4600
1141	Scanner, department, i5200, i5600
1142	Scanner, department, i5200v, i5600v
1143	Scanner, department, i5800
1144	Scanner, desktop, i2900
1158	Single-ply, white, polyester reinforced PVC roofing membrane, 48 mils (1.219 mm)
1186	Soy-based polyol, at plant
1187	Soy-based resin, at plant
1203	Steel product, primary structural, beams and columns, at plant
1204	Steel product, secondary structural, girts and purlins, at plant
1205	Steel, billets, at plant
1207	Steel, liquid, at plant
1208	Steel, stainless 304, flat rolled coil
1209	Steel, stainless 304, quarto plate
1210	Steel, stainless 304, scrap
1237	Toluene diisocyanate, at plant, CTR
1463	Wood fuel, unspecified
1470	Zinc, sheet
1471	Zinc, Special High Grade

Table S3: US LCI processes and categorized ISIC code

Index	Product	New functional unit	ISIC code
1	Acetic acid, at plant	kg	2011
2	Acrylonitrile-butadiene-styrene copolymer, resin, at plant	kg	2011
3	Alumimum scrap, at lost foam casting	kg	2420

4	Alumina, at plant	kg	2420
5	Aluminium, extrusion, at plant	kg	2591
6	Aluminum ingot, production mix, at plant	kg	2591
7	Aluminum recovery, transport, to plant	kg	3830
8	Aluminum scrap, at precision sand casting	kg	2420
9	Aluminum scrap, at semi-permanent mold casting	kg	2420
10	Aluminum, cast, lost foam, at plant	kg	2420
11	Aluminum, cast, precision sand casting	kg	2420
12	Aluminum, cast, semi-permanent mold (SPM), at plant	kg	2420
13	Aluminum, primary, ingot, at plant, 1998	kg	2591
14	Aluminum, primary, smelt, at plant	kg	2420
15	Aluminum, secondary, extruded	kg	2420
16	Aluminum, secondary, ingot, at plant, 1998	kg	2591
17	Aluminum, secondary, ingot, from automotive scrap, at plant	kg	2591
18	Aluminum, secondary, ingot, from beverage cans, at plant	kg	2591
19	Aluminum, secondary, rolled	kg	2591
20	Aluminum, secondary, shape casted	kg	2420
21	Ammonia, steam reforming, liquid, at plant	kg	2012
22	Aniline, at plant	kg	2011
23	Anode, at plant	kg	2591
24	Anthracite coal, at mine	kg	510
25	Anthracite coal, combusted in industrial boiler	kg	COAL
26	Automotive painting, electrocoating, per m2	m2	2930
27	Automotive painting, electrocoating, per vehicle	m2	2930
28	Automotive painting, pretreatment	m2	2930
29	Automotive painting, top coat, per m2	m2	2930
30	Automotive painting, top coat, per vehicle	m2	2930
31	Bark mulch, at oriented strand board production, US SE	kg	1610
32	Bark, at sawmill, US SE	kg	1610
33	Bark, at MDF mill	kg	1610
34	Bark, at plywood plant, US PNW	kg	1610
35	Bark, at plywood plant, US SE	kg	1610
36	Bark, at rough green lumber sawmill, softwood, US PNW	kg	1610
37	Bark, hardwood, average, High Intensity Management, NE-NC	kg	1610
38	Bark, hardwood, average, Low Intensity Management, NE-NC	kg	1610
39	Bark, hardwood, average, Med Intensity Management, NE-NC	kg	1610
40	Bark, hardwood, average, at forest road, NE-NC	kg	1610
41	Bark, hardwood, green, at logyard, NE-NC	kg	1610
42	Bark, hardwood, green, at logyard, SE	kg	1610
43	Bark, hardwood, green, at mill, E	kg	1610
44	Bark, hardwood, green, at mill, NE-NC	kg	1610

45	Bark, hardwood, green, at mill, SE	kg	1610
46	Bark, hardwood, green, at sawmill, NE-NC	kg	1610
47	Bark, hardwood, green, at sawmill, SE	kg	1610
48	Bark, hardwood, green, at veneer mill, E	kg	1610
49	Bark, sftwd, state-private moist cold forest, steep slope, at forest rd,INW	kg	1610
50	Bark, softwd, state or private dry forest, gentle slope, at forest rd, INW	kg	1610
51	Bark, softwd, state or private dry forest, steep slope, at forest rd, INW	kg	1610
52	Bark, softwood, average, High Intensity Management, NE-NC	kg	1610
53	Bark, softwood, average, Low Intensity Management, NE-NC	kg	1610
54	Bark, softwood, average, Med Intensity Management, NE-NC	kg	1610
55	Bark, softwood, average, at forest road, INW	kg	1610
56	Bark, softwood, average, at forest road, NE-NC	kg	1610
57	Bark, softwood, average, state or private dry forest, at forest road, INW	kg	1610
58	Bark, softwood, average, state or private moist cold forest, at forest road, INW	kg	1610
59	Bark, softwood, green, at logyard, INW	kg	1610
60	Bark, softwood, green, at logyard, NE-NC	kg	1610
61	Bark, softwood, green, at mill, INW	kg	1610
62	Bark, softwood, green, at mill, NE-NC	kg	1610
63	Bark, softwood, green, at sawmill, INW	kg	1610
64	Bark, softwood, green, at sawmill, NE-NC	kg	1610
65	Bark, softwood, national forest, average, at forest road, INW	kg	1610
66	Bark, softwood, national forest, gentle slope, at forest road, INW	kg	1610
67	Bark, softwood, national forest, steep slope, at forest road, INW	kg	1610
68	Bark, softwood, state-private moist cold forest, gentle slope, at frst rd, INW	kg	1610
69	Bauxite, at mine	kg	729
70	Benzene, at plant	kg	2011
71	Biodegradable loose fill		2011
72	Bitumen, at refinery	kg	1920
73	Bituminous coal, at mine	kg	510
74	Bituminous coal, combusted in industrial boiler	kg	COAL
75	Bituminous coal, combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	COAL
76	Board trimmings and rejects, for recovery/recycling	kg	1702
77	Bucked and debarked log, hardwood, green, at veneer mill, E	kg	1610
78	Butadiene, at plant	kg	2011
79	Byproduct of aluminum casting, SPM, liquid residuals	kg	2420

80	Byproduct of aluminum casting, precision sand, liquid residuals	kg	2420
81	CUTOFF 2,4-D, at regional storehouse	kg	2021
82	CUTOFF Accelerator, at plant	item	2811
83	CUTOFF Acetone from butane, at plant	kg	2011
84	CUTOFF Acetone from butane, at plant. RER	kg	2011
85	CUTOFF Acetone, liquid	kg	2011
86	CUTOFF Additive, low-profile, at plant	kg	2011
87	CUTOFF Adhesive tube dispensers, at plant	kg	2029
88	CUTOFF Adhesive, UPR-based, at plant	kg	2029
89	CUTOFF Adhesives and binders, at plant	kg	2029
90	CUTOFF Agricultural machinery, general, production	kg	2821
91	CUTOFF Agrochemicals, at plant	kg	2021
92	CUTOFF Alachlor, at regional storehouse	kg	2011
93	CUTOFF Alkaline cleaner, unspecified	kg	2011
94	CUTOFF Alloying additives, at plant	kg	2011
95	CUTOFF Alloying metals and additives, at plant	kg	2410
96	CUTOFF Aluminium, at plant	kg	2420
97	CUTOFF Aluminum hydroxide, at plant	kg	2011
98	CUTOFF Aluminum oxide sealer, 100% solids	kg	2011
99	CUTOFF Aluminum scrap, automotive	kg	2420
100	CUTOFF Aluminum scrap, used beverage cans	kg	2420
101	CUTOFF Aluminum sheet	kg	2420
102	CUTOFF Aluminum, liquid, at plant	kg	2420
103	CUTOFF Aluminum, scrap	kg	2420
104	CUTOFF Ammonium sulfate 30% solids	kg	2012
105	CUTOFF Ammonium sulfate, 20% solids, at plant	kg	2012
106	CUTOFF Ammonium sulfate, at plant	kg	2012
107	CUTOFF Anthracite coal, at mine	kg	510
108	CUTOFF Application of plant protection products, by field sprayer	ha	161
109	CUTOFF Argon, liquid, at plant	kg	2011
110	CUTOFF Atrazine, at regional storehouse	kg	2021
111	CUTOFF BOD5, Biochemical Oxygen Demand, to municipal wastewater treatment	kg	WASTE_FLOW
112	CUTOFF BOD5, to municipal wastewater treatment	kg	WASTE_FLOW
113	CUTOFF Baling	kg	2821
114	CUTOFF Balsa wood, at plant	kg	1610
115	CUTOFF Bark, hardwood, at forest road, SE	kg	1610
116	CUTOFF Biocide, at plant	kg	2021
117	CUTOFF Body washer, at plant	kg	2023
118	CUTOFF Borax, anhydrous, powder, at plant	kg	2011

119	CUTOFF Boric acid, at plant	kg	2011
120	CUTOFF Bottom ash, unspecified origin	kg	3811
121	CUTOFF Butyl acetate, liquid	kg	2011
122	CUTOFF Cable, connector for computer, without plugs, at plant	kg	2732
123	CUTOFF Calcium borates, at plant	kg	2011
124	CUTOFF Carbon black, at plant	kg	2011
125	CUTOFF Carbon dioxide, liquid, at plant	kg	2011
126	CUTOFF Carbon monoxide, at plant	kg	2011
127	CUTOFF Cement bags, at plant	kg	2220
128	CUTOFF Ceramic filters, at plant	kg	2821
129	CUTOFF Chains, at plant	kg	2599
130	CUTOFF Chemicals (unspecified)	kg	2011
131	CUTOFF Chemicals inorganic, at plant	kg	2011
132	CUTOFF Chemicals organic, at plant	kg	2011
133	CUTOFF Chemicals, unspecified, used for wastewater treatment	kg	2011
134	CUTOFF Chlorine, at plant	kg	2011
135	CUTOFF Chromic acid	kg	2011
136	CUTOFF Chromium III chromate sealer	kg	2011
137	CUTOFF Citric Acid, at plant	kg	2011
138	CUTOFF Clay, at mine	kg	810
139	CUTOFF Cleaner alkaline, at plant	kg	2011
140	CUTOFF Cleaning blast, at plant	kg	2011
141	CUTOFF Clearcoat material, at plant	kg	2011
142	CUTOFF Co-resin, UPR and styrene-based, at plant	kg	2011
143	CUTOFF Coatings	kg	2022
144	CUTOFF Cold impact extrusion, aluminium, 1 stroke	kg	2220
145	CUTOFF Colorant, at plant	kg	2022
146	CUTOFF Combine harvesting	ha	161
147	CUTOFF Compressed natural gas, at plant	m3	3520
148	CUTOFF Continuous strand mat, glass fiber based, at plant	kg	2310
149	CUTOFF Converted corrugated box, with average bleaching, at plant	kg	1702
150	CUTOFF Conveyor belt, at plant	m	2219
151	CUTOFF Copper Chromium Arsenate (CCA), at plant	kg	2011
152	CUTOFF Copper product manufacturing, average metal working	kg	2420
153	CUTOFF Copper, at plant	kg	2420
154	CUTOFF Copper, at regional storage	kg	2420
155	CUTOFF Copper, primary, at refinery	kg	2420
156	CUTOFF Core additives and catalyst for iron casting	kg	2011

157	CUTOFF Core board, at plant	kg	1702
158	CUTOFF Core coating for aluminum casting	kg	2592
159	CUTOFF Core wash and paste for aluminum casting	kg	2592
160	CUTOFF Corn Starch, at plant	kg	1061
161	CUTOFF Corrugated board, mixed fibre, single wall, at plant	kg	1702
162	CUTOFF Corrugated cardboard	kg	1702
163	CUTOFF Creosote, at plant	kg	2011
164	CUTOFF Curing agent, at plant	kg	2011
165	CUTOFF DTPA	kg	2011
166	CUTOFF Defoamant, unspecified	kg	2011
167	CUTOFF Dichloromethane, at plant	kg	2011
168	CUTOFF Disodium octaborate tetrahydrate (DOT), at plant	kg	2011
169	CUTOFF Disposal, 1-methoxy-2-propanol, to sanitary landfill	kg	3811
170	CUTOFF Disposal, BOF dust, to unspecified treatment	kg	3811
171	CUTOFF Disposal, BOF slag, to unspecified treatment	kg	3811
172	CUTOFF Disposal, acetone, to sanitary landfill	kg	3811
173	CUTOFF Disposal, acid pickling waste, to sanitary landfill	kg	3811
174	CUTOFF Disposal, anthracite coal combustion byproducts, to unspecified reuse	kg	3811
175	CUTOFF Disposal, ash and flue gas desulfurization sludge, to unspecified reuse	kg	3811
176	CUTOFF Disposal, baghouse dust, to sanitary landfill	kg	3811
177	CUTOFF Disposal, benzene, 1,2,4-trimethyl-, to sanitary landfill	kg	3811
178	CUTOFF Disposal, biohazard waste, to sanitary landfill	kg	3811
179	CUTOFF Disposal, carbon black, to residual material landfill	kg	3811
180	CUTOFF Disposal, carbon black, to sanitary landfill	kg	3811
181	CUTOFF Disposal, carbon black, to wastewater treatment	kg	3811
182	CUTOFF Disposal, cement kiln dust, in residual material landfill	kg	3811
183	CUTOFF Disposal, chemical waste, unspecified, to residual material landfill	kg	3811
184	CUTOFF Disposal, chemical waste, unspecified, to residual materials landfill	kg	3811
185	CUTOFF Disposal, chemical waste, unspecified, to sanitary landfill	kg	3811
186	CUTOFF Disposal, chemical waste, unspecified, to unspecified treatment	kg	3811
187	CUTOFF Disposal, contaminated carbon, to sanitary landfill	kg	3811
188	CUTOFF Disposal, copper compounds, to sanitary landfill	kg	3811
189	CUTOFF Disposal, corrosive and toxic liquids, unspecified, to sanitary landfill	kg	3811
190	CUTOFF Disposal, empty pails and drums, to sanitary landfill	kg	3811
191	CUTOFF Disposal, ferric oxide, to sanitary landfill	kg	3811

192	CUTOFF Disposal, filters, to sanitary landfill	kg	3811
193	CUTOFF Disposal, fly ash, to unspecified landfill	kg	3811
194	CUTOFF Disposal, formaldehyde, to unspecified treatment	kg	3811
195	CUTOFF Disposal, grinding residue, to sanitary landfill	kg	3811
196	CUTOFF Disposal, heavy alkalide naphtha, to sanitary landfill	kg	3811
197	CUTOFF Disposal, inert material, 0% water, to sanitary landfill	kg	3811
198	CUTOFF Disposal, inert solid waste, to inert material landfill	kg	3811
199	CUTOFF Disposal, inert solid waste, to inert material landfill	kg	3811
200	CUTOFF Disposal, inert solid waste, to unspecified treatment	kg	3811
201	CUTOFF Disposal, inert solid waste, to unspecified treatment	kg	3811
202	CUTOFF Disposal, inert waste, 5% water, to inert material landfill	kg	3811
203	CUTOFF Disposal, lead containing waste, to sanitary landfill	kg	3811
204	CUTOFF Disposal, light aromatic solvent naphtha, to sanitary landfill	kg	3811
205	CUTOFF Disposal, lignite coal combustion byproducts, to unspecified reuse	kg	3811
206	CUTOFF Disposal, liquid wastes, unspecified to waste water treatment	m3	3700
207	CUTOFF Disposal, liquid wastes, unspecified, to sanitary landfill	kg	3811
208	CUTOFF Disposal, mineral waste, underground deposit	kg	3811
209	CUTOFF Disposal, mining waste, underground deposit	kg	3811
210	CUTOFF Disposal, msw, to sanitary landfill	kg	3811
211	CUTOFF Disposal, municipal solid wastes, to sanitary landfill	kg	3811
212	CUTOFF Disposal, n-butyl alcohol, to sanitary landfill	kg	3811
213	CUTOFF Disposal, packaging-biocide carboys (HDPE), to sanitary landfill	kg	3811
214	CUTOFF Disposal, petroleum based wastes, unspecified, to sanitary landfill	kg	3811
215	CUTOFF Disposal, propylene glycol butyl ether, to sanitary landfill	kg	3811
216	CUTOFF Disposal, radioactive waste, unspecified hazardous waste landfill	kg	3811
217	CUTOFF Disposal, refractory material, to sanitary landfill	kg	3811
218	CUTOFF Disposal, resins, unspecified, to sanitary landfill	kg	3811
219	CUTOFF Disposal, rubber, to sanitary landfill	kg	3811
220	CUTOFF Disposal, sand, to sanitary landfill	kg	3811
221	CUTOFF Disposal, slag, to unspecified treatment	kg	3811
222	CUTOFF Disposal, slags & ash waste, unspecified reuse	kg	3811
223	CUTOFF Disposal, sludge, containing 1-methoxy-2-propanol, to sanitary landfill	kg	3811
224	CUTOFF Disposal, sludge, containing glycol ethers, to sanitary landfill	kg	3811

225	CUTOFF Disposal, sludge, containing manganese compounds, to sanitary landfill	kg	3811
226	CUTOFF Disposal, sludge, containing nitrate compounds, to sanitary landfill	kg	3811
227	CUTOFF Disposal, sludge, containing phosphorous, to sanitary landfill	kg	3811
228	CUTOFF Disposal, sludge, containing zinc compounds, to sanitary landfill	kg	3811
229	CUTOFF Disposal, sludge, to sanitary landfill	kg	3811
230	CUTOFF Disposal, solid waste to incineration with energy recovery	kg	3811
231	CUTOFF Disposal, solid waste to incineration without energy recovery	kg	3811
232	CUTOFF Disposal, solid waste to sanitary landfill	kg	3811
233	CUTOFF Disposal, solid waste, fuel, to municipal incineration	kg	3811
234	CUTOFF Disposal, solid waste, process, to sanitary landfill	kg	3811
235	CUTOFF Disposal, solid waste, process, to waste-to-energy	kg	3811
236	CUTOFF Disposal, solid waste, unspecified, to incineration with energy recovery	kg	3811
237	CUTOFF Disposal, solid waste, unspecified, to inert material landfill	kg	3811
238	CUTOFF Disposal, solid waste, unspecified, to inert material landfill	kg	3811
239	CUTOFF Disposal, solid waste, unspecified, to municipal incineration	kg	3811
240	CUTOFF Disposal, solid waste, unspecified, to sanitary landfill	kg	3811
241	CUTOFF Disposal, solid waste, unspecified, to underground deposit	kg	3811
242	CUTOFF Disposal, solid waste, unspecified, to unspecified beneficial use	kg	3811
243	CUTOFF Disposal, solid waste, unspecified, to unspecified incinerator	kg	3811
244	CUTOFF Disposal, solid waste, unspecified, to unspecified land application	kg	3811
245	CUTOFF Disposal, solid waste, unspecified, to unspecified landfill	kg	3811
246	CUTOFF Disposal, solid waste, unspecified, to unspecified treatment	kg	3811
247	CUTOFF Disposal, solid waste, unspecified, to unspecified treatment	kg	3811
248	CUTOFF Disposal, solid waste, unspecified, to waste-to-energy	kg	3811
249	CUTOFF Disposal, solid waste,process, to municipal incineration	kg	3811
250	CUTOFF Disposal, stoddard solvent, to sanitary landfill	kg	3811
251	CUTOFF Disposal, tailings waste, underground deposit	kg	3811

252	CUTOFF Disposal, unspecified ashes, to unspecified beneficial use	kg	3811
253	CUTOFF Disposal, unspecified ashes, to unspecified land application	kg	3811
254	CUTOFF Disposal, unspecified ashes, to unspecified landfill	kg	3811
255	CUTOFF Disposal, wastewater treatment plant residuals, to uns. beneficial use	kg	3811
256	CUTOFF Disposal, wastewater treatment plant residuals, to uns. incinerator	kg	3811
257	CUTOFF Disposal, wastewater treatment plant residuals, to uns. land application	kg	3811
258	CUTOFF Disposal, wastewater treatment plant residuals, to uns. landfill	kg	3811
259	CUTOFF Disposal, wood ash mixture, pure, 0% water, to sanitary landfill	kg	3811
260	CUTOFF Disposal, wood waste, to residual material landfill	kg	3811
261	CUTOFF Disposal, wood waste, to unspecified treatment	kg	3811
262	CUTOFF Dried roughage store, non ventilated	kg	161
263	CUTOFF Dry rough lumber, at kiln	kg	1610
264	CUTOFF Dry strengths, at plant	kg	1702
265	CUTOFF Electricity from hydro	kWh	3510
266	CUTOFF Electricity, MSW, non-biogenic, at power plant	kWh	3510
267	CUTOFF Electricity, at grid, BC	kWh	3510
268	CUTOFF Electricity, at grid, MB	kWh	3510
269	CUTOFF Electricity, at grid, NB	kWh	3510
270	CUTOFF Electricity, at grid, ON	kWh	3510
271	CUTOFF Electricity, at grid, QC	kWh	3510
272	CUTOFF Electricity, at wind power plant, unspecified	kWh	3510
273	CUTOFF Electricity, biomass, gas, landfill, at power plant	kWh	3510
274	CUTOFF Electricity, biomass, gas, unspecified, at power plant	kWh	3510
275	CUTOFF Electricity, biomass, liquid, sludge, at power plant	kWh	3510
276	CUTOFF Electricity, biomass, solid, agriculture by-products, at power plant	kWh	3510
277	CUTOFF Electricity, biomass, solid, biogenic MSW, at power plant	kWh	3510
278	CUTOFF Electricity, biomass,liquid, unspecified, at power plant	kWh	3510
279	CUTOFF Electricity, biomass,solid, unspecified, at power plant	kWh	3510
280	CUTOFF Electricity, cogenerated, at plant	kWh	3510
281	CUTOFF Electricity, fossil, unspecified, at power plant	kWh	3510
282	CUTOFF Electricity, from renewable source, unspecified	kWh	3510
283	CUTOFF Electricity, geothermal, unspecified	kWh	3510
284	CUTOFF Electricity, hydropower, at power plant, unspecified	kWh	3510
285	CUTOFF Electricity, low voltage, at grid	kWh	3510

286	CUTOFF Electricity, low voltage, at grid	kWh	3510
287	CUTOFF Electricity, low voltage, at grid/CN U	kWh	3510
288	CUTOFF Electricity, other fuels, at power plant, unspecified	kWh	3510
289	CUTOFF Electricity, other fuels, unspecified, at power plant	kWh	3510
290	CUTOFF Electricity, other gases, unspecified, at power plant	kWh	3510
291	CUTOFF Electricity, petroleum coke, at power plant	kWh	3510
292	CUTOFF Electricity, petroleum, waste oil, at power plant	kWh	3510
293	CUTOFF Electricity, photovoltaic, unspecified	kWh	3510
294	CUTOFF Electricity, solar, unspecified, at power plant	kWh	3510
295	CUTOFF Electricity, tire derived fuel, at power plant	kWh	3510
296	CUTOFF Electricity, waste oil, at power plant	kWh	3510
297	CUTOFF Electrocoat resin, at plant	kg	2013
298	CUTOFF Electronic component, unspecified, at plant	kg	2610
299	CUTOFF Emulsion wax 53% solids	kg	2011
300	CUTOFF Energy, output	MJ	ENERGY
301	CUTOFF Energy, unspecified	MJ	ENERGY
302	CUTOFF Epoxy, resin, at plant	kg	2011
303	CUTOFF Ethanol fermentation plant	Item(s)	4290
304	CUTOFF Ethanol, at plant	kg	2011
305	CUTOFF Ethanol, denatured, corn stover, biochemical	kg	2011
306	CUTOFF Ethylene glycol, at plant	kg	2011
307	CUTOFF Expandable polystyrene, at plant	kg	2011
308	CUTOFF Expanded polystyrene foam, at plant	kg	2011
309	CUTOFF Explosives, at plant	kg	2011
310	CUTOFF Fatty acides	kg	2011
311	CUTOFF Fertilising, by broadcaster	ha	161
312	CUTOFF Filler, synthetic, at plant	kg	2011
313	CUTOFF Filter bags, at plant	kg	2220
314	CUTOFF Filter media, at plant	kg	2011
315	CUTOFF Flat glass, coated, at plant	kg	2310
316	CUTOFF Flat glass, uncoated, at plant	kg	2310
317	CUTOFF Flouropolymer (PVDF)	kg	2013
318	CUTOFF Flux, at plant	kg	161
319	CUTOFF Fly ash, unspecified origin	kg	3811
320	CUTOFF Fodder loading, by self-loading trailer	m3	5224
321	CUTOFF Formic acid, 10% solution, at plant	kg	2011
322	CUTOFF Formic acid, at plant	kg	2011
323	CUTOFF Foundry sand, at mine	kg	810
324	CUTOFF Galvanized steel scrap, at plant	kg	2420
325	CUTOFF Gasoline, used in personal vehicle	kg	1920
326	CUTOFF Gelcoat, UPR & styrene-based, at plant	kg	2011

327	CUTOFF Glass fibre, at plant	kg	2310
328	CUTOFF Glue, at plant	kg	2029
329	CUTOFF Glue-adhesive(30-50% terpene,30-50% polybutene,5-10% polyolefin), at plant	kg	2029
330	CUTOFF Glyphosate, at regional storehouse	kg	2011
331	CUTOFF Grain refiners, at plant	kg	2821
332	CUTOFF Grass seed IP, at regional storehouse	kg	161
333	CUTOFF Grinding aids, at plant	kg	2011
334	CUTOFF Grinding media, at plant	kg	2011
335	CUTOFF Ground calcium carbonate, at plant	kg	2011
336	CUTOFF Hay grown for feed	kg	1080
337	CUTOFF Haying, by rotary tedder	ha	161
338	CUTOFF Heat, at cogen with ignition biogas engine, allocation exergy	MJ	ENERGY
339	CUTOFF Heat, from biomass	MJ	ENERGY
340	CUTOFF Heat, from landfill gas	MJ	RECOVERED ENERGY
341	CUTOFF Hexane, at plant	kg	2011
342	CUTOFF Highlighter, at plant	kg	3290
343	CUTOFF Hogfuel-Biomass (50% MC), combusted in industrial boiler	kg	BIOFUEL
344	CUTOFF Hydraulic fluid, at plant	kg	2011
345	CUTOFF Hydrochloric Acid, at plant	kg	2011
346	CUTOFF Hydrochloric acid, 30% in H2O, at plant	kg	2011
347	CUTOFF Hydrogen peroxide	kg	2011
348	CUTOFF Hydrogen peroxide, at plant	kg	2011
349	CUTOFF In-mold coating, styrene-based, at plant	kg	2220
350	CUTOFF Initiator, MEKP, at plant	kg	2011
351	CUTOFF Injection moulding	kg	2220
352	CUTOFF Ink	kg	2022
353	CUTOFF Irrigating	kg	161
354	CUTOFF Isobutyl acetate, liquid	kg	2011
355	CUTOFF Isocyanate resin, at plant	kg	2011
356	CUTOFF Isoproponal, liquid	kg	2011
357	CUTOFF Kerosene, combusted in industrial boiler	kg	FOSSIL FUEL
358	CUTOFF LCD glass, at plant	kg	2610
359	CUTOFF LCD module, at plant	kg	2610
360	CUTOFF Latex, at plant	kg	2013
361	CUTOFF Light emitting diode, LED, at plant	kg	2011
362	CUTOFF Liquid storage tank, chemicals, organics	kg	2512
363	CUTOFF Loading bales	kg	161
364	CUTOFF Low Density Polyethylene Film	kg	2012
365	CUTOFF Lube oil, at plant	kg	1920

366	CUTOFF Lubricants, unspecified, at plant	kg	1920
367	CUTOFF Lubricating oil	kg	1920
368	CUTOFF Magnesium oxide, at plant	kg	2011
369	CUTOFF Maize drying	kg	161
370	CUTOFF Maleic anhydride, at plant	kg	2011
371	CUTOFF Materials for basecoat painting, at plant	kg	2022
372	CUTOFF Materials for basecoat painting, at plant	kg	2022
373	CUTOFF Measuring and dispensing pumps	item	2811
374	CUTOFF Melamine, at plant	kg	2011
375	CUTOFF Metallurgical coke, combusted in industrial boiler	kg	FOSSIL FUEL
376	CUTOFF Metolachlor, at regional storehouse	kg	2011
377	CUTOFF Middle distillates, combusted in industrial boiler	kg	FOSSIL FUEL
378	CUTOFF Mineral spirits	kg	2011
379	CUTOFF Miscellaneous metal scrap	kg	2410
380	CUTOFF Mixed deposit containers, at source	kg	3830
381	CUTOFF Mixed paper	kg	1701
382	CUTOFF Mixed recyclables, at source	kg	3830
383	CUTOFF Mixed recyclables, at source	kg	3830
384	CUTOFF Mold-release agent, at plant	kg	2011
385	CUTOFF Monoethanolamine (MEA), at plant	kg	2011
386	CUTOFF Monoethanolamine, at plant	kg	2011
387	CUTOFF Mowing, by rotary mower	ha	161
388	CUTOFF Natural gas, processed, for olefins production, at plant, internal offgas use	m3	3520
389	CUTOFF Natural gas, processed, for olefins production, at plant, material use	m3	3520
390	CUTOFF Neo pentyl glycol, at plant	kg	2011
391	CUTOFF Nitrogen, at plant	kg	2011
392	CUTOFF Nylon 6, at plant	kg	2011
393	CUTOFF Oil and grease, at plant	kg	1920
394	CUTOFF Oil, at plant	kg	1920
395	CUTOFF Old corrugated containers	kg	3830
396	CUTOFF Old magazines	kg	3830
397	CUTOFF Old news paper	kg	3830
398	CUTOFF Optical brightner, at plant	kg	2011
399	CUTOFF Organophosphorus-compounds, at regional storehouse	kg	2011
400	CUTOFF Other biomass fuel, unspecified	kg	119
401	CUTOFF Overburden, stockpiled, on-site, for unspecified beneficial use	kg	990
402	CUTOFF PVOH, at plant	kg	2011
403	CUTOFF Packaging, unspecified, at plant	kg	8292

404	CUTOFF Pallet, for packaging	kg	1623
405	CUTOFF Palm kernel oil, crude, at plant	kg	111
406	CUTOFF Paper, woodcontaining, LWC, at plant	kg	1701
407	CUTOFF Pentane	kg	2011
408	CUTOFF Petroleum coke, combusted in industrial boiler	kg	1920
409	CUTOFF Petroleum refining, for olefins production, at plant, internal offgas use	kg	1920
410	CUTOFF Petroleum refining, for olefins production, at plant, material use	kg	1920
411	CUTOFF Phenol, at plant	kg	2011
412	CUTOFF Phosphate anti-corrosion	kg	2011
413	CUTOFF Phosphate anti-corrosion makeup	kg	2011
414	CUTOFF Phosphate anti-corrosion post-rinse	kg	2011
415	CUTOFF Phosphate pre-treat	kg	2011
416	CUTOFF Phosphoric Acid, at plant	kg	2011
417	CUTOFF Phosphorous Fertilizer (TSP as P2O5), at plant	kg	2012
418	CUTOFF Phthalic anhydride, at plant	kg	2011
419	CUTOFF Pigment, at plant	kg	2022
420	CUTOFF Pigment, at plant	kg	2022
421	CUTOFF Planting	ha	161
422	CUTOFF Plastic baggies, low density polyethylene, at plant	kg	2220
423	CUTOFF Plastic band, for packaging	kg	2220
424	CUTOFF Plasticshot, polymethylmethacrylate, at plant	kg	2220
425	CUTOFF Plasticshot, polyurea formaldehyde, at plant	kg	2220
426	CUTOFF Polycarbonate, at plant	kg	2013
427	CUTOFF Polyethylene low density granulate (PE-LD), production mix, at plant	kg	2013
428	CUTOFF Polyethylene terephthalate, granulate, amorphous, at plant	kg	2013
429	CUTOFF Polyethylene-film (PE)	kg	2013
430	CUTOFF Polymers, at plant	kg	2013
431	CUTOFF Polymethyl methacrylate, beads, at plant	kg	2013
432	CUTOFF Polyphenylene sulfide, at plant	kg	2013
433	CUTOFF Polypropylene-film (oriented) (PP)	kg	2013
434	CUTOFF Polyurethane Caulk	kg	2013
435	CUTOFF Polyurethane, flexible foam, at plant	kg	2013
436	CUTOFF Polyvinyl Acetate	kg	2013
437	CUTOFF Polyvinylidene fluoride	kg	2013
438	CUTOFF Potash Fertilizer (K2O), at plant	kg	2012
439	CUTOFF Potassium chloride, as K2O, at regional storehouse	kg	2012
440	CUTOFF Potassium fertilizer, production mix, at plant	kg	2012
441	CUTOFF Potassium hydroxide, production mix, at plant, for polyol foams	kg	2012

442	CUTOFF Potassium nitrate, as K2O, at regional storehouse	kg	2012
443	CUTOFF Potato Starch, at plant	kg	113
444	CUTOFF Power adapter, for laptop, at plant	kg	2610
445	CUTOFF Precipitated calcium carbonate, at plant	kg	2011
446	CUTOFF Prewipe, at plant	kg	2011
447	CUTOFF Printed wiring board, power supply unit desktop PC, Pb free, at plant	kg	2610
448	CUTOFF Printed wiring board, surface mounted, unspec., Pb free, at plant	kg	2610
449	CUTOFF Process wastewater, to municipal wastewater treatment	kg	3700
450	CUTOFF Propane, combusted in equipment	MJ	ENERGY
451	CUTOFF Propylene Glycol, liquid, at plant	kg	2011
452	CUTOFF Pulp chips, at sawmill, US	kg	1610
453	CUTOFF Pulp chips, at sawmill, US SE/kg, in black liquor	kg	1610
454	CUTOFF Pulp chips, at sawmill, US SE/kg, in pulp	kg	1610
455	CUTOFF Pulp slurry, groundwood, bleached, average production, at mill	kg	1610
456	CUTOFF Pulp slurry, kraft market, bleached, average production, at mill	kg	1610
457	CUTOFF Pulp slurry, sulfite, bleached, average production, at mill	kg	1610
458	CUTOFF Pulp, deinked market, bleached, at mill	kg	1610
459	CUTOFF Pulp, refiner market, bleached, average production, at mill	kg	1610
460	CUTOFF Pulpwood, hardwood, average, at forest road, US S	m3	220
461	CUTOFF Pulpwood, in black liquor solids	m3	220
462	CUTOFF Pulpwood, in pulp	m3	220
463	CUTOFF Pulpwood, in wood fuel	m3	220
464	CUTOFF Pulpwood, softwood, average, at forest road, US S	m3	220
465	CUTOFF Purified terephthalic acid, at plant	kg	2011
466	CUTOFF Pyretroid-compounds, at regional storehouse	kg	2011
467	CUTOFF Quaternary (DDAC), at plant	kg	2011
468	CUTOFF Recovered paper	kg	3830
469	CUTOFF Recycling, Aluminum scrap	kg	3830
470	CUTOFF Recycling, Steel scrap	kg	3830
471	CUTOFF Recycling, baghouse dust, unspecified	kg	3830
472	CUTOFF Recycling, batteries	kg	3830
473	CUTOFF Recycling, biohazard waste, unspecified	kg	3830
474	CUTOFF Recycling, cardboard	kg	3830
475	CUTOFF Recycling, cement kiln dust	kg	3830
476	CUTOFF Recycling, construction debris, unspecified	kg	3830

477	CUTOFF Recycling, fluorescent tubes and other mercury-containing wastes	kg	3830
478	CUTOFF Recycling, municipal solid wastes, unspecified	kg	3830
479	CUTOFF Recycling, petroleum based wastes, unspecified	kg	3830
480	CUTOFF Recycling, refractory material	kg	3830
481	CUTOFF Recycling, rubber	kg	3830
482	CUTOFF Recycling, solid waste, unspecified	kg	3830
483	CUTOFF Recycling, waste, unspecified	kg	3830
484	CUTOFF Recycling, wood waste, unspecified	kg	3830
485	CUTOFF Refractory material, unspecified, at plant	kg	3830
486	CUTOFF Release agent, unspecified, at plant	kg	2011
487	CUTOFF Resorcinol, at plant	kg	2011
488	CUTOFF Retention aid, at plant	kg	2011
489	CUTOFF Rinse conditioner, at plant	kg	2512
490	CUTOFF Roundwood, hardwood, at forest road, SE	m3	220
491	CUTOFF Rubber and plastics hose and belting	USD	2211
492	CUTOFF Sawdust, at sawmill, US	kg	1610
493	CUTOFF Sawn Lumber, softwood, planed, green, at planer, PNW	kg	1610
494	CUTOFF Secondary fuel	MJ	RECOVERED ENERGY
495	CUTOFF Secondary fuel renewable	MJ	RECOVERED ENERGY
496	CUTOFF Shot blast, unspecified	kg	2410
497	CUTOFF Silica sand, at mine	kg	810
498	CUTOFF Silica sand, at plant	kg	2391
499	CUTOFF Silicon, multi-Si, casted, at plant	kg	2011
500	CUTOFF Silicone dioxide, at plant	kg	2011
501	CUTOFF Silicone sealing compound	kg	2011
502	CUTOFF Silver, at regional storage	kg	2420
503	CUTOFF Sizer, at plant	kg	2821
504	CUTOFF Slag, at blast furnace	kg	2394
505	CUTOFF Slag, production residue, recovered	kg	2394
506	CUTOFF Slurry spreading, by vacuum tanker	kg	161
507	CUTOFF Sodium Methylate, at plant	kg	2011
508	CUTOFF Sodium borate	kg	2011
509	CUTOFF Sodium chlorate	kg	2011
510	CUTOFF Sodium chlorate, at plant	kg	2011
511	CUTOFF Sodium hydrosulfite	kg	2011
512	CUTOFF Sodium hydrosulfite, at plant	kg	2011
513	CUTOFF Sodium hydroxide	kg	2011
514	CUTOFF Sodium hydroxide, 50% solids, at plant	kg	2011
515	CUTOFF Sodium hydroxide, at plant	kg	2011

516	CUTOFF Sodium sulfate	kg	2011
517	CUTOFF Sodium sulfate, at plant	kg	2011
518	CUTOFF Softwood seed, at greenhouse, INW	ha	210
519	CUTOFF Softwood with bark, avg. intst. harvest, at mill, US SE, in black liquor	kg	1610
520	CUTOFF Softwood with bark, avg. intst. harvest, at mill, US SE, in pulp	kg	1610
521	CUTOFF Softwood with bark, avg.intst. harvest, at mill, US SE, in self-gen. hogged fuel	kg	1610
522	CUTOFF Solid manure loading and spreading, by hydraulic loader and spreader	kg	161
523	CUTOFF Solution corrosion inhibitor, at plant	kg	2011
524	CUTOFF Solvent-based stain, 30% solids	kg	2011
525	CUTOFF Sorted office paper	kg	1701
526	CUTOFF Spring wheat straw, production, average, US, 2022	kg	111
527	CUTOFF Starch	kg	1062
528	CUTOFF Starch, at plant	kg	1062
529	CUTOFF Steam	MJ	ENERGY
530	CUTOFF Steel band, for packaging	kg	2420
531	CUTOFF Steel cast part (machined)	kg	2420
532	CUTOFF Steel product manufacturing, average metal working	kg	2420
533	CUTOFF Steel scrap (st)	kg	2420
534	CUTOFF Steel scrap, at plant	kg	2420
535	CUTOFF Steel, low-alloyed, at plant	kg	2420
536	CUTOFF Steel, secondary, at plant	kg	2420
537	CUTOFF Sulfur dioxide, at plant	kg	2011
538	CUTOFF Sulfuric acid, at plant	kg	2011
539	CUTOFF Sulphite, at plant	kg	2011
540	CUTOFF Sulphuric acid, liquid, at plant	kg	2011
541	CUTOFF Surfactant, unspecified	kg	2011
542	CUTOFF Swath, by rotary windrower	ha	161
543	CUTOFF Synthetic rubber, at plant	kg	2013
544	CUTOFF TEA gas scrubber, at plant	kg	2011
545	CUTOFF TEA gas, at plant	kg	2011
546	CUTOFF TEA-DMEA (trimethyl amine, dimethylamine), at plant	kg	2011
547	CUTOFF TSS, Total Suspended Solids, to municipal wastewater treatment	kg	3811
548	CUTOFF TSS, to municipal wastewater treatment	kg	3811
549	CUTOFF Tailings, stockpiled, on-site, for unspecified beneficial use	kg	990
550	CUTOFF Talc, at plant	kg	2011
551	CUTOFF Tap water, at user	kg	3600

552	CUTOFF Tetrabromophthalic acid, at plant	kg	2011
553	CUTOFF Tetrafluoroethane (R-134a)	kg	2011
554	CUTOFF Tetrafluoroethylene, at plant	kg	2011
555	CUTOFF Textile, woven cotton, at plant	kg	1312
556	CUTOFF Thermal energy from propane (MJ)	MJ	ENERGY
557	CUTOFF Thermochemical Conversion Plant	Item(s)	4290
558	CUTOFF Thickener, at plant	kg	2011
559	CUTOFF Tillage, cultivating, chiselling	ha	161
560	CUTOFF Tillage, ploughing	ha	161
561	CUTOFF Tillage, rolling	ha	161
562	CUTOFF Tillage, rotary cultivator	ha	161
563	CUTOFF Tinted clearcoat materials, at plant	kg	2011
564	CUTOFF Tire derived fuel	MJ	RECOVERED ENERGY
565	CUTOFF Titanium dioxide	kg	2011
566	CUTOFF Titanium dioxide, at plant	kg	2011
567	CUTOFF Transport, ocean tanker, average fuel mix	t*km	5012
568	CUTOFF Transport, pipeline, coal slurry	t*km	4930
569	CUTOFF Transport, tractor and trailer	t*km	4923
570	CUTOFF Treatment gases, unspecified, at plant	kg	3811
571	CUTOFF Treatment salts, unspecified, at plant	kg	3811
572	CUTOFF Treatment, electrocoating wastewater, unspecified treatment	m3	3700
573	CUTOFF Treatment, sewage, to wastewater treatment, class 1	kg	3700
574	CUTOFF Treatment, sewage, to wastewater treatment, class 1/CH U	kg	3700
575	CUTOFF Treatment, sewage, unpolluted, to wastewater treatment, class 3	m3	3700
576	CUTOFF Treatment,maize starch production effluent,to wastewater treatment,class2	m3	3811
577	CUTOFF UV-cured filler, 100% solids	kg	2022
578	CUTOFF UV-cured sealer, 100% solids	kg	2022
579	CUTOFF UV-cured stain, 100% solids	kg	2022
580	CUTOFF UV-cured topcoat, 100% solids	kg	2022
581	CUTOFF Urea 40% solids	kg	2011
582	CUTOFF Urea, at regional storehouse	kg	2011
583	CUTOFF Waste, industrial	kg	3811
584	CUTOFF Waste, miscellaneous, combusted in industrial boiler	kg	3811
585	CUTOFF Waste, oil, combusted in industrial boiler	MJ	RECOVERED ENERGY
586	CUTOFF Waste, other solid, combusted in industrial boiler	kg	3811
587	CUTOFF Waste, solvents, combusted in industrial boiler	kg	3811
588	CUTOFF Waste, tire derived, combusted in industrial boiler	kg	3811

589	CUTOFF Wastewater, unspecified, to unspecified treatment	kg	3700
590	CUTOFF Water, at plant	kg	3600
591	CUTOFF Water, at user	kg	3600
592	CUTOFF Water, process	kg	3600
593	CUTOFF Water, process, deionized	kg	3600
594	CUTOFF Water-based stain, 20% solids	kg	2011
595	CUTOFF Wax	kg	1920
596	CUTOFF Wetting agent, unspecified	kg	2011
597	CUTOFF Wood and bark hogged fuel from harvesting residues	kg	1629
598	CUTOFF Wood and bark hogged fuel from manufacturing residues, unspecified	kg	1629
599	CUTOFF Wood waste, unspecified	kg	3811
600	CUTOFF Yeast paste, from whey, at fermentation	kg	2011
601	CUTOFF Zeolite, powder, at plant	kg	2011
602	CUTOFF Zinc scrap, life cycle production residue, recovered	kg	2420
603	CUTOFF Zinc stearate, at plant	kg	2420
604	CUTOFF Zinc waste inputs (50% Zn), life cycle production residue, recovered	kg	2420
605	CUTOFF [sulfonyl]urea-compounds, at regional storehouse	kg	2011
606	Chainsawing, delimbing, NE-NC	kg	1610
607	Chainsawing, hand felling and delimbing, INW	kg	1610
608	Chainsawing, hand felling, NE-NC	kg	1610
609	Chlor-alkali electrolysis, chlorine for PVC, at plant	kg	2011
610	Chlorine, production mix, at plant	kg	2011
611	Cladding, roll formed, at plant	kg	2511
612	Clippings, hardwood, dry, at veneer mill, E	kg	1610
613	Co-products of glue laminated beam production, at plant, unspecified, US PNW	kg	1621
614	Co-products of glue laminated beam production, at plant, unspecified, US SE	kg	1621
615	Co-products of laminated veneer lumber production, unspecified, US PNW	kg	1610
616	Combustion, dry wood residue, AP-42	kg	BIOFUEL
617	Combustion, wet wood residue, AP-42	kg	BIOFUEL
618	Composite scrap, from composites compression molding, at plant	kg	2220
619	Composite scrap, from composites open mold casting, at plant	kg	2220
620	Composite scrap, from composites open molding, at plant	kg	2220
621	Composite scrap, from composites vacuum infusion, at plant	kg	2220
622	Compression molding, rigid composites part, at plant	kg	2220
623	Conditioned log, at plywood plant, US PNW	kg	1621
624	Conditioned log, at plywood plant, US SE	kg	1621
625	Conditioned log, hardwood, green, at veneer mill, E	kg	1610

626	Containerboard, average production, at mill	kg	1701
627	Coproducts of laminated veneer lumber production, unspecified, US SE	kg	1610
628	Corn grain, at conversion plant, 2022	kg	119
629	Corn grain, harvested and stored	kg	119
630	Corn steep liquor	kg	1061
631	Corn stover, at conversion plant, 2022	kg	119
632	Corn stover, at field	kg	119
633	Corn stover, carted	kg	119
634	Corn stover, ground and stored	kg	119
635	Corn stover, production, average, US, 2022	kg	119
636	Corn wet mill, gluten drying, AP-42	kg	1061
637	Corn wet mill, gluten drying, AP-42	kg	1061
638	Corn wet milling, operations, AP-42	kg	1061
639	Corn, at field	kg	119
640	Corn, decomposition, 15.5% moisture	kg	119
641	Corn, production, average, US, 2022	kg	119
642	Corrugate packaging, from LDPE injection molding, for shipping	kg	8292
643	Corrugate packaging, from PP injection molding, for shipping	kg	8292
644	Corrugate packaging, from PP thermoforming, for shipping	kg	8292
645	Corrugate packaging, from compression molding, for shipping	kg	8292
646	Corrugate packaging, from open molding, for shipping	kg	BIOFUEL
647	Corrugated Product	kg	1702
648	Corrugated Product	kg	1702
649	Cotton straw, at field	kg	116
650	Cotton, at field	kg	116
651	Crew to Burn Bole Only slash in the Woods, INW	ha	240
652	Crude oil, at production	kg	610
653	Crude oil, extracted	kg	1920
654	Crude palm kernel oil, at plant	kg	111
655	Debarked wood, at plywood plant, US PNW	kg	1610
656	Debarked wood, at plywood plant, US SE	kg	1610
657	Delimbing, slide boom delimber	ha	240
658	Deposit containers, at collection	kg	3830
659	Deposit containers, at collection, CRV	kg	3830
660	Diesel(1), at refinery	kg	1920
661	Diesel, at refinery	kg	1920
662	Diesel, combusted in industrial boiler	kg	FOSSIL FUEL
663	Diesel, combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	FOSSIL FUEL
664	Diesel, combusted in industrial equipment	kg	FOSSIL FUEL

665	Distillers dried grains with solubles, 2022	kg	2011
666	Dry rough lumber, at kiln, US PNW	kg	1610
667	Dry rough lumber, at kiln, US SE	kg	1610
668	Dry veneer, at plywood plant, US PNW	kg	1621
669	Dry veneer, at plywood plant, US SE	kg	1621
670	Dry veneer, sold, at plywood plant, US PNW	kg	1621
671	Dust and scrap, at oriented strand board production, US SE	kg	1610
672	E-glass, at plant	kg	2310
673	EPS insulation board, at plant	kg	2013
674	Electricity, alumina refining regions	kWh	3510
675	Electricity, aluminum smelting and ingot casting regions	kWh	3510
676	Electricity, anthracite coal, at power plant	kWh	3510
677	Electricity, at Grid, ASCC, 2008	kWh	3510
678	Electricity, at Grid, ASCC, 2010	kWh	3510
679	Electricity, at Grid, FRCC, 2008	kWh	3510
680	Electricity, at Grid, FRCC, 2010	kWh	3510
681	Electricity, at Grid, HICC, 2008	kWh	3510
682	Electricity, at Grid, HICC, 2010	kWh	3510
683	Electricity, at Grid, MRO, 2008	kWh	3510
684	Electricity, at Grid, MRO, 2010	kWh	3510
685	Electricity, at Grid, NPCC, 2008	kWh	3510
686	Electricity, at Grid, NPCC, 2010	kWh	3510
687	Electricity, at Grid, RFC, 2008	kWh	3510
688	Electricity, at Grid, RFC, 2010	kWh	3510
689	Electricity, at Grid, SERC, 2008	kWh	3510
690	Electricity, at Grid, SERC, 2010	kWh	3510
691	Electricity, at Grid, SPP, 2008	kWh	3510
692	Electricity, at Grid, SPP, 2010	kWh	3510
693	Electricity, at Grid, TRE, 2008	kWh	3510
694	Electricity, at Grid, TRE, 2010	kWh	3510
695	Electricity, at Grid, US, 2010	kWh	3510
696	Electricity, at Grid, WECC, 2008	kWh	3510
697	Electricity, at Grid, WECC, 2010	kWh	3510
698	Electricity, at bleached kraft market pulp mill	kWh	3510
699	Electricity, at coated freesheet mill	kWh	3510
700	Electricity, at coated mechanical paper mill	kWh	3510
701	Electricity, at cogen, for natural gas turbine	kWh	3510
702	Electricity, at cogen, for natural gas turbine	kWh	3510
703	Electricity, at eGrid, AKGD, 2008	kWh	3510
704	Electricity, at eGrid, AKGD, 2010	kWh	3510
705	Electricity, at eGrid, AKMS, 2008	kWh	3510

706	Electricity, at eGrid, AKMS, 2010	kWh	3510
707	Electricity, at eGrid, AZNM, 2008	kWh	3510
708	Electricity, at eGrid, AZNM, 2010	kWh	3510
709	Electricity, at eGrid, CAMX, 2008	kWh	3510
710	Electricity, at eGrid, CAMX, 2010	kWh	3510
711	Electricity, at eGrid, ERCT, 2008	kWh	3510
712	Electricity, at eGrid, ERCT, 2010	kWh	3510
713	Electricity, at eGrid, FRCC, 2008	kWh	3510
714	Electricity, at eGrid, FRCC, 2010	kWh	3510
715	Electricity, at eGrid, HIMS, 2008	kWh	3510
716	Electricity, at eGrid, HIMS, 2010	kWh	3510
717	Electricity, at eGrid, HIOA, 2008	kWh	3510
718	Electricity, at eGrid, HIOA, 2010	kWh	3510
719	Electricity, at eGrid, MROE, 2008	kWh	3510
720	Electricity, at eGrid, MROE, 2010	kWh	3510
721	Electricity, at eGrid, MROW, 2008	kWh	3510
722	Electricity, at eGrid, MROW, 2010	kWh	3510
723	Electricity, at eGrid, NEWE, 2008	kWh	3510
724	Electricity, at eGrid, NEWE, 2010	kWh	3510
725	Electricity, at eGrid, NWPP, 2008	kWh	3510
726	Electricity, at eGrid, NWPP, 2010	kWh	3510
727	Electricity, at eGrid, NYCW, 2008	kWh	3510
728	Electricity, at eGrid, NYCW, 2010	kWh	3510
729	Electricity, at eGrid, NYLI, 2008	kWh	3510
730	Electricity, at eGrid, NYLI, 2010	kWh	3510
731	Electricity, at eGrid, NYUP, 2008	kWh	3510
732	Electricity, at eGrid, NYUP, 2010	kWh	3510
733	Electricity, at eGrid, RFCE, 2008	kWh	3510
734	Electricity, at eGrid, RFCE, 2010	kWh	3510
735	Electricity, at eGrid, RFCM, 2008	kWh	3510
736	Electricity, at eGrid, RFCM, 2010	kWh	3510
737	Electricity, at eGrid, RFCW, 2008	kWh	3510
738	Electricity, at eGrid, RFCW, 2010	kWh	3510
739	Electricity, at eGrid, RMPA, 2008	kWh	3510
740	Electricity, at eGrid, RMPA, 2010	kWh	3510
741	Electricity, at eGrid, SPNO, 2008	kWh	3510
742	Electricity, at eGrid, SPNO, 2010	kWh	3510
743	Electricity, at eGrid, SPSO, 2008	kWh	3510
744	Electricity, at eGrid, SPSO, 2010	kWh	3510
745	Electricity, at eGrid, SRMV, 2008	kWh	3510
746	Electricity, at eGrid, SRMV, 2010	kWh	3510

747	Electricity, at eGrid, SRMW, 2008	kWh	3510
748	Electricity, at eGrid, SRMW, 2010	kWh	3510
749	Electricity, at eGrid, SRSO, 2008	kWh	3510
750	Electricity, at eGrid, SRSO, 2010	kWh	3510
751	Electricity, at eGrid, SRTV, 2008	kWh	3510
752	Electricity, at eGrid, SRTV, 2010	kWh	3510
753	Electricity, at eGrid, SRVC, 2008	kWh	3510
754	Electricity, at eGrid, SRVC, 2010	kWh	3510
755	Electricity, at grid, Eastern US, 2000	kWh	3510
756	Electricity, at grid, Texas US, 2000	kWh	3510
757	Electricity, at grid, US, 2000	kWh	3510
758	Electricity, at grid, US, 2008	kWh	3510
759	Electricity, at grid, Western US, 2000	kWh	3510
760	Electricity, at unbleached kraft bag and sack paper mill	kWh	3510
761	Electricity, at uncoated freesheet mill	kWh	3510
762	Electricity, at uncoated mechanical paper mill	kWh	3510
763	Electricity, bauxite mining regions	kWh	3510
764	Electricity, bituminous coal, at power plant	kWh	3510
765	Electricity, diesel, at power plant	kWh	3510
766	Electricity, lignite coal, at power plant	kWh	3510
767	Electricity, natural gas, at power plant	kWh	3510
768	Electricity, nuclear, at power plant	kWh	3510
769	Electricity, onsite boiler, hardwood mill, average, NE-NC	kWh	3510
770	Electricity, onsite boiler, hardwood mill, average, SE	kWh	3510
771	Electricity, onsite boiler, softwood mill, average, NE-NC	kWh	3510
772	Electricity, residual fuel oil, at power plant	kWh	3510
773	Engineered flooring, hardwood, unfinished, E	kg	1610
774	Ethanol, 85%, at blending terminal, 2022	kg	1920
775	Ethanol, 85%, blended, at service station, 2022	kg	2011
776	Ethanol, denatured, at refueling station, 2022	kg	2011
777	Ethanol, denatured, corn dry mill	kg	2011
778	Ethanol, denatured, corn stover, biochemical	kg	2011
779	Ethanol, denatured, forest residues, thermochem	kg	2011
780	Ethanol, denatured, mixed feedstocks, at conversion facility, 2022	kg	2011
781	Ethanol, denatured, switchgrass, biochemical	kg	2011
782	Ethanol, denatured, wheat straw, biochemical	kg	2011
783	Ethylbenzene styrene, at plant	kg	2011
784	Ethylene dichloride-vinyl chloride monomer, at plant	kg	2011
785	Ethylene oxide, at plant	kg	2011
786	Ethylene, at plant	kg	2011
787	Felling, feller buncher, >200 HP, INW	ha	240

788	Felling, feller buncher, >200 HP, NE-NC	ha	240
789	Fertilizer, corn, 2022	kg	2012
790	Fertilizer, stover, 2022	kg	2012
791	Fertilizer, switchgrass, 2022	kg	2012
792	Fertilizer, winter wheat straw, 2022	kg	2012
793	Fines, at oriented strand board production, US SE	kg	1610
794	Forest residue, dried, stored	ha	210
795	Forest residue, preprocessed, at conversion facility	kg	1610
796	Forest residue, processed and loaded, at landing system	kg	1610
797	Fuel grade uranium, at regional storage	kg	721
798	Fuel wood, hardwood, kiln-dried, at planer mill, NE-NC	kg	1629
799	Fuel wood, softwood, green, at sawmill, NE-NC	kg	1629
800	Fuels, burned at bleached kraft market pulp mill, average production, at mill	MJ	ENERGY
801	Fuels, burned at coated freesheet, average production, at mill	MJ	ENERGY
802	Fuels, burned at coated mechanical paper, average production, at mill	MJ	ENERGY
803	Fuels, burned at unbleached kraft bag sack paper, average production, at mill	MJ	ENERGY
804	Fuels, burned at uncoated freesheet, average production, at mill	MJ	ENERGY
805	Fuels, burned at uncoated mechanical paper, average production, at mill	MJ	ENERGY
806	Gasoline, at refinery	kg	1920
807	Gasoline, combusted in equipment	kg	FOSSIL FUEL
808	Gasoline, combusted in equipment, at pulp and paper mill (EXCL.)	kg	FOSSIL FUEL
809	Glycerin, at biodiesel plant	kg	2011
810	Glycerine, at plant	kg	2011
811	Green veneer, at plywood plant, US PNW	kg	1621
812	Green veneer, at plywood plant, US SE	kg	1621
813	Green veneer, sold, at plywood plant, US PNW	kg	1621
814	Green veneer, sold, at plywood plant, US SE	kg	1621
815	Greenhouse seedling, softwood, INW	ha	210
816	Grinding	ha	161
817	Harvest, corn, single pass	ha	161
818	Harvest, switchgrass	ha	161
819	Harvest, wheat, single pass	ha	161
820	Harvesting, fresh fruit bunch, at farm	ha	161
821	Hazardous waste (deposited)	kg	3811
822	Hazardous waste (deposited)	kg	3811
823	Hazardous waste (deposited)	kg	3811
824	Heat, block conditiong, at veneer mill, E	MJ	ENERGY

825	Heat, drying stain, at engineered wood flooring mill, E	MJ	ENERGY
826	Heat, drying veneer, hardwood, at veneer mill, E	MJ	ENERGY
827	Heat, indirect, heated zones, softwood, plywood veneer drying, AP-42	MJ	ENERGY
828	Heat, onsite boiler, hardwood mill, average, NE-NC	MJ	ENERGY
829	Heat, onsite boiler, hardwood mill, average, SE	MJ	ENERGY
830	Heat, onsite boiler, softwood mill, average, NE-NC	MJ	ENERGY
831	Heat, pressing panels, hardwood, at engineered wood flooring plant, E	MJ	ENERGY
832	High radioactive wastes	kg	3811
833	High radioactive wastes	kg	3811
834	Hog fuel, pur., combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	BIOFUEL
835	Hog fuel, self-gen., combusted in ind. boiler, at pulp and paper mill (EXCL.)	kg	BIOFUEL
836	Hogfuel, from trim and saw at plywood plant, US PNW	kg	1629
837	Hogfuel, from trim&saw, plywood plant, US SE	kg	1629
838	Hogged fuel, hardwood, green, at sawmill, NE-NC	kg	1629
839	Hogged fuel, hardwood, green, at sawmill, SE	kg	1629
840	Hydrogen, liquid, synthesis gas, at plant	kg	2011
841	Injection molding, rigid LLDPE part, at plant	kg	2220
842	Injection molding, rigid polypropylene part, at plant	kg	2220
843	Iron and steel, production mix	kg	2410
844	Iron, sand casted	kg	2410
845	Kerosene, at refinery	kg	1920
846	LLDPE scrap, from LLDPE injection molding, at plant	kg	2220
847	LPG, combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	FOSSIL FUEL
848	Laminated veneer lumber, at plant, US PNW	kg	1621
849	Laminated veneer lumber, at plant, US SE	kg	1621
850	Lignite coal, at surface mine	kg	520
851	Lignite coal, combusted in industrial boiler	kg	COAL
852	Lime, agricultural, corn production	ha	161
853	Limestone, at mine	kg	810
854	Liquefied petroleum gas, at refinery	kg	1920
855	Liquefied petroleum gas, combusted in industrial boiler	kg	FOSSIL FUEL
856	Loader operation, large, INW	ha	240
857	Loader operation, large, NE-NC	ha	240
858	Low radioactive wastes	kg	3811
859	Low radioactive wastes	kg	3811
860	Lumber, softwood, ACQ treated, SE	kg	1610
861	Lumber, softwood, borate treated, PNW	kg	1610
862	Marine piling, softwood, CCA treated, SE	kg	1610

863	Medium density fiberboard (MDF), at MDF mill	kg	1610
864	Medium density fiberboard (MDF), at MDF mill	kg	1610
865	Medium radioactive wastes	kg	3811
866	Medium radioactive wastes	kg	3811
867	Melamine urea formaldehyde resin, neat, 60% solids	kg	2013
868	Metal composite material (MCM) panel, at plant	kg	2511
869	Metal composite material (MCM) sheet, at plant	kg	2511
870	Metal panel, insulated, at plant	kg	2511
871	Metallurgical coke, at plant	kg	892
872	Methanol, at plant	kg	2011
873	Methylene diphenyl diisocyanate resin, at plant, US PNW	kg	2013
874	Methylene diphenyl diisocyanate resin, at plant, US SE	kg	2013
875	Methylene diphenyl diisocyanate resin, at plant, US SE	kg	2013
876	Methylene diphenyl diisocyanate, resin, at plant	kg	2011
877	Mixed Alcohols, thermochemical process	kg	2011
878	Mixed recyclables, at collection, commercial	kg	3830
879	Mixed recyclables, at collection, curbside, volume basis	kg	3830
880	Mixed recyclables, at collection, curbside, weight basis	kg	3830
881	Mixed recyclables, at collection, dropoff center	kg	3830
882	Mixed recyclables, sorted at MRF	kg	3830
883	Mixed recyclables, to MRF	kg	3830
884	Mixings, hardwood, kiln-dried, at planer mill, NE-NC	kg	1610
885	Natural gas, at extraction site	m3	620
886	Natural gas, combusted in industrial boiler	m3	NATURAL GAS
887	Natural gas, combusted in industrial boiler, at hydrocracker, for butadiene	m3	NATURAL GAS
888	Natural gas, combusted in industrial boiler, at hydrocracker, for ethylene	m3	NATURAL GAS
889	Natural gas, combusted in industrial boiler, at hydrocracker, for propylene	m3	NATURAL GAS
890	Natural gas, combusted in industrial boiler, at hydrocracker, for pyrolysis gas	m3	NATURAL GAS
891	Natural gas, combusted in industrial boiler, at pulp and paper mill (EXCL.)	m3	NATURAL GAS
892	Natural gas, combusted in industrial equipment	m3	NATURAL GAS
893	Natural gas, extracted	m3	620
894	Natural gas, processed, at plant	m3	3520
895	Natural gas, processed, for olefins production, at plant	m3	3520
896	Natural soda ash (Sodium carbonate), at plant	kg	2011
897	Natural soda ash (Sodium carbonate), at plant	kg	2011
898	Nitrogen fertilizer, production mix, at plant	kg	2012
899	Office scanner	Item(s)	2620
900	Open mold casting, rigid composites part, at plant	kg	2220

901	Open molding, rigid composites part, at plant	kg	2220
902	Oriented strand board product, US SE	kg	1610
903	Overburden (deposited)	kg	3811
904	Overburden (deposited)	kg	3811
905	Oxygen, liquid, at plant	kg	2011
906	Packaging and information sheets, i2900 desktop scanner	kg	8292
907	Packaging, production scanners	kg	8292
908	Palm kernel oil, processed, at plant	kg	2029
909	Palm kernels, at plant	kg	111
910	Panel trim, from trim and saw at plywood plant, US PNW	kg	1610
911	Panel trim, from trim and saw, at plywood plant, US SE	kg	1610
912	Paper, bag and sack, unbleached kraft, average production, at mill	kg	1702
913	Paper, freesheet, coated, average production, at mill	kg	1701
914	Paper, freesheet, uncoated, average production, at mill	kg	1701
915	Paper, freesheet, uncoated, average production, at mill, 2006	kg	1701
916	Paper, mechanical, coated, average production, at mill	kg	1701
917	Paper, mechanical, uncoated, average production, at mill	kg	1701
918	Paraxylene, at plant	kg	2011
919	Particleboard, average, softwood, particleboard mill	kg	1610
920	Particleboard, average, softwood, particleboard mill	kg	1610
921	Peeler core, from green veneer production at plywood plant, US PNW	kg	1610
922	Peeler core, from green veneer production at plywood plant, US SE	kg	1610
923	Pesticide, Switchgrass	kg	2011
924	Pesticide, corn, 2022	kg	2011
925	Petroleum coke, at refinery	kg	1920
926	Petroleum refining coproduct, at refinery	kg	1920
927	Petroleum refining coproduct, unspecified, at refinery	kg	1920
928	Petroleum refining, at refinery	kg	1920
929	Petroleum refining, for olefins production, at plant	kg	1920
930	Phenol Resorcinol Formaldehyde resin, neat, 60% solids	kg	2013
931	Phenol formaldehyde resin, neat, 47% solids	kg	2013
932	Phosphorous fertilizer, production mix, at plant	kg	2012
933	Phosphorous fertilizer, production mix, at plant	kg	2012
934	Piling, bole slash, in forest, steep slope forest, INW	ha	240
935	Piling, whole tree slash, at landing, gentle slope forest, INW	ha	240
936	Planer shavings, at planer mill, US SE	kg	1610
937	Planer shavings, from dried lumber, at planer mill, US PNW	kg	1610
938	Planer shavings, from green lumber, at planer mill, US PNW	kg	1610
939	Planting, switchgrass, 2022	ha	161

940	Plywood, at plywood plant, US PNW	kg	1621
941	Plywood, at plywood plant, US SE	kg	1621
942	Plywood, from open molding, for shipping	kg	1621
943	Poles, softwood, PCP treated	kg	1610
944	Polybutadiene, at plant	kg	2013
945	Polyethylene terephthalate, resin, at plant	kg	2013
946	Polyethylene, high density, resin, at plant	kg	2013
947	Polyethylene, linear low density, resin, at plant	kg	2013
948	Polyethylene, low density, resin, at plant	kg	2013
949	Polylactide Biopolymer Resin, at plant	kg	2013
950	Polyol ether, for flexible foam polyurethane production, at plant	kg	2013
951	Polyol ether, for rigid foam polyurethane production, at plant	kg	2013
952	Polypropylene resin, at plant	kg	2013
953	Polypropylene scrap, from PP injection molding, at plant	kg	2220
954	Polypropylene scrap, from PP thermoforming, at plant	kg	2220
955	Polystyrene, general purpose, at plant	kg	2013
956	Polystyrene, high impact, resin, at plant	kg	2013
957	Polyvinyl chloride, resin, at plant	kg	2013
958	Portland cement, at plant	kg	2394
959	Post, softwood, CCA treated, SE	kg	1610
960	Potato leaves, at field	kg	113
961	Potato, at field	kg	113
962	Prefinished engineered wood flooring, at engineered wood flooring plant, E	kg	1610
963	Pressed raw panels, hardwood, at engineered wood flooring plant, E	kg	1610
964	Pressed raw panels, purchased, hardwood, at eng wood flooring plant, E	kg	1610
965	Pressed raw plywood, from lay-up, at plywood plant, US PNW	kg	1621
966	Pressed raw plywood, from lay-up, at plywood plant, US SE	kg	1621
967	Propylene oxide, at plant	kg	2011
968	Propylene, at plant	kg	2013
969	Pulp chips, at rough green lumber production, US PNW	kg	1610
970	Pulp chips, at sawmill, US SE	kg	1610
971	Pulp chips, from dried lumber, at planer mill, US PNW	kg	1610
972	Pulp chips, from green lumber, at planer mill, US PNW	kg	1610
973	Pulp chips, from green veneer production at plywood plant, US PNW	kg	1610
974	Pulp chips, from green veneer production at plywood plant, US SE	kg	1610
975	Pulp, kraft market, bleached, average production, at mill	kg	1702

976	Pulpwood, hardwood, average, High Intensity Management, NE-NC	m3	220
977	Pulpwood, hardwood, average, Low Intensity Management, NE-NC	m3	220
978	Pulpwood, hardwood, average, Med Intensity Management, NE-NC	m3	220
979	Pulpwood, hardwood, average, at forest road, NE-NC	m3	220
980	Pulpwood, sftwd, state-private moist cold forest, gentle slope, at frst rd, INW	m3	220
981	Pulpwood, sftwd, state-private moist cold forest, steep slope, at forest rd,INW	m3	220
982	Pulpwood, softwd, avg, state or private moist forest, at forest rd, INW	m3	220
983	Pulpwood, softwd, state or private dry forest, gentle slope, at forest rd, INW	m3	220
984	Pulpwood, softwd, state or private dry forest, steep slope, at forest rd, INW	m3	220
985	Pulpwood, softwood, average, High Intensity Management, NE-NC	m3	220
986	Pulpwood, softwood, average, Low Intensity Management, NE-NC	m3	220
987	Pulpwood, softwood, average, Med Intensity Management, NE-NC	m3	220
988	Pulpwood, softwood, average, at forest road, INW	m3	220
989	Pulpwood, softwood, average, at forest road, NE-NC	m3	220
990	Pulpwood, softwood, average, state or private dry forest, at forest road, INW	m3	220
991	Pulpwood, softwood, national forest, average, at forest road, INW	m3	220
992	Pulpwood, softwood, national forest, gentle slope, at forest road, INW	m3	220
993	Pulpwood, softwood, national forest, steep slope, at forest road, INW	m3	220
994	Pyrolysis gasoline, at plant	kg	2011
995	RFO, combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	FOSSIL FUEL
996	Radioactive tailings	kg	3811
997	Radioactive tailings	kg	3811
998	Railroad tie, hardwood, rough, green, at sawmill, SE	kg	1610
999	Railroad ties, hardwood, creosote treated, SE	kg	1610
1000	Rapeseed residues, at field	kg	111
1001	Rapeseed, at field	kg	111
1002	Recovered energy	MJ	RECOVERED ENERGY
1003	Recovered energy, at acetic acid production	MJ	RECOVERED ENERGY

1004	Recovered energy, for Acrylonitrile-butadiene-styrene copolymer, CTR	MJ	RECOVERED ENERGY
1005	Recovered energy, for Methylene diphenyl diisocyanate, CTR	MJ	RECOVERED ENERGY
1006	Recovered energy, for Polyethylene terephthalate, resin, at plant, CTR	MJ	RECOVERED ENERGY
1007	Recovered energy, for Polyethylene, high density, resin, at plant, CTR	MJ	RECOVERED ENERGY
1008	Recovered energy, for Polyethylene, linear low density, resin, at plant, CTR	MJ	RECOVERED ENERGY
1009	Recovered energy, for Polyethylene, low density, resin, at plant, CTR	MJ	RECOVERED ENERGY
1010	Recovered energy, for Polyol ether, for flexible foam polyurethane production, at plant, CTR	MJ	RECOVERED ENERGY
1011	Recovered energy, for Polyol ether, for rigid foam polyurethane production, at plant, CTR	MJ	RECOVERED ENERGY
1012	Recovered energy, for Polypropylene, resin, at plant, CTR	MJ	RECOVERED ENERGY
1013	Recovered energy, for Polystyrene, general purpose, at plant, CTR	MJ	RECOVERED ENERGY
1014	Recovered energy, for Polystyrene, high impact, resin, at plant, CTR	MJ	RECOVERED ENERGY
1015	Recovered energy, for Toluene diisocyanate, CTR	MJ	RECOVERED ENERGY
1016	Recovered energy, for acrylonitrile	MJ	RECOVERED ENERGY
1017	Recovered energy, for ethylene glycol, CTR	MJ	RECOVERED ENERGY
1018	Recovered energy, for polyvinyl chloride, CTR	MJ	RECOVERED ENERGY
1019	Recycled postconsumer HDPE pellet	kg	3830
1020	Recycled postconsumer PET flake	kg	3830
1021	Recycled postconsumer PET pellet	kg	3830
1022	Refinery gas, at refinery	kg	1920
1023	Reforesting, average national softwood forest, INW	ha	210
1024	Reforesting, average state or private dry softwood forest, INW	ha	210
1025	Reforesting, average state or private moist cold softwood forest, INW	ha	210
1026	Reforesting, high intensity site, US PNW	ha	210
1027	Reforesting, high intensity site, US SE	ha	210
1028	Reforesting, low intensity site, US PNW	ha	210
1029	Reforesting, low intensity site, US SE	ha	210
1030	Reforesting, medium intensity site, US PNW	ha	210
1031	Reforesting, medium intensity site, US SE	ha	210
1032	Residual fuel oil, at refinery	kg	1920

1033	Residual fuel oil, combusted in industrial boiler	kg	FOSSIL FUEL
1034	Rice grain, at field	kg	112
1035	Rice straw, at field	kg	112
1036	Rough green lumber, at sawmill, US SE	kg	1610
1037	Rough green lumber, softwood, at sawmill, US PNW	kg	1610
1038	Roundwood, hardwood, average, High Intensity Management, NE-NC	m3	220
1039	Roundwood, hardwood, average, Low Intensity Management, NE-NC	m3	220
1040	Roundwood, hardwood, average, Med Intensity Management, NE-NC	m3	220
1041	Roundwood, hardwood, average, at forest road, NE-NC	m3	220
1042	Roundwood, hardwood, green, at logyard, NE-NC	m3	220
1043	Roundwood, hardwood, green, at logyard, SE	m3	220
1044	Roundwood, hardwood, green, at mill, E	m3	220
1045	Roundwood, hardwood, green, at mill, NE-NC	m3	220
1046	Roundwood, hardwood, green, at mill, SE	m3	220
1047	Roundwood, sftwd, state-private moist cold forest, gentle slope, at frst rd, INW	m3	220
1048	Roundwood, sftwd, state-private moist cold forest, steep slope, at forest rd,INW	m3	220
1049	Roundwood, softwd, avg, state or private moist cold forest, at forest rd, INW	m3	220
1050	Roundwood, softwd, state or private dry forest, gentle slope, at forest rd, INW	m3	220
1051	Roundwood, softwd, state or private dry forest, steep slope, at forest rd, INW	m3	220
1052	Roundwood, softwood, average, High Intensity Management, NE-NC	m3	220
1053	Roundwood, softwood, average, Low Intensity Management, NE-NC	m3	220
1054	Roundwood, softwood, average, Med Intensity Management, NE-NC	m3	220
1055	Roundwood, softwood, average, at forest road, INW	m3	220
1056	Roundwood, softwood, average, at forest road, NE-NC	m3	220
1057	Roundwood, softwood, average, state or private dry forest, at forest road, INW	m3	220
1058	Roundwood, softwood, green, at logyard, INW	m3	220
1059	Roundwood, softwood, green, at logyard, NE-NC	m3	220
1060	Roundwood, softwood, green, at mill, INW	m3	220
1061	Roundwood, softwood, green, at mill, NE-NC	m3	220
1062	Roundwood, softwood, national forest, average, at forest road, INW	m3	220
1063	Roundwood, softwood, national forest, gentle slope, at forest road, INW	m3	220

1064	Roundwood, softwood, national forest, steep slope, at forest road, INW	m3	220
1065	Sawdust from I-Joist processing, at plant, US SE	kg	1610
1066	Sawdust, at planer mill, US SE	kg	1610
1067	Sawdust, at rough green lumber production, US PNW	kg	1610
1068	Sawdust, at sawmill, US SE	kg	1610
1069	Sawdust, from I-Joist processing, at plant, US PNW	kg	1610
1070	Sawdust, from dried lumber, at planer mill, US PNW	kg	1610
1071	Sawdust, from green lumber, at planer mill, US PNW	kg	1610
1072	Sawdust, from trim and saw at plywood plant, US PNW	kg	1610
1073	Sawdust, from trim and saw, plywood plant, US SE	kg	1610
1074	Sawdust, hardwood, dry, at engineered wood flooring plant, E	kg	1610
1075	Sawdust, hardwood, green, at sawmill, NE-NC	kg	1610
1076	Sawdust, hardwood, green, at sawmill, SE	kg	1610
1077	Sawdust, hardwood, kiln-dried, at planer mill, NE-NC	kg	1610
1078	Sawdust, hardwood, kiln-dried, at planer mill, SE	kg	1610
1079	Sawdust, softwood, green, at sawmill, INW	kg	1610
1080	Sawdust, softwood, green, at sawmill, NE-NC	kg	1610
1081	Sawn Lumber, softwood, planed, kiln dried, at planer mill, INW	kg	1610
1082	Sawn lumber, hardwood, planed, kiln dried, at planer mill, NE-NC	kg	1610
1083	Sawn lumber, hardwood, planed, kiln dried, at planer mill, SE	kg	1610
1084	Sawn lumber, hardwood, rough, green, at sawmill, NE-NC	kg	1610
1085	Sawn lumber, hardwood, rough, green, at sawmill, SE	kg	1610
1086	Sawn lumber, hardwood, rough, kiln dried, at kiln, NE-NC	kg	1610
1087	Sawn lumber, hardwood, rough, kiln dried, at kiln, SE	kg	1610
1088	Sawn lumber, softwood, planed, kiln dried, at planer, NE-NC	kg	1610
1089	Sawn lumber, softwood, rough, green, at sawmill, INW	kg	1610
1090	Sawn lumber, softwood, rough, green, at sawmill, NE-NC	kg	1610
1091	Sawn lumber, softwood, rough, kiln dried, at kiln, INW	kg	1610
1092	Sawn lumber, softwood, rough, kiln dried, at kiln, NE-NC	kg	1610
1093	Scanner, department, i3200, i3400	Item(s)	2620
1094	Scanner, department, i4200, i4600	Item(s)	2620
1095	Scanner, department, i5200, i5600	Item(s)	2620
1096	Scanner, department, i5200v, i5600v	Item(s)	2620
1097	Scanner, department, i5800	Item(s)	2620
1098	Scanner, desktop, i2900	Item(s)	2620
1099	Scanner, packaging and information sheets	Item(s)	2620
1100	Secondary bonding application, rigid composites part, at plant	kg	2220

1101	Secondary fuel	MJ	RECOVERED ENERGY
1102	Secondary fuel	MJ	RECOVERED ENERGY
1103	Secondary fuel renewable	MJ	RECOVERED ENERGY
1104	Secondary fuel renewable	MJ	RECOVERED ENERGY
1105	Seedlings, at greenhouse, US PNW	Item(s)	130
1106	Seedlings, at greenhouse, US SE	Item(s)	130
1107	Shavings, hardwood, dry, at engineered wood flooring plant, E	kg	1610
1108	Shavings, hardwood, kiln-dried, at planer mill, NE-NC	kg	1610
1109	Shavings, hardwood, kiln-dried, at planer mill, SE	kg	1610
1110	Shavings, softwood, kiln dried, NE-NC	kg	1610
1111	Shavings, softwood, kiln dried, at planer mill, INW	kg	1610
1112	Site preparation, national softwood forest, gentle slope, INW	ha	240
1113	Site preparation, national softwood forest, steep slope, INW	ha	240
1114	Site preparation, state or private dry softwood forest, gentle slope, INW	ha	240
1115	Site preparation, state or private dry softwood forest, steep slope, INW	ha	240
1116	Site preparation, state or private moist cold softwood forest, gentle slope, INW	ha	240
1117	Site preparation, state or private moist cold softwood forest, steep slope, INW	ha	240
1118	Skidding, aerial cable yarder, medium	ha	240
1119	Skidding, grapple skidder, >140 HP	ha	240
1120	Skidding, wheeled cable skidder, 120-160 HP	ha	240
1121	Skidding, wheeled skidder, 120-140 HP	ha	240
1122	Slack wax, at plant, US SE	kg	2011
1123	Soap stock, at plant	kg	2023
1124	Soda powder, at plant	kg	2011
1125	Sodium chloride, at plant	kg	2011
1126	Sodium hydroxide, production mix, at plant	kg	2011
1127	Softwood logs with bark, harvested at average intensity site, at mill, US PNW	m3	220
1128	Softwood logs with bark, harvested at average intensity site, at mill, US SE	m3	220
1129	Softwood logs with bark, harvested at high intensity site, at mill, US PNW	m3	220
1130	Softwood logs with bark, harvested at high intensity site, at mill, US SE	m3	220
1131	Softwood logs with bark, harvested at low intensity site, at mill, US PNW	m3	220

1132	Softwood logs with bark, harvested at low intensity site, at mill, US SE	m3	220
1133	Softwood logs with bark, harvested at medium intensity site, at mill, US PNW	m3	220
1134	Softwood logs with bark, harvested at medium intensity site, at mill, US SE	m3	220
1135	Solid strip and plank flooring, hardwood, E	kg	1610
1136	Soy biodiesel, production, at plant	kg	2011
1137	Soy meal, at plant	kg	1061
1138	Soy oil, refined, at plant	kg	1040
1139	Soy-based polyol, at plant	kg	2011
1140	Soy-based resin, at plant	kg	2011
1141	Soybean grains, at field	kg	111
1142	Soybean grains, at field, 1998-2001	kg	111
1143	Soybean oil, crude, degummed, at plant	kg	1040
1144	Soybean residues, at field	kg	111
1145	Soybean residues, at field, 1998-2001	kg	111
1146	Soybeans, at field, 1998-2001	kg	111
1147	Spoil (deposited)	kg	3811
1148	Spoil (deposited)	kg	3811
1149	Spring wheat straw, carted, 2022	kg	111
1150	Spring wheat straw, ground and stored, 2022	kg	111
1151	Steam, at bleached kraft market pulp mill	MJ	ENERGY
1152	Steam, at coated freesheet mill	MJ	ENERGY
1153	Steam, at coated mechanical paper mill	MJ	ENERGY
1154	Steam, at uncoated freesheet mill	MJ	ENERGY
1155	Steam, at uncoated mechanical paper mill	MJ	ENERGY
1156	Steel, cold-formed studs and track, at plant	kg	2591
1157	Sulfur, at plant	kg	2011
1158	Sulfur, thermochemical process	kg	2011
1159	Sulfuric acid, at plant	kg	2011
1160	Surfaced dried lumber, at planer mill, US PNW	kg	1610
1161	Surfaced dried lumber, at planer mill, US SE	kg	1610
1162	Surfaced dried lumber, from open molding, for shipping	kg	2220
1163	Surfaced green lumber, at planer mill, US PNW	kg	1610
1164	Switchgrass, at conversion plant, 2022	kg	119
1165	Switchgrass, carted, 2022	kg	119
1166	Switchgrass, ground and stored, 2022	kg	119
1167	Switchgrass, harvested, wet	kg	119
1168	Switchgrass, production, US, 2022	kg	119
1169	TDF, combusted in industrial boiler, at pulp and paper mill (EXCL.)	kg	FOSSIL FUEL

1170	Tailings (deposited)	kg	3811
1171	Tailings (deposited)	kg	3811
1172	Tall oil, at bleached kraft market pulp mill	kg	2022
1173	Tall oil, at coated freesheet mill	kg	2022
1174	Tall oil, at coated mechanical paper mill	kg	2022
1175	Tall oil, at unbleached kraft bag and sack paper mill	kg	2022
1176	Tall oil, at uncoated freesheet mill	kg	2022
1177	Tall oil, at uncoated mechanical paper mill	kg	2022
1178	Thermoforming, rigid polypropylene part, at plant	kg	2220
1179	Tillage, conservation, corn production	ha	161
1180	Tillage, intensive, corn production	ha	161
1181	Tillage, reduce, corn production	ha	161
1182	Toluene diisocyanate, at plant	kg	2011
1183	Toluene, at plant	kg	2011
1184	Transport, aircraft, freight	t*km	5120
1185	Transport, barge, average fuel mix	t*km	5022
1186	Transport, barge, diesel powered	t*km	5022
1187	Transport, barge, residual fuel oil powered	t*km	5022
1188	Transport, combination truck, average fuel mix	t*km	4923
1189	Transport, combination truck, diesel powered	t*km	4923
1190	Transport, combination truck, gasoline powered	t*km	4923
1191	Transport, combination truck, long-haul, diesel powered	t*km	4923
1192	Transport, combination truck, long-haul, diesel powered, Alaska	t*km	4923
1193	Transport, combination truck, long-haul, diesel powered, Central	t*km	4923
1194	Transport, combination truck, long-haul, diesel powered, East North Central	t*km	4923
1195	Transport, combination truck, long-haul, diesel powered, Hawaii	t*km	4923
1196	Transport, combination truck, long-haul, diesel powered, Northeast	t*km	4923
1197	Transport, combination truck, long-haul, diesel powered, Northwest	t*km	4923
1198	Transport, combination truck, long-haul, diesel powered, South	t*km	4923
1199	Transport, combination truck, long-haul, diesel powered, Southeast	t*km	4923
1200	Transport, combination truck, long-haul, diesel powered, Southwest	t*km	4923
1201	Transport, combination truck, long-haul, diesel powered, West	t*km	4923
1202	Transport, combination truck, long-haul, diesel powered, West North Central	t*km	4923

1203	Transport, combination truck, short-haul, diesel powered	t*km	4923
1204	Transport, combination truck, short-haul, diesel powered, Alaska	t*km	4923
1205	Transport, combination truck, short-haul, diesel powered, Central	t*km	4923
1206	Transport, combination truck, short-haul, diesel powered, East North Central	t*km	4923
1207	Transport, combination truck, short-haul, diesel powered, Hawaii	t*km	4923
1208	Transport, combination truck, short-haul, diesel powered, Northeast	t*km	4923
1209	Transport, combination truck, short-haul, diesel powered, Northwest	t*km	4923
1210	Transport, combination truck, short-haul, diesel powered, South	t*km	4923
1211	Transport, combination truck, short-haul, diesel powered, Southeast	t*km	4923
1212	Transport, combination truck, short-haul, diesel powered, Southwest	t*km	4923
1213	Transport, combination truck, short-haul, diesel powered, West	t*km	4923
1214	Transport, combination truck, short-haul, diesel powered, West North Central	t*km	4923
1215	Transport, combination truck, short-haul, gasoline powered	t*km	4923
1216	Transport, intercity bus, diesel powered	p*km	4922
1217	Transport, intercity bus, diesel powered, Alaska	p*km	4922
1218	Transport, intercity bus, diesel powered, Central	p*km	4922
1219	Transport, intercity bus, diesel powered, East North Central	p*km	4922
1220	Transport, intercity bus, diesel powered, Hawaii	p*km	4922
1221	Transport, intercity bus, diesel powered, Northeast	p*km	4922
1222	Transport, intercity bus, diesel powered, Northwest	p*km	4922
1223	Transport, intercity bus, diesel powered, South	p*km	4922
1224	Transport, intercity bus, diesel powered, Southeast	p*km	4922
1225	Transport, intercity bus, diesel powered, Southwest	p*km	4922
1226	Transport, intercity bus, diesel powered, West	p*km	4922
1227	Transport, intercity bus, diesel powered, West North Central	p*km	4922
1228	Transport, light commercial truck, diesel powered	t*km	4923
1229	Transport, light commercial truck, diesel powered, Alaska	t*km	4923
1230	Transport, light commercial truck, diesel powered, Central	t*km	4923
1231	Transport, light commercial truck, diesel powered, East North Central	t*km	4923
1232	Transport, light commercial truck, diesel powered, Hawaii	t*km	4923
1233	Transport, light commercial truck, diesel powered, Northeast	t*km	4923
1234	Transport, light commercial truck, diesel powered, Northwest	t*km	4923

1235	Transport, light commercial truck, diesel powered, South	t*km	4923
1236	Transport, light commercial truck, diesel powered, Southeast	t*km	4923
1237	Transport, light commercial truck, diesel powered, Southwest	t*km	4923
1238	Transport, light commercial truck, diesel powered, West	t*km	4923
1239	Transport, light commercial truck, diesel powered, West North Central	t*km	4923
1240	Transport, light commercial truck, gasoline powered	t*km	4923
1241	Transport, light commercial truck, gasoline powered, Alaska	t*km	4923
1242	Transport, light commercial truck, gasoline powered, Central	t*km	4923
1243	Transport, light commercial truck, gasoline powered, East North Central	t*km	4923
1244	Transport, light commercial truck, gasoline powered, Hawaii	t*km	4923
1245	Transport, light commercial truck, gasoline powered, Northeast	t*km	4923
1246	Transport, light commercial truck, gasoline powered, Northwest	t*km	4923
1247	Transport, light commercial truck, gasoline powered, South	t*km	4923
1248	Transport, light commercial truck, gasoline powered, Southeast	t*km	4923
1249	Transport, light commercial truck, gasoline powered, Southwest	t*km	4923
1250	Transport, light commercial truck, gasoline powered, West	t*km	4923
1251	Transport, light commercial truck, gasoline powered, West North Central	t*km	4923
1252	Transport, motor home, diesel powered	p*km	4921
1253	Transport, motor home, gasoline powered	p*km	4921
1254	Transport, motorcycle, gasoline powered	p*km	4921
1255	Transport, ocean freighter, average fuel mix	t*km	5012
1256	Transport, ocean freighter, diesel powered	t*km	5012
1257	Transport, ocean freighter, residual fuel oil powered	t*km	5012
1258	Transport, passenger car, diesel powered	p*km	4921
1259	Transport, passenger car, gasoline powered	p*km	4921
1260	Transport, passenger truck, diesel powered	p*km	4921
1261	Transport, passenger truck, gasoline powered	p*km	4921
1262	Transport, pipeline, natural gas	t*km	4930
1263	Transport, pipeline, unspecified petroleum products	t*km	4930
1264	Transport, refuse truck, diesel powered	t*km	4923
1265	Transport, refuse truck, diesel powered, Alaska	t*km	4923
1266	Transport, refuse truck, diesel powered, Central	t*km	4923
1267	Transport, refuse truck, diesel powered, East North Central	t*km	4923
1268	Transport, refuse truck, diesel powered, Hawaii	t*km	4923
1269	Transport, refuse truck, diesel powered, Northeast region	t*km	4923
1270	Transport, refuse truck, diesel powered, Northwest	t*km	4923

1271	Transport, refuse truck, diesel powered, South	t*km	4923
1272	Transport, refuse truck, diesel powered, Southeast	t*km	4923
1273	Transport, refuse truck, diesel powered, Southwest	t*km	4923
1274	Transport, refuse truck, diesel powered, West North Central	t*km	4923
1275	Transport, refuse truck, diesel powered, West region	t*km	4923
1276	Transport, refuse truck, gasoline powered	t*km	4923
1277	Transport, school bus, diesel powered	p*km	4921
1278	Transport, school bus, diesel powered, Alaska	p*km	4921
1279	Transport, school bus, diesel powered, Central	p*km	4921
1280	Transport, school bus, diesel powered, East North Central	p*km	4921
1281	Transport, school bus, diesel powered, Hawaii	p*km	4921
1282	Transport, school bus, diesel powered, Northeast	p*km	4921
1283	Transport, school bus, diesel powered, Northwest	p*km	4921
1284	Transport, school bus, diesel powered, South	p*km	4921
1285	Transport, school bus, diesel powered, Southeast	p*km	4921
1286	Transport, school bus, diesel powered, Southwest	p*km	4921
1287	Transport, school bus, diesel powered, West	p*km	4921
1288	Transport, school bus, diesel powered, West North Central	p*km	4921
1289	Transport, school bus, gasoline powered	p*km	4921
1290	Transport, single unit truck, diesel powered	t*km	4923
1291	Transport, single unit truck, gasoline powered	t*km	4923
1292	Transport, single unit truck, long-haul, diesel powered	t*km	4923
1293	Transport, single unit truck, long-haul, diesel powered, Alaska	t*km	4923
1294	Transport, single unit truck, long-haul, diesel powered, Central	t*km	4923
1295	Transport, single unit truck, long-haul, diesel powered, East North Central	t*km	4923
1296	Transport, single unit truck, long-haul, diesel powered, Hawaii	t*km	4923
1297	Transport, single unit truck, long-haul, diesel powered, Northeast region	t*km	4923
1298	Transport, single unit truck, long-haul, diesel powered, Northwest	t*km	4923
1299	Transport, single unit truck, long-haul, diesel powered, South	t*km	4923
1300	Transport, single unit truck, long-haul, diesel powered, Southeast	t*km	4923
1301	Transport, single unit truck, long-haul, diesel powered, Southwest	t*km	4923
1302	Transport, single unit truck, long-haul, diesel powered, West	t*km	4923
1303	Transport, single unit truck, long-haul, diesel powered, West North Central	t*km	4923
1304	Transport, single unit truck, long-haul, gasoline powered	t*km	4923
1305	Transport, single unit truck, long-haul, gasoline powered, Alaska	t*km	4923

1306	Transport, single unit truck, long-haul, gasoline powered, Central	t*km	4923
1307	Transport, single unit truck, long-haul, gasoline powered, East North Central	t*km	4923
1308	Transport, single unit truck, long-haul, gasoline powered, Hawaii	t*km	4923
1309	Transport, single unit truck, long-haul, gasoline powered, Northeast region	t*km	4923
1310	Transport, single unit truck, long-haul, gasoline powered, Northwest	t*km	4923
1311	Transport, single unit truck, long-haul, gasoline powered, South	t*km	4923
1312	Transport, single unit truck, long-haul, gasoline powered, Southeast	t*km	4923
1313	Transport, single unit truck, long-haul, gasoline powered, Southwest	t*km	4923
1314	Transport, single unit truck, long-haul, gasoline powered, West	t*km	4923
1315	Transport, single unit truck, long-haul, gasoline powered, West North Central	t*km	4923
1316	Transport, single unit truck, short-haul, diesel powered	t*km	4923
1317	Transport, single unit truck, short-haul, diesel powered, Alaska	t*km	4923
1318	Transport, single unit truck, short-haul, diesel powered, Central	t*km	4923
1319	Transport, single unit truck, short-haul, diesel powered, East North Central	t*km	4923
1320	Transport, single unit truck, short-haul, diesel powered, Hawaii	t*km	4923
1321	Transport, single unit truck, short-haul, diesel powered, Northeast	t*km	4923
1322	Transport, single unit truck, short-haul, diesel powered, Northwest	t*km	4923
1323	Transport, single unit truck, short-haul, diesel powered, South	t*km	4923
1324	Transport, single unit truck, short-haul, diesel powered, Southeast	t*km	4923
1325	Transport, single unit truck, short-haul, diesel powered, Southwest	t*km	4923
1326	Transport, single unit truck, short-haul, diesel powered, West	t*km	4923
1327	Transport, single unit truck, short-haul, diesel powered, West North Central	t*km	4923
1328	Transport, single unit truck, short-haul, gasoline powered	t*km	4923
1329	Transport, single unit truck, short-haul, gasoline powered, Alaska	t*km	4923
1330	Transport, single unit truck, short-haul, gasoline powered, Central	t*km	4923

1331	Transport, single unit truck, short-haul, gasoline powered, East North Central	t*km	4923
1332	Transport, single unit truck, short-haul, gasoline powered, Hawaii	t*km	4923
1333	Transport, single unit truck, short-haul, gasoline powered, Northeast	t*km	4923
1334	Transport, single unit truck, short-haul, gasoline powered, Northwest	t*km	4923
1335	Transport, single unit truck, short-haul, gasoline powered, South	t*km	4923
1336	Transport, single unit truck, short-haul, gasoline powered, Southeast	t*km	4923
1337	Transport, single unit truck, short-haul, gasoline powered, Southwest	t*km	4923
1338	Transport, single unit truck, short-haul, gasoline powered, West	t*km	4923
1339	Transport, single unit truck, short-haul, gasoline powered, West North Central	t*km	4923
1340	Transport, train, diesel powered	t*km	4912
1341	Transport, transit bus, CNG powered	p*km	4921
1342	Transport, transit bus, diesel powered	p*km	4921
1343	Transport, transit bus, diesel powered, Alaska	p*km	4921
1344	Transport, transit bus, diesel powered, Central	p*km	4921
1345	Transport, transit bus, diesel powered, East North Central	p*km	4921
1346	Transport, transit bus, diesel powered, Hawaii	p*km	4921
1347	Transport, transit bus, diesel powered, Northeast	p*km	4921
1348	Transport, transit bus, diesel powered, Northwest	p*km	4921
1349	Transport, transit bus, diesel powered, South	p*km	4921
1350	Transport, transit bus, diesel powered, Southeast	p*km	4921
1351	Transport, transit bus, diesel powered, Southwest	p*km	4921
1352	Transport, transit bus, diesel powered, West	p*km	4921
1353	Transport, transit bus, diesel powered, West North Central	p*km	4921
1354	Transport, transit bus, gasoline powered	p*km	4921
1355	Turpentine, at bleached kraft market pulp mill	kg	2022
1356	Turpentine, at coated freesheet mill	kg	2022
1357	Turpentine, at coated mechanical paper mill	kg	2022
1358	Turpentine, at unbleached kraft bag and sack paper mill	kg	2022
1359	Turpentine, at uncoated freesheet mill	kg	2022
1360	Turpentine, at uncoated mechanical paper mill	kg	2022
1361	Unsaturated polyester scrap, resin, at plant	kg	2013
1362	Unsaturated polyester, resin, at plant	kg	2013
1363	Urea formaldehyde resin, neat, 65% solids	kg	2011
1364	Vacuum infusion, rigid composites part, at plant	kg	2220
1365	Veneer, hardwood, dry, at veneer mill, E	kg	1621

1366	Veneer, hardwood, green, at veneer mill, E	kg	1621
1367	Waste (deposited)	kg	3811
1368	Waste (deposited)	kg	3811
1369	Waste (deposited)	kg	3811
1370	Wheat grains, at field	kg	111
1371	Wheat straw, at conversion plant, 2022	kg	111
1372	Wheat straw, at field	kg	111
1373	White mineral oil, at plant	kg	2029
1374	Winter wheat straw, carted	kg	111
1375	Winter wheat straw, ground and stored	kg	111
1376	Winter wheat straw, production, average, US, 2022	kg	111
1377	Wood chips, hardwood, green, at sawmill, NE-NC	kg	1610
1378	Wood chips, hardwood, green, at sawmill, SE	kg	1610
1379	Wood chips, hardwood, green, at veneer mill, E	kg	1610
1380	Wood chips, softwood, green, at sawmill, INW	kg	1610
1381	Wood chips, softwood, green, at sawmill, NE-NC	kg	1610
1382	Wood chips, softwood, kiln dried, at planer mill, INW	kg	1610
1383	Wood fiber, softwood, green, at sawmill, INW	kg	1610
1384	Wood fuel, MDF, generated on-site, combusted in industrial boiler	kg	BIOFUEL
1385	Wood fuel, MDF, purchased, combusted in industrial boiler	kg	BIOFUEL
1386	Wood fuel, at MDF mill	kg	1629
1387	Wood fuel, hardwood, dry, at engineered wood flooring plant, E	kg	1629
1388	Wood fuel, hardwood, dry, at veneer mill, E	kg	1629
1389	Wood fuel, hardwood, from flooring production, E	kg	1610
1390	Wood fuel, hardwood, gen at lumber mill, combusted in industrial boiler, NE-NC	kg	BIOFUEL
1391	Wood fuel, hardwood, generated at lumber mill, combusted in industrial boiler, SE	kg	BIOFUEL
1392	Wood fuel, hardwood, generated at mill, combusted in industrial boiler, E	kg	BIOFUEL
1393	Wood fuel, hardwood, green, at sawmill, NE-NC	kg	1610
1394	Wood fuel, hardwood, green, at veneer mill, E	kg	1629
1395	Wood fuel, hardwood, green,at sawmill, SE	kg	1610
1396	Wood fuel, hardwood, kiln-dried, at planer mill, SE	kg	1610
1397	Wood fuel, hardwood, purchased, combusted in industrial boiler, E	kg	BIOFUEL
1398	Wood fuel, hardwood, purchased, combusted in industrial boiler, NE-NC	kg	BIOFUEL
1399	Wood fuel, hardwood, purchased, combusted in industrial boiler, SE	kg	BIOFUEL
1400	Wood fuel, hardwood,gen at flooring prod plant, combusted in industrial boiler, E	kg	BIOFUEL

1401	Wood fuel, hogfuel, particleboard mill	kg	1629
1402	Wood fuel, sanderdust, at MDF mill	kg	1629
1403	Wood fuel, sanderdust, particleboard mill	kg	1629
1404	Wood fuel, softwood, gen at lumber mill, combusted in industrial boiler, NE-NC	kg	BIOFUEL
1405	Wood fuel, softwood, green, at sawmill, INW	kg	1610
1406	Wood fuel, softwood, kiln dried, NE-NC	kg	1610
1407	Wood fuel, softwood, purchased, combusted in industrial boiler, NE-NC	kg	BIOFUEL
1408	Wood fuel, unspecified	kg	1610
1409	Wood waste, at MDF mill	kg	3811
1410	Wood waste, softwood, particleboard mill	kg	3811
1411	Wood waste, unspecified, combusted in industrial boiler	kg	BIOFUEL
1412	Wood, particleboard, generated onsite, combusted in industrial boiler	kg	BIOFUEL
1413	Wood, softwood, INW, generated at lumber mill, combusted in industrial boiler	kg	BIOFUEL
1414	Xylenes, mixed, at plant	kg	2011
1415	Zinc, Special High Grade	kg	2420
1416	Zinc, sheet	kg	2420

Table S4: Code, name and abbreviation of ISIC industries in the study, similar industries are highlighted by the same color.

ISIC code	Industry name	Abbreviation
0111	Growing of cereals (except rice), leguminous crops and oil seeds	Grow. Cereals
0112	Growing of rice	Grow. Rice
0113	Growing of vegetables and melons, roots and tubers	Grow. Vege
0116	Growing of fibre crops	Grow. Fiber
0119	Growing of other non-perennial crops	Grow Other Crop
0130	Plant propagation	Plant Propagat
0161	Support activities for crop production	Support Crop (ha)
0161	Support activities for crop production	Support Crop (kg)
0210	Silviculture and other forestry activities	Silviculture Forestry
0220	Logging	Logging
0240	Support services to forestry	Support Forestry
0510	Mining of hard coal	Mining H. Coal
0520	Mining of lignite	Mining Lig. Coal
0610	Extraction of crude petroleum	Extract. Crude
0620	Extraction of natural gas	Extract. NG
0721	Mining of uranium and thorium ores	Mining Uranium
0729	Mining of other non-ferrous metal ores	Mining Non-ferrous
0810	Quarrying of stone, sand and clay	Quarrying
0892	Extraction of peat	Extract. Peat
0990	Support activities for other mining and quarrying	Support Mining
1040	Manufacture of vegetable and animal oils and fats	Manu. Vege
1061	Manufacture of grain mill products	Manu. Grain Mill
1062	Manufacture of starches and starch products	Manu. Starches
1080	Manufacture of prepared animal feeds	Manufacture Animal
1312	Weaving of textiles	Weaving Textiles
1610	Sawmilling and planing of wood	Sawmilling
1621	Manufacture of veneer sheets and wood-based panels	Manu. Veneer
1623	Manufacture of wooden containers	Manu. Wooden contain.
1629	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials	Manu. Other Wood
1701	Manufacture of pulp, paper and paperboard	Manu. Pulp
1702	Manufacture of corrugated paper and paperboard and of containers of paper and paperboard	Manu. Paper

1920	Manufacture of refined petroleum products	Manu. Petrol. Pro
2011	Manufacture of basic chemicals	Manu. Chemical
2012	Manufacture of fertilizers and nitrogen compounds	Manu. Fertilizer
2013	Manufacture of plastics and synthetic rubber in primary forms	Manu. Pre. Plast/Rub
2021	Manufacture of pesticides and other agrochemical products	Manu. Pesticides
2022	Manufacture of paints, varnishes and similar coatings, printing ink and mastics	Manu. Paints
2023	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	Manu. Soap
2029	Manufacture of other chemical products n.e.c.	Manu. Other Chemical
2211	Manufacture of rubber tyres and tubes; retreading and rebuilding of rubber tyres	Manu. Rubber tube
2219	Manufacture of other rubber products	Manu. Other Rubber
2220	Manufacture of plastics products	Manu. Plastic. Prodt
2310	Manufacture of glass and glass products	Manu. Glass
2391	Manufacture of refractory products	Manu. Refractory
2394	Manufacture of cement, lime and plaster	Manu. Cement
2410	Manufacture of basic iron and steel	Manu. Bsc. Iron Steel
2420	Manufacture of basic precious and other non-ferrous metals	Manu. Non-ferrous
2511	Manufacture of structural metal products	Manu. Struct Metal (kg)
2512	Manufacture of tanks, reservoirs and containers of metal	Manu. Tanks
2591	Forging, pressing, stamping and roll-forming of metal; powder metallurgy	Forging
2592	Treatment and coating of metals; machining	Treatment. Metal
2599	Manufacture of other fabricated metal products n.e.c.	Manu. Other. Fab. Metal
2610	Manufacture of electronic components and boards	Manu. Electronic
2620	Manufacture of computers and peripheral equipment	Manu. Computer
2732	Manufacture of other electronic and electric wires and cables	Manu. Other Elec
2811	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines	Manu. Engine
2821	Manufacture of fluid power equipment	Manu. Fluid power
2930	Manufacture of parts and accessories for motor vehicles	Manu. Parts
3290	Other manufacturing n.e.c.	Other Manu.
3510	Electric power generation, transmission and distribution	Elect. Power Gene

3520	Manufacture of gas; distribution of gaseous fuels through mains	Manu/dist. Gas.
3600	Water collection, treatment and supply	Water. Treat
3700	Sewerage	Sewerage
3811	Collection of non-hazardous waste	Collect. Non-haz. Waste
3830	Materials recovery	Materials Recvy
4290	Construction of other civil engineering projects	Construction
4912	Freight rail transport	Rail Transt
4921	Urban and suburban passenger land transport	Land Passanger Transt
4922	Other passenger land transport	Other Passanger Transt
4923	Freight transport by road	Road Transt
4930	Transport via pipeline	Pipe Transt
5012	Sea and coastal freight water transport	Sea Water Transt
5022	Inland freight water transport	Inland Water Transt
5120	Freight air transport	Air Transt
5224	Cargo handling	Cargo handling
8292	Packaging activities	Packaging
BIOFUEL	BIOFUEL	BIOFUEL
COAL	COAL	COAL
ENERGY	ENERGY	ENERGY
FOSSIL FUEL	FOSSIL FUEL	FOSSIL FU
NATURAL GAS	NATURAL GAS	NATURAL G
RECOVERED ENERGY	RECOVERED ENERGY	RECOVERED
WASTE_FLOW	WASTE_FLOW	WASTE_FLO

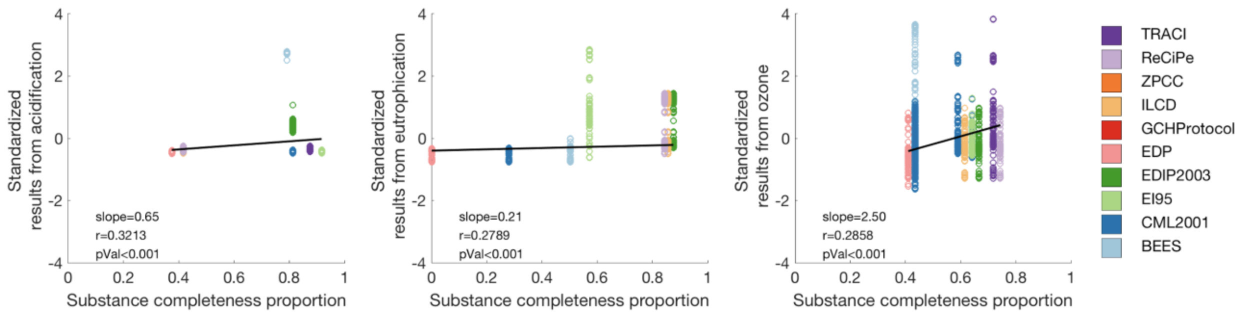


Figure S1: Testing the relation between the results from three different environmental impacts: acidification (left), eutrophication (middle), and ozone (right).The marker color indicates different alternative scenarios. The black line is the fit obtained from a linear weighted least squares regression.

Table S5: characterization factor values (in kg CFC eq) for all ozone depletion substances generalized from 11 latest version impact methods provided in SimaPro software.

	BEES+ V4.03	CML 2001 V2.05								Eco-indicator 95 V2.06	EDIP 2003 V1.04	EPD (2008) V1.04	ILCD 2011 Midpoint V1.02	ReCiPe Midpoint (I) V1.08	ReCiPe Midpoint (H) V1.08	ReCiPe Midpoint (E) V1.08	TRACI 2.1 V1.01	Ranges
		5a	10a	15a	20a	25a	30a	40a	sted									
Ethane, 1,1,1,2-tetrafluoro-2-bromo-, Halon 2401									0.25	0.25			0.25	0.25	0.25	0.25		0.25 - 0.25
Ethane, 1,1,1-trichloro-, HCFC-140	0.1	1.03	0.75	0.57	0.45	0.38	0.32	0.26	0.11	0.12	0.12	0.45		0.12	0.12	0.12	0.12	0.1 - 1.03
Ethane, 1,1,2,2-tetrachloro-1-fluoro-, HCFC-121											0.82						0.025	0.03 - 0.82
Ethane, 1,1,2-trichloro-													0.12	0.12	0.12	0.12		0.12 - 0.12
Ethane, 1,1,2-trichloro-1,2,2-trifluoro-, CFC-113		0.55	0.56	0.58	0.59	0.6	0.62	0.64	0.9	1.07	0.9	0.59	1	1	1	1	1	0.55 - 1.07
Ethane, 1,1-dichloro-1-fluoro-, HCFC-141b		0.54	0.45	0.38	0.33	0.3	0.26	0.22	0.09	0.11	0.12	0.33	0.12	0.12	0.12	0.12	0.12	0.09 - 0.54
Ethane, 1,2-dibromotetrafluoro-, Halon 2402									7	7	8.5	11	6	6	6	6	11.5	6 - 11.5
Ethane, 1,2-dichloro-1,1,2,2-tetrafluoro-, CFC-114									0.85	0.8	0.94		0.94	0.94	0.94	0.94	1	0.8 - 1
Ethane, 1-chloro-1,1-difluoro-, HCFC-142b		0.17	0.16	0.15	0.14	0.13	0.13	0.12	0.04	0.065	0.07	0.14	0.07	0.07	0.07	0.07	0.07	0.04 - 0.17
Ethane, 2,2-dichloro-1,1,1-trifluoro-, HCFC-123		0.51	0.19	0.11	0.08	0.07	0.06	0.04	0.01	0.02		0.08	0.02	0.02	0.02	0.02	0.02	0.01 - 0.51
Ethane, 2-chloro-1,1,1,2-tetrafluoro-, HCFC-124		0.17	0.12	0.1	0.08	0.07	0.06	0.05	0.03	0.022	0.02	0.08	0.02	0.02	0.02	0.02	0.022	0.02 - 0.17
Ethane, chloropentafluoro-, CFC-115									0.4	0.5	0.44		0.44	0.44	0.44	0.44	0.44	0.4 - 0.5
Halothane									0.14	0.14			0.14	0.14	0.14	0.14		0.14 - 0.14
Hydrocarbons, chlorinated														0.00617	0.00617	0.00617		0.01 - 0.006
Methane, bromo-, Halon 1001	0.6	15.3	5.4	3.1	2.3	1.8	1.5	1.2	0.37	0.6	0.38		0.38	0.38	0.38	0.38	0.51	0.37 - 15.3
Methane, bromochlorodifluoro-, Halon 1211		11.3	10.5	9.7	9	8.5	8	7.1	5.1	4	6	9	6	6	6	6	7.1	4 - 11.3
Methane, bromodifluoro-, Halon 1201									1.4	1.4			1.4	1.4	1.4	1.4	0.74	0.74 - 1.4
Methane, bromotrifluoro-, Halon 1301	10	10.3	10.4	10.5	10.5	10.6	10.7	10.8	12	16	12	10.5	12	12	12	12	16	10 - 16
Methane, chlorodifluoro-, HCFC-22	0.055	0.19	0.17	0.15	0.14	0.13	0.12	0.1	0.03	0.055	0.05	0.14	0.05	0.05	0.05	0.05	0.05	0.03 - 0.19
Methane, chlorotrifluoro-, CFC-13										1							1	1 - 1
Methane, dibromodifluoro-, Halon 1202									1.25	1.25	1.3		1.3	1.3	1.3	1.3		1.25 - 1.3
Methane, dichlorodifluoro-, CFC-12	1								0.82	1	1		1	1	1	1	1	0.82 - 1
Methane, monochloro-, R-40									0.02		0.02		0.02	0.02	0.02	0.02	0.2	0.02 - 0.2
Methane, tetrachloro-, CFC-10	1.1	1.26	1.25	1.23	1.22	1.22	1.2	1.14	1.2	1.08	0.73	1.23	0.73	0.73	0.73	0.73	0.73	0.73 - 1.26
Methane, trichlorofluoro-, CFC-11		1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1 - 1
Propane, 1,3-dichloro-1,1,2,2,3-pentafluoro-, HCFC-225cb									0.02	0.033	0.03	0.11	0.03	0.03	0.03	0.03	0.03	0.02 - 0.11
Propane, 3,3-dichloro-1,1,1,2,2-pentafluoro-, HCFC-225ca									0.02	0.025	0.02	0.1	0.02	0.02	0.02	0.02	0.02	0.02 - 0.1

Table S6: characterization factor values for all Eutrophication substances generalized from 11 latest version impact methods provided in SimaPro software.

		BEES+ V4.03	CML 2001 (all impact categories) V2.05	Eco-indicator 95 V2.06	EDIP/UMIP 97 V2.05	EDIP 2003 V1.04	EPD (2008) V1.04	ILCD 2011 Midpoint V1.02	ReCiPe Midpoint (I) V1.08	ReCiPe Midpoint (H) V1.08	ReCiPe Midpoint (E) V1.08	TRACI 2.1 V1.01
		g N eq	kg PO4 eq	kg PO4 / k	g NO3 / g	kg N / kg	kg PO4 eq	kg N eq / k	kg P eq	kg P eq	kg P eq	kg N eq
Acrylonitrile	Air				1.17							
Ammonia	Air	0.119	0.35	0.33	3.64	101	0.35	13.5	0.092	0.092	0.092	0.1186
Ammonium carbonate	Air		0.12	0.12	0.532		0.12					
Ammonium nitrate	Air		0.074	0.074	0.328		0.074					
Ammonium, ion	Air		0.33	0.33	3.44		0.33	12.7	0.087	0.087	0.087	0.1186
Cyanide	Air				2.38	1.285						
Dinitrogen monoxide	Air	0.092					0.13					
Ethylene diamine	Air				2.06							
Nitrate	Air		0.1	0.1	1	0.0736	0.1	3.16	0.028	0.028	0.028	0.03602
Nitric acid	Air		0.1	0.093	0.983	18.5	0.1					0.03448
Nitric oxide	Air	0.0443	0.2	0.2	2.07	38.8	0.2	6.53	0.06	0.06	0.06	0.06858
Nitrobenzene	Air				0.51							
Nitrogen dioxide	Air	0.0443	0.13	0.13	1.35	0.096	0.13	4.26	0.039	0.039	0.039	0.04429
Nitrogen oxides	Air	0.0443	0.13	0.13	1.35	25.4	0.13	4.26	0.039	0.039	0.039	0.04429
Nitrogen, total	Air		0.42	0.42	4.43		0.42					
Nitrogen	Air											0.15012
Phosphate	Air		1	1	10.45		1					0.36565
Phosphoric acid	Air	0.354	0.97	0.97	10.12		0.97					0.35482
Phosphorus	Air	1.12	3.06	3.06	32.03	1	3.06					1.12
Ammonia	Soil		0.35	0.33	3.64		0.35					
Nitric acid	Soil		0.1	0.093	0.983	0.1219	0.1					
Nitrogen	Soil		0.42			0.53	0.42					
Phosphate	Soil		1	1	10.45	0.0198	1	0.33	0.33	0.33	0.33	
Phosphorus	Soil		3.06	3.06	32.03	0.06	3.06	1	1	1	1	
Phosphorus	Soil								1	1	1	
Phosphorus	Soil								1	1	1	
Phosphorus	Soil								1	1	1	
Acrylonitrile	Water				1.17							
Ammonia, as N	Water	0.986			3.64				1	1	1	
Ammonia	Water		0.35	0.33	3.64		0.35	0.824	0.824	0.824	0.824	0.7793
Ammonium, ion	Water	0.986	0.33	0.33	3.44		0.33	0.778	0.78	0.78	0.78	0.7793
BOD5, Biological Oxygen Demand	Water	0.05										0.05
COD, Chemical Oxygen Demand	Water	0.05	0.022	0.022			0.022					0.05
Ammonia, as N	Water								1.42857	1.43	1.42857	
Ammonia	Water								1.17714	1.18	1.17714	
Ammonium, ion	Water								1.11429	1.11	1.11429	

Table S7: characterization factor values for all Acidification substances generalized from 11 latest version impact methods provided in SimaPro software.

	BEES+ V4.03	CML 2001 V2.05	Eco-indicator 95 V2.06	EDIP 2003 V1.04	EPD (2008) V1.04	ILCD 2011 Midpoint V1.02	ReCiPe Midpoint (I) V1.08	ReCiPe Midpoint (H) V1.08	ReCiPe Midpoint (E) V1.08	TRACI 2.1 V1.01
	H+ mmole eq	kg SO2 eq / kg	kg SO2 / kg	g SO2 / g	kg SO2 eq / kg	molc H+ eq / kg	kg SO2 eq	kg SO2 eq	kg SO2 eq	kg SO2 eq
Ammonia	95.5	95.5	1.88	23.1	1.6	3.02	2.89	2.45	1.99	1.88
Ammonium carbonate			0.67							
Ammonium nitrate			0.4							
Ammonium, ion			1.78							
Hydrogen chloride	44.7	44.7	0.88	62						0.88
Hydrogen cyanide	60.4	60.4								
Hydrogen fluoride	81.3	81.3	1.6	113						1.6
Hydrogen sulfide	95.9	95.9		33.2						1.88
Nitric acid			0.51	6.3						0.51
Nitric oxide			1.07	13.1		1.13				1.07
Nitrogen dioxide	40	40	0.7	8.6	0.5	0.74	0.71	0.56	0.49	0.7
Nitrogen oxides	40	40	0.7	8.6	0.5	0.74	0.71	0.56	0.49	0.7
Phosphoric acid										0.98
Sulfur dioxide	50.8	50.8	1	17.7	1	1.31	1	1	1	1
Sulfur monoxide	50.8	50.8	1		1	1.31	1	1	1	1
Sulfur oxides							1	1	1	1
Sulfur trioxide			0.8	14.1		1.05				0.8
Sulfuric acid	33.3	33.3	0.65	11.5						0.65

Table S8: characterization factor values for 50 Ecotoxicity substances generalized from 8 latest version impact methods provided in SimaPro software. The remaining 30472 substances are not shown in the table.

			BEES+ V4.03	CML 2001 (all impact categori es)	EDIP/UM IP 97 V2.05	EDIP 2003 V1.04	ILCD 2011 Midpoint V1.02	ReCiPe Midpoint (I) V1.08	TRACI 2.1 V1.01	USEtox
			g 2,4-D e	kg 1,4-DE	m3 / kg	m3 / g	CTUe / kg	kg 1,4-DE	CTUe	CTUe
1,4-Butanediol	Air	(unspecified)	0	0	0	0	0.856	0	0.856	0.856
1,4-Butanediol	Air	high. pop.	0	0	0	0	0.878	0	0.878	0.878
1,4-Butanediol	Air	low. pop., long-term	0	0	0	0	0	0	0.835	0.835
1,4-Butanediol	Air	low. pop.	0	0	0	0	0.835	0	0.835	0.835
1,4-Butanediol	Air	stratosphere + troposphere	0	0	0	0	0.835	0	0.835	0.835
1-Butanol	Air	(unspecified)	0	0	0.09	30.35	0.109	0.0002	0.109	0.109
1-Butanol	Air	high. pop.	0	0	0	0	0.11	0.0002	0.11	0.11
1-Butanol	Air	low. pop., long-term	0	0	0	0	0	0.0001	0.108	0.108
1-Butanol	Air	low. pop.	0	0	0	0	0.108	0.0001	0.108	0.108
1-Butanol	Air	stratosphere + troposphere	0	0	0	0	0.108	0.0001	0.108	0.108
1-Methyl-2-pyrrolidinone	Air	(unspecified)	0	0	0	0	0.93	0	0.93	0.93
1-Methyl-2-pyrrolidinone	Air	high. pop.	0	0	0	0	0.965	0	0.965	0.965
1-Methyl-2-pyrrolidinone	Air	low. pop., long-term	0	0	0	0	0	0	0.894	0.894
1-Methyl-2-pyrrolidinone	Air	low. pop.	0	0	0	0	0.894	0	0.894	0.894
1-Methyl-2-pyrrolidinone	Air	stratosphere + troposphere	0	0	0	0	0.894	0	0.894	0.894
1-Pentanol	Air	(unspecified)	0	0	0	0	0.212	0.0002	0.212	0.212
1-Pentanol	Air	high. pop.	0	0	0	0	0.214	0.0002	0.214	0.214
1-Pentanol	Air	low. pop., long-term	0	0	0	0	0	0.0001	0.211	0.211
1-Pentanol	Air	low. pop.	0	0	0	0	0.211	0.0001	0.211	0.211
1-Pentanol	Air	stratosphere + troposphere	0	0	0	0	0	0.0001	0.211	0.211
1-Propanol	Air	(unspecified)	0	0	0	0	0.0925	0.0001	0.0925	0.0925
1-Propanol	Air	high. pop.	0	0	0	0	0.0933	0.0001	0.0933	0.0933
1-Propanol	Air	low. pop., long-term	0	0	0	0	0	0.0001	0.0917	0.0917
1-Propanol	Air	low. pop.	0	0	0	0	0.0917	0.0001	0.0917	0.0917
1-Propanol	Air	stratosphere + troposphere	0	0	0	0	0.0917	0.0001	0.0917	0.0917
2,4-D	Air	(unspecified)	1	38.7	0	0	106	0.0841	106	106
2,4-D	Air	high. pop.	0	0	0	0	109	0.0841	109	109
2,4-D	Air	low. pop., long-term	0	0	0	0	0	0.0884	103	103
2,4-D	Air	low. pop.	0	0	0	0	103	0.0884	103	103
2,4-D	Air	stratosphere + troposphere	0	0	0	0	103	0.0884	103	103
2-Butanol	Air	(unspecified)	0	0	0	0	0.131	5E-05	0.131	0.131
2-Butanol	Air	high. pop.	0	0	0	0	0.133	5E-05	0.133	0.133
2-Butanol	Air	low. pop., long-term	0	0	0	0	0	4E-05	0.13	0.13
2-Butanol	Air	low. pop.	0	0	0	0	0.13	4E-05	0.13	0.13
2-Butanol	Air	stratosphere + troposphere	0	0	0	0	0.13	4E-05	0.13	0.13
2-Chloroacetophenone	Air	(unspecified)	0	0	0	0	2280	0	2280	2280
2-Chloroacetophenone	Air	high. pop.	0	0	0	0	2380	0	2380	2380
2-Chloroacetophenone	Air	low. pop., long-term	0	0	0	0	0	0	2190	2190
2-Chloroacetophenone	Air	low. pop.	0	0	0	0	2190	0	2190	2190
2-Chloroacetophenone	Air	stratosphere + troposphere	0	0	0	0	2190	0	2190	2190
2-Methyl-1-propanol	Air	(unspecified)	0	0	0	31.52	0.2	0.0001	0.2	0.2
2-Methyl-1-propanol	Air	high. pop.	0	0	0	0	0.202	0.0001	0.202	0.202
2-Methyl-1-propanol	Air	low. pop., long-term	0	0	0	0	0	0.0001	0.199	0.199
2-Methyl-1-propanol	Air	low. pop.	0	0	0	0	0.199	0.0001	0.199	0.199
2-Methyl-1-propanol	Air	stratosphere + troposphere	0	0	0	0	0.199	0.0001	0.199	0.199
2-Propanol	Air	(unspecified)	0	0	0.46	152.4	0.08	2E-05	0.08	0.08
2-Propanol	Air	high. pop.	0	0	0	0	0.0805	2E-05	0.0805	0.0805
2-Propanol	Air	low. pop., long-term	0	0	0	0	0	1E-05	0.0794	0.0794
2-Propanol	Air	low. pop.	0	0	0	0	0.0794	1E-05	0.0794	0.0794
2-Propanol	Air	stratosphere + troposphere	0	0	0	0	0.0794	1E-05	0.0794	0.0794

Matlab code to map US LCI inventories into the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices

```
data=xml2struct('Acetic acid, at plant.xml');
%%    % add xml files, the information is put into different cells.
% name_sub_all % 1. the names of input/output for each flow from the files
% category_sub_all % 2. the names of subcategory of input/output for each flow
from the files
% mean_sub_all  % 3. the values of input/output for each flow from the files
% unit_sub_all % 4. the functional unit of input/output for each flow from the
files
% number_sub_all % 5. the index number of input/output for each flow from the
files
% input_sub_all % 6. the index number of inputs for each flow from the files
% output_sub_all % 7. the index number of outputs for each flow from the files
%
% % values from each 701 process
% name_all % 1. name of the process
% category_all % 2. subcategory of a process
% value_all % 3. the output value of a process
% unit_all % 4. functional unit of a process

files = dir('*.xml');
% values from inputs/ouputs for each 701 process
name_sub_all=cell(length(files),1); % 1. name
category_sub_all=cell(length(files),1); % 2. sub category
category_local_all=cell(length(files),1); % 2.1 local category
mean_sub_all=cell(length(files),1); % 3. mean value
unit_sub_all=cell(length(files),1); % 4. functional unit
number_sub_all=cell(length(files),1); % 5. number
input_sub_all=cell(length(files),1); % 6. input category index number
output_sub_all=cell(length(files),1); % 7. output category index number

% values from each 701 process
name_all=cell(length(files),1); % 1. name
category_all=cell(length(files),1); % 2. sub category
value_all=cell(length(files),1); % 3. mean value
unit_all=cell(length(files),1); % 4. functional unit

%%
parfor i=1:length(files)
data = xml2struct([files(i).name]);
Num_exchange=length(data.ecoSpold.dataset.flowData.exchange);

name=data.ecoSpold.dataset.metaInformation.processInformation.referenceFunctio
n.Attributes.localName;
category=data.ecoSpold.dataset.metaInformation.processInformation.referenceFun
ction.Attributes.localSubCategory;
value=
data.ecoSpold.dataset.metaInformation.processInformation.referenceFunction.Att
ributes.amount;
unit=data.ecoSpold.dataset.metaInformation.processInformation.referenceFunctio
n.Attributes.unit;
```

```
name_all{i,1}=name;
category_all{i,1}=category;
value_all{i,1}=value;
unit_all{i,1}=unit;

name_sub=cell(Num_exchange,1);
category_sub=cell(Num_exchange,1);
category_local=cell(Num_exchange,1);
mean_sub=nan(Num_exchange,1);
unit_sub=cell(Num_exchange,1);
number_sub=nan(Num_exchange,1);

% information from the input/outputs from each process
for j=1:Num_exchange

    name_sub{j}=data.ecoSpold.dataset.flowData.exchange{j}.Attributes.name;

    % same for subcategory, if subcategory is not avaiable, use"NaN"
    if
isfield(data.ecoSpold.dataset.flowData.exchange{j}.Attributes,'subCategory')==
1

category_sub{j}=data.ecoSpold.dataset.flowData.exchange{j}.Attributes.subCateg
ory;
    else
       category_sub{j}='NaN';
    end
    % same for localsubcategory, if subcategory is not avaiable, use"NaN"
    if
isfield(data.ecoSpold.dataset.flowData.exchange{j}.Attributes,'localCategory')
==1

category_local{j}=data.ecoSpold.dataset.flowData.exchange{j}.Attributes.localC
ategory;
    else
       category_local{j}='NaN';
    end


mean_sub(j)=str2double(data.ecoSpold.dataset.flowData.exchange{j}.Attributes.m
eanValue);
    unit_sub{j}=data.ecoSpold.dataset.flowData.exchange{j}.Attributes.unit;

number_sub(j)=str2double(data.ecoSpold.dataset.flowData.exchange{j}.Attributes
.number);
% import the index numbers for input or output, the matrix eg.
"input_category_all" returns the
% index values for inputs shown in the file. use 999 to replace the values
% that are not available
    if isfield(data.ecoSpold.dataset.flowData.exchange{j}, 'outputGroup')~=0

output_sub_all{i,:}(j,1)=str2double(data.ecoSpold.dataset.flowData.exchange{j}
.outputGroup.Text);
    else
        output_sub_all{i,:}(j,1)=999;
    end
```

```
    if isfield(data.ecoSpold.dataset.flowData.exchange{j}, 'inputGroup')~=0

input_sub_all{i,:}(j,1)=str2double(data.ecoSpold.dataset.flowData.exchange{j}.
inputGroup.Text);
    else
        input_sub_all{i,:}(j,1)=999;
    end
end
name_sub_all{i,1}=name_sub;
category_sub_all{i,1}=category_sub;
category_local_all{i,1}=category_local;
mean_sub_all{i,1}=mean_sub;
unit_sub_all{i,1}=unit_sub;
number_sub_all{i,1}=number_sub;

end
% in "input_category_all" and "output_category_all". replace the zero value
(output category as zero)
% with "888", and change all 999 to zero.
% the output_category_all returns the revised index number, 888 indicates
% the output is in "0" category from the orignial file, 0 indicates the
% index number is not available from the orignial file.
parfor i=1:length(output_sub_all)
    for j=1:length(output_sub_all{i,1})
        if output_sub_all{i,1}(j,1)==0
           output_sub_all{i,1}(j,1)=888;
        elseif output_sub_all{i,1}(j,1)==999
           output_sub_all{i,1}(j,1)=0;
        end
    end
    output_sub_all{i,1}=-output_sub_all{i,1}; %%use negative number for
outputs
end

parfor i=1:length(input_sub_all)
    for j=1:length(input_sub_all{i,1})
        if input_sub_all{i,1}(j,1)==0
           input_sub_all{i,1}(j,1)=888;
        elseif input_sub_all{i,1}(j,1)==999
           input_sub_all{i,1}(j,1)=0;
        end
    end
end

% add input and output index number together
input_output_sub_all=cell(length(input_sub_all),1);
for i =1:length(input_sub_all)
    input_output_sub_all{i,1}=input_sub_all{i,1}+output_sub_all{i,1};
end

%%
% fine all index numbers from all the inputs/outputs in the files
%"unique_numbers" returns all the index numbers avaiable from the
inputs/outputs

A=zeros(length(files),1);
```

```
for i=1:length(A)
    A(i,1)=length(number_sub_all{i,1});
end
% combine all index numbers from input/output together. "matrix_size"
% returns a matrix that have columns that presents the processes(all
% files), the rows for the combination of all input/ouput for each process
name_sub_matrix=cell(max(A),length(A));
category_sub_matrix=cell(max(A),length(A));
category_local_matrix=cell(max(A),length(A));
unit_sub_matrix=cell(max(A),length(A));
number_sub_matrix=zeros(max(A),length(A));
mean_sub_matrix=zeros(max(A),length(A));
input_output_sub_matrix=zeros(max(A),length(A));

for i = 1:length(number_sub_matrix(1,:))% could put name, category, etc here
    name_sub_matrix(1:length(number_sub_all{i,1}),i)= name_sub_all{i,1};
    category_sub_matrix(1:length(number_sub_all{i,1}),i)=
category_sub_all{i,1};
    category_local_matrix(1:length(number_sub_all{i,1}),i)=
category_local_all{i,1};
    unit_sub_matrix(1:length(number_sub_all{i,1}),i)= unit_sub_all{i,1};
    number_sub_matrix(1:length(number_sub_all{i,1}),i)=number_sub_all{i,1};
    mean_sub_matrix(1:length(mean_sub_all{i,1}),i)=mean_sub_all{i,1};

input_output_sub_matrix(1:length(input_output_sub_all{i,1}),i)=input_output_su
b_all{i,1};

end

%% % find unique index numbers of the process/flow and their input/output
categories
[unique_numbers,ia1,ic1] = unique(number_sub_matrix,'first','legacy');
unique_numbers(:,2)=input_output_sub_matrix(ia1);
unique_numbers(1,:)=[];

%%
%Build A+R matrix: "All_matrix" returns the matrix with all
%inputss/ouputs information combined together. All columns are 701
processes,all rows are flows go to one process
%Build category index matrix: "category_index" returns the matrix with all
%inputss/ouputs index information combined together.
index=zeros(size(number_sub_matrix));

%find index number connecting numbers of the input/output with unique numbers
for i = 1:size(number_sub_matrix)
    for j=1:size(files)
        [Lia_1, index(i,j)]=ismember(number_sub_matrix(i,j),unique_numbers);
    end
end
%%
% find correspoding names, mean, category, etc according to index
name_sub_1=cell(length(unique_numbers),length(files));
category_sub_1=cell(length(unique_numbers),length(files));
category_local_1=cell(length(unique_numbers),length(files));
mean_sub_1=zeros(length(unique_numbers),length(files));
unit_sub_1=cell(length(unique_numbers),length(files));
```

```
number_sub_1=zeros(length(unique_numbers),length(files));
input_output_sub_1=zeros(length(unique_numbers),length(files));

for i = 1:size(number_sub_matrix)
    for j=1:size(files)
        if index(i,j)>0
           name_sub_1{index(i,j),j}=name_sub_matrix{i,j};
           unit_sub_1{index(i,j),j}=unit_sub_matrix{i,j};
           category_sub_1{index(i,j),j}=category_sub_matrix{i,j};
           category_local_1{index(i,j),j}=category_local_matrix{i,j};
           mean_sub_1(index(i,j),j)=mean_sub_matrix(i,j);
           number_sub_1(index(i,j),j)=number_sub_matrix(i,j);
           input_output_sub_1(index(i,j),j)=input_output_sub_matrix(i,j);
        end
    end
end


%%
% find unique names and corresponding functional unit, category of
inputs/outputs and subcategory (important)
% Locb returns the matrix index of numbers from unique numbers, using Locb
% reqires the size of a matrix the same size of "number_sub_matrix" (1201,701)
unique_names=cell(length(unique_numbers),1);
unique_category=cell(length(unique_numbers),1);
unique_local_category=cell(length(unique_numbers),1);
unique_unit=cell(length(unique_numbers),1);

for i = 1:length(unique_numbers)
    [Lia,Locb] = ismember(unique_numbers(i,1),number_sub_matrix);   % ismember
function returns the subscript number of the location of a index number
    unique_names{i,1}=name_sub_matrix{Locb}; % find the name from
"matrix_name" using the coordinates
    unique_category{i,1}=category_sub_matrix(Locb);
    unique_local_category{i,1}=category_local_matrix(Locb);
    unique_unit(i,1)=unit_sub_matrix(Locb);
end


%%
% find the matrix index numbers of 701 processes' names. Locb_2 returns the
% index numbers. there are processes that are within the 701 files but not
% within the inputs/outputs (4176), assign numbers to these proceses, from
% 10000+max number (10000+4176))
Locb_2=zeros(length(files),1);
for i = 1:length(name_all)
    [Lia_1(i,1),Locb_2(i,1)] = ismember(name_all{i,1},unique_names);
end
max_index=max(length(unique_names),max(Locb_2)); % find the largest number of
all the processes
extra_No=sum(Locb_2(:)==0); % find how many processes are not within all
inputs/outputs
extra_index=max_index+10000; %assign numbers for those processes that are not
within inputs/outputs
for i = 1:length(Locb_2)
    if Locb_2(i,1)==0
```

```
        Locb_2(i,1)=extra_index;
        extra_index=extra_index+1;
    end
end
%% build A+R matrix. all processes and flows are in the matrix, values from
4177 to 4128 are the processes that are not input for any other processses
All_matrix_number=zeros(length(number_sub_1),length(number_sub_1));
All_matrix_mean=zeros(length(mean_sub_1),length(mean_sub_1));
All_matrix_input_output=zeros(length(input_output_sub_1),length(input_output_s
ub_1));

for i = 1:length(Locb_2)
if Locb_2(i,1)<10000
   All_matrix_number(:,Locb_2(i,1))=number_sub_1(:,i);
   All_matrix_mean(:,Locb_2(i,1))=mean_sub_1(:,i);
   All_matrix_input_output(:,Locb_2(i,1))=input_output_sub_1(:,i);
else
   All_matrix_number(:,(Locb_2(i,1)-10000+1))=number_sub_1(:,i);
   All_matrix_mean(:,(Locb_2(i,1)-10000+1))=mean_sub_1(:,i);
   All_matrix_input_output(:,(Locb_2(i,1)-10000+1))=input_output_sub_1(:,i);
end
end
% add missing rows
All_matrix_mean(max_index+1:length(All_matrix_mean),:)=0;
All_matrix_number(max_index+1:length(All_matrix_number),:)=0;
All_matrix_input_output(max_index+1:length(All_matrix_input_output),:)=0;
%%
%find norminator for all processes (in A matrix)
Norm=zeros(length(All_matrix_mean),1);

for i = 1:length(Locb_2)
if Locb_2(i,1)<10000
   Norm(Locb_2(i,1),1)=str2double(value_all{i,1});
else
   Norm((Locb_2(i,1)-10000+1),1)=str2double(value_all{i,1});
end
end
%%
% make output/input category negative or positive, to show the correct
% category;
% -888:
% -2, -3: process as output
% -4 :elementary flow as output (emission)
% 4 : elementary flow as input(resource)
% 5 : process as input
All_matrix_mean_modi=zeros(size(All_matrix_mean));
for i = 1: length(All_matrix_mean)
    for j = 1: length(All_matrix_mean)
        if All_matrix_input_output(i,j)<0
           All_matrix_mean_modi(i,j)=-All_matrix_mean(i,j);
        elseif All_matrix_input_output(i,j)==888
           All_matrix_mean_modi(i,j)=-All_matrix_mean(i,j);
        else
           All_matrix_mean_modi(i,j)=All_matrix_mean(i,j);
        end
    end
```

```
end
 All_matrix_mean= All_matrix_mean_modi;
%%
% separte A matrix and R matrix, and their names
A_matrix=All_matrix_mean;
R_matrix=All_matrix_mean;
R_matrix((end-extra_No+1):end,:)=[]; %delete extra rows in R
Norm_A=Norm;
Norm_R=Norm;
unique_names_A=unique_names;
unique_names_R=unique_names;
unique_category_A=unique_category;
unique_category_R=unique_category;
unique_local_category_A=unique_local_category;
unique_local_category_R=unique_local_category;
unique_unit_A=unique_unit;
unique_unit_R=unique_unit;
unique_number_A=unique_numbers;
unique_number_R=unique_numbers;
% find A matrix, use NaN to replace values that should be in R (find input
% only)
for i = 1:length(unique_numbers)
if abs(unique_numbers(i,2))==4
   A_matrix(:,i)= NaN;
   A_matrix(i,:)= NaN;
   Norm_A(i,:)=NaN;
   unique_names_A{i,1}= 'NaN';
   unique_category_A{i,1}='NaN';
   unique_local_category_A{i,1}='NaN';
   unique_unit_A{i,1}= 'NaN';
   unique_number_A(i,1)= NaN;
end
end

A_matrix(length(unique_number_A)+1:length(A_matrix),:)=0;
% find R matrix, use NaA to replace values that should be in A (find output
% only)

for i = 1:length(unique_numbers)
if abs(unique_numbers(i,2))~=4
    R_matrix(i,:)= NaN;
%     Norm_R(i,:)=NaN; %this is not going to be used
    unique_names_R{i,1}='NaN';
    unique_category_R{i,1}='NaN';
    unique_local_category_R{i,1}='NaN';
    unique_unit_R{i,1}='NaN';
    unique_number_R(i,1)= NaN;
end
end

%replace outputs columns in R matrix with NaN
for i=1:length(unique_numbers)
if  abs(unique_numbers(i,2))==4
    R_matrix(:,i)= NaN;
end
```

```
end
%%
% delete NaN in A and R matrices
%delete NaN rows in A and R matrix
A_matrix=A_matrix(any(~isnan(A_matrix),2),:);
R_matrix=R_matrix(any(~isnan(R_matrix),2),:);
%delete NaN columns in A and R matrix
A_matrix=A_matrix(:,all(~isnan(A_matrix)));
R_matrix=R_matrix(:,all(~isnan(R_matrix)));

%delete NaN in unique numbers
unique_number_A=unique_number_A(:,1);
unique_number_R=unique_number_R(:,1);
unique_number_A(isnan(unique_number_A))=[];
unique_number_R(isnan(unique_number_R))=[];
Norm_A(isnan(Norm_A))=[];
Norm_R(isnan(Norm_R))=[];
%%
%delete NaN in names, category, functional units for A and R
% use while function, delete a row if the values is "NaN", delete from the
% last row to the first row
i = length(unique_numbers);
while i>0
    if strcmp(unique_names_A(i,1),'NaN')==1
        unique_names_A(i,:)=[];
        unique_category_A(i,:)=[];
        unique_local_category_A(i,:)=[];
        unique_unit_A(i,:)=[];
    end
    i=i-1;
end
% same for R
i = length(unique_numbers);

while i >0
    if strcmp(unique_names_R(i,1),'NaN')==1
        unique_names_R(i,:)=[];
        unique_category_R(i,:)=[];
        unique_local_category_R(i,:)=[];
        unique_unit_R(i,:)=[];
    end
    i=i-1;
end

%%
% find extra processes names in the files but not in the inputs/outputs
unique_name_extra=cell(extra_No,1);
unique_category_extra=cell(extra_No,1);
unique_unit_extra=cell(extra_No,1);
for i = 1:length(Locb_2)
if Locb_2(i,1)>10000
   unique_name_extra{i,1}=name_all{i,1};
   unique_category_extra{i,1}=category_all{i,1};
   unique_unit_extra{i,1}=unit_all{i,1};

else
```

```
   unique_name_extra{i,1}=NaN;
   unique_category_extra{i,1}=NaN;
   unique_unit_extra{i,1}=NaN;
end
end

% delete NaN
unique_name_extra(cellfun(@(unique_name_A_plus)
any(isnan(unique_name_A_plus)),unique_name_extra))=[];
unique_category_extra(cellfun(@(unique_subCategory_A_plus)
any(isnan(unique_subCategory_A_plus)),unique_category_extra))=[];
unique_unit_extra(cellfun(@(unique_unit_A_plus)
any(isnan(unique_unit_A_plus)),unique_unit_extra))=[];

%%
%add extra names, categories, units
 unique_names_A_all=unique_names_A;
 unique_category_A_all= unique_category_A;
 unique_local_category_A_all= unique_local_category_A;
 unique_unit_A_all=unique_unit_A;

h=length(unique_number_A)+1;
for i = 1:extra_No
    unique_names_A_all{h+i-1,1}=unique_name_extra{i,1};
    unique_category_A_all{h+i-1,1}=unique_category_extra{i,1};
    unique_local_category_A_all{h+i-1,1}=unique_category_extra{i,1};
    unique_unit_A_all{h+i-1,1}=unique_unit_extra{i,1};
end
%% % m_R returns the number of flows in R, n_A returns the number of processes
in A
[m_R,n_A]=size(R_matrix);
%%
% sort R matrix by names of emissions ; meta_info_R returns the sorted meta
% information (by names)
[SortR_names,IndR_names]=sort(unique_names_R);

SortR_names_category=cell(m_R,1);
SortR_names_local_category=cell(m_R,1);
SortR_names_unit=cell(m_R,1);
R_matrix_sortNames=R_matrix;
for i = 1:m_R
    SortR_names_category(i,1)=unique_category_R(IndR_names(i,1),1);

SortR_names_local_category(i,1)=unique_local_category_R(IndR_names(i,1),1);
    SortR_names_unit(i,1)=unique_unit_R(IndR_names(i,1),1);
    R_matrix_sortNames(i,:)=R_matrix(IndR_names(i,1),:);
end

%% sort
% sort names, find index number
[SortA_names,IndA_names]=sort(unique_names_A_all);
% SortA_name_category=unique_category_A_all(IndA_names);
% SortA_name_unit=unique_unit_A_all(IndA_names);

% sort A matrix by index number, pay attention to the way
SortA_name_category=cell(n_A,1);
```

```
SortA_name_local_category=cell(n_A,1);
SortA_name_unit=cell(n_A,1);
SortA_name_mean_inter=zeros(size(A_matrix));
SortA_name_mean=SortA_name_mean_inter;
for i = 1: n_A
    SortA_name_category(i,1)=unique_category_A_all(IndA_names(i,1),1);

SortA_name_local_category(i,1)=unique_local_category_A_all(IndA_names(i,1),1);
    SortA_name_unit(i,1)=unique_unit_A_all(IndA_names(i,1),1);
    SortA_name_mean_inter(i,:)=A_matrix(IndA_names(i,1),:);
end
% sort columns for A
for i = 1: n_A
    SortA_name_mean(:,i)=SortA_name_mean_inter(:,IndA_names(i,1));
end

%%
% use index number to sort Norm
SortA_Norm_A=zeros(size(Norm_A));
for i = 1: n_A
    SortA_Norm_A(i,1)=Norm_A(IndA_names(i,1),1);
end

%%
% use index number to sort R matrix columns
SortA_name_Rmean=zeros(size(R_matrix_sortNames));
for i = 1:n_A
    SortA_name_Rmean(:,i)=R_matrix_sortNames(:,IndA_names(i,1));
end
SortA_name_Rmean=-SortA_name_Rmean;
%%
%combine information together, returns R matrix, A matrix, functional
%units; names, categories, functional units for R and A matrix

%values of functional units
funct_units_2016=zeros(length(SortA_Norm_A),1);
for i = 1:length(SortA_Norm_A)
    if SortA_Norm_A(i,1)==0
       funct_units_2016(i,1)=1;
    else
       funct_units_2016(i,1)=SortA_Norm_A(i,1);
    end
end
% the A matrix
USLCI_Atech_raw_2016=SortA_name_mean;
% the R matrix
env_factors_2016=SortA_name_Rmean;

% meta information for the A matrix
meta_info_A=cell(n_A,3);
for i = 1:n_A
meta_info_A{i,1}=SortA_names{i,1};
meta_info_A{i,2}=SortA_name_category{i,1};
meta_info_A{i,3}=SortA_name_unit{i,1};
meta_info_A{i,4}=SortA_name_local_category{i,1};
end
```

```
% meta information for the R matrix
meta_info_R=cell(m_R,3);
for i = 1:m_R
meta_info_R{i,1}=SortR_names{i,1};
meta_info_R{i,2}=SortR_names_category{i,1};
meta_info_R{i,3}=SortR_names_unit{i,1};
meta_info_R{i,4}=SortR_names_local_category{i,1};
end
%% %save matrices and export A and R matrix to excel file
save('matrices2016_1107.mat','meta_info_R','meta_info_A','funct_units_2016','U
SLCI_Atech_raw_2016','env_factors_2016')
```

Matlab code used to identify cradle-to-gate processes

```
%  data=xml2struct('Alumina, at plant.xml');
%%    % add xml files, the information is put into different cells.
% name_sub_all % 1. the names of input/output for each flow from the files
% category_sub_all % 2. the names of subcategory of input/output for each flow
from the files
% mean_sub_all  % 3. the values of input/output for each flow from the files
% unit_sub_all % 4. the functional unit of input/output for each flow from the
files
% number_sub_all % 5. the index number of input/output for each flow from the
files
% input_sub_all % 6. the index number of inputs for each flow from the files
% output_sub_all % 7. the index number of outputs for each flow from the files
%
% % values from each 701 process
% name_all % 1. name of the process
% category_all % 2. subcategory of a process
% value_all % 3. the output value of a process
% unit_all % 4. functional unit of a process

files = dir('*.xml');

% values from each 701 process
name_all=cell(length(files),1); % 1. name
category_all=cell(length(files),1); % 2. sub category
value_all=cell(length(files),1); % 3. mean value
unit_all=cell(length(files),1); % 4. functional unit
generalComment_all=cell(length(files),1); % 5.
title_all=cell(length(files),1); % 5.
title=cell(1,1);


for i=1:701
data = xml2struct([files(i).name]);
Num_exchange=length(data.ecoSpold.dataset.flowData.exchange);

name=data.ecoSpold.dataset.metaInformation.processInformation.referenceFunctio
n.Attributes.localName;
category=data.ecoSpold.dataset.metaInformation.processInformation.referenceFun
ction.Attributes.localSubCategory;
value=
data.ecoSpold.dataset.metaInformation.processInformation.referenceFunction.Att
ributes.amount;
unit=data.ecoSpold.dataset.metaInformation.processInformation.referenceFunctio
n.Attributes.unit;
if
isfield(data.ecoSpold.dataset.metaInformation.processInformation.referenceFunc
tion.Attributes,'generalComment')~=0

generalComment=data.ecoSpold.dataset.metaInformation.processInformation.refere
nceFunction.Attributes.generalComment;
else
   generalComment='NA';
end
```

```
if
length(data.ecoSpold.dataset.metaInformation.modellingAndValidation.source)==1
    if
isfield(data.ecoSpold.dataset.metaInformation.modellingAndValidation.source.At
tributes,'title')~=0

title{1,1}=data.ecoSpold.dataset.metaInformation.modellingAndValidation.source
.Attributes.title;
    else
       title{1,1}='NA';
    end
else
%     for nn =
1:length(data.ecoSpold.dataset.metaInformation.modellingAndValidation.source)
    for nn = 1:1

    if
isfield(data.ecoSpold.dataset.metaInformation.modellingAndValidation.source{1,
nn}.Attributes,'title')~=0

title{1,nn}=data.ecoSpold.dataset.metaInformation.modellingAndValidation.sourc
e{1,nn}.Attributes.title;
    else
       title{1,nn}='NA';
    end
    end
end

name_all{i,1}=name;
category_all{i,1}=category;
value_all{i,1}=value;
unit_all{i,1}=unit;
generalComment_all{i,1}=generalComment;
for h=1:length(title)
    title_all{i,h}=title{1,h};
end

end
%% find the crade to gate processes
load ctg.mat
Cradel2Gate_11=zeros(7,1);
for i = 1:701
    a=strfind(generalComment_all{i,1},'radle');
    if length(a)==1
       Cradel2Gate_11(i,1)=strfind(generalComment_all{i,1},'radle');
    elseif length(a)>1
       Cradel2Gate_11(i,1)=a(1,1);
    else
       Cradel2Gate_11(i,1)=0;
    end
end

Cradel2Gate_x=find(Cradel2Gate_11);
%%
Cradel2Gate_2=zeros(701,1);
for i = 1:701
```

```
    if strfind(title_all{i,1},'CRADLE-TO-GATE')>0
       Cradel2Gate_2(i,1)=strfind(title_all{i,1},'CRADLE-TO-GATE');
    else
         if strfind(title_all{i,1},'radle')>0
             Cradel2Gate_2(i,1)=strfind(title_all{i,1},'radle');
         else
             Cradel2Gate_2(i,1)=0;
         end
    end
end
Cradel2Gate_y=find(Cradel2Gate_2);

%%
Cradel2Gate_all=[Cradel2Gate_x;Cradel2Gate_y];
Cradel2Gate=unique(Cradel2Gate_all);
c2g=name_all(Cradel2Gate);
```

Matlab code used to match substances from different methods with the US LCI elementary flows, GW impact category as an example

```
load matrices2016_alo.mat
load index_by_ISIC.mat % change index number can be a function
% load GWP_methods.mat
load CTG_Cutoff.mat
%%
% GWP_All_CF_comparments(:,6)=strrep(GWP_All_CF_comparments(:,6),char(39),'');

%%
TARGET1=GlobalWarming;
parm=1;

if parm==1
    aws1=1;
    aws2=1030;
    AWS='Air';
elseif parm==2
    aws1=1784;
    aws2=2070;
    AWS='Water';
elseif parm==3
    aws1=1547;
    aws2=1783;
    AWS='Soil';
end
% air: 1:1030. water: 1784:2070  soil: 1547:1783
%%
[hh,inddd]=sort(TARGET1(:,1));


TARGET2=TARGET1(inddd,:);
TARGET=cell(1,size(TARGET2,2));
for i = 1:size(TARGET2,1)
    [lia,det]=ismember(TARGET2{i,1},AWS);
    if det(1,1)>0
        TARGET(i,:)=TARGET2(i,:);
    end
end

%%
TARGET(all(cellfun('isempty',TARGET),2),:) = [];

TARGET(:,2)=strrep(TARGET(:,2),char(40),'');
TARGET(:,2)=strrep(TARGET(:,2),char(41),'');
% Remove () from the texts
% need to clean the data for "unspecific" no ()

%%
funct_units_updated=funct_units_2016_updated_alo';
funct_units_mat=repmat(funct_units_updated,length(USLCI_Atech_raw_2016_alo),1)
;  %makes a "repeated matrix" with funct_units down columns
```

```
unit_conv_mat=repmat(unit_conv,1,length(USLCI_Atech_raw_2016_alo));
%divide by functional units
norm_Atech_raw=USLCI_Atech_raw_2016_alo./funct_units_mat; % normalizes the A
matrix by functional units
norm_Atech_raw=norm_Atech_raw.*unit_conv_mat;
norm_Atech_raw(logical(eye(size(norm_Atech_raw))))=-1;
funct_units_env=repmat(funct_units_updated,length(env_factors_2016_alo),1);  %
same as above except has 2708 rows
env_factors_norm=env_factors_2016_alo./funct_units_env;

%%
% sort R matrix
sort_env_factors_norm=env_factors_norm(index_R,:);
sort_meta_R=meta_info_R(index_R,:);
[Lia,ImpactInR_uiq] = ismember(TARGET(:,3), sort_meta_R(aws1:aws2,1));

%%
sort_meta_R(:,1)= deblank(sort_meta_R(:,1));
% Remove trailing whitespace from end of string or character array
sort_meta_R_AWS=sort_meta_R(aws1:aws2,:);
%%
[uniqueA unique_num j] = unique(sort_meta_R_AWS(:,1),'first');
[par,asw]=ismember(TARGET(:,3),uniqueA);
% unique_num = index number of the first unique in sort_meta_R
% j = index number of the names in UniqueA, 620 names in total

index1 = (find(ismember(j,asw)))';
[a,b]=ismember(j,asw);
c=zeros(length(b),1);
for h = 1:size(sort_meta_R_AWS,1)
    if b(h,1)>0
    c(h,1)= asw(b(h,1),1);
    else
    c(h,1)=0;
    end
end

LL = c(c~=0);

[Lia,ImpactInR_uiq_2] = ismember(sort_meta_R_AWS(:,1),TARGET(:,3));

ImpactInR_uiq_2 = ImpactInR_uiq_2(ImpactInR_uiq_2~=0);
duplicate_names_2=cell(length(LL),1);
for h=1:length(ImpactInR_uiq_2)
    for k=1:size(TARGET,2)
        duplicate_names_2{h,k}=TARGET{ImpactInR_uiq_2(h,1),k};
    end
end

equl_Eflow_in_R=cell(length(ImpactInR_uiq_2),1);

for i = 1:size(sort_meta_R_AWS,1)
    if b(i,1)>0,
        equl_Eflow_in_R{i,1}=sort_meta_R_AWS{i,1};
        equl_Eflow_in_R{i,2}=sort_meta_R_AWS{i,2};
```

```
        equl_Eflow_in_R{i,3}=sort_meta_R_AWS{i,3};
    else
        equl_Eflow_in_R{i,1}=[];
    end
end
equl_Eflow_in_R(all(cellfun('isempty',equl_Eflow_in_R),2),:) = [];

for i = 1: length(equl_Eflow_in_R)
    equl_Eflow_in_R{i,4}=duplicate_names_2{i,5};
    equl_Eflow_in_R{i,5}=duplicate_names_2{i,6};
    equl_Eflow_in_R{i,6}=duplicate_names_2{i,1};
    equl_Eflow_in_R{i,7}=duplicate_names_2{i,7};

end

%delete all empty values
equl_CF_in_R=cell(length(duplicate_names_2),6);
for i = 1: length(equl_Eflow_in_R)
    if ismember(duplicate_names_2{i,2},equl_Eflow_in_R{i,2})==1
        equl_CF_in_R{i,1}=duplicate_names_2{i,3};
        equl_CF_in_R{i,2}=equl_Eflow_in_R{i,2};
        equl_CF_in_R{i,3}=equl_Eflow_in_R{i,3};
        equl_CF_in_R{i,4}=duplicate_names_2{i,5};
        equl_CF_in_R{i,5}=duplicate_names_2{i,6};
        equl_CF_in_R{i,6}=duplicate_names_2{i,1};
%          equl_CF_in_R{i,7}=duplicate_names_2{i,7}; % only for all methods

    else
        equl_CF_in_R{i,1}=[];
    end
end
equl_CF_in_R(all(cellfun('isempty',equl_CF_in_R),2),:) = [];

% equl_CF_in_R returns stricker elementary flows that have coressponding CF
% in each method. both the name of the chemical (eg carbon dioxide, fossil)
% and the category of the chemial (eg. unspecific) should match
% equl_Eflow_in_R returns general matches, only the names of the chemical
% matches

%%
[SortA_mean,SortR_mean_s,Sort_meta_info_A,Sort_meta_info_R] =
Sort_matrix(norm_Atech_raw,sort_env_factors_norm,meta_info_A_updated,sort_meta
_R_AWS,index_by_ISIC);

%%
%find the index numbers of elementary flows from the method under
%assessemnt

[lia1,l2]=ismember(ImpactInR_uiq,unique_num);
for i =1:length(unique_num)-1
    num(i,1)=unique_num(i+1,1)-unique_num(i,1);

end
ImpactInR=zeros(length(ImpactInR_uiq),max(num));
```

```
for i = 1:length(ImpactInR_uiq)
    if l2(i,1)~=0
        if l2(i,1)<length(unique_num)
            num1=unique_num(l2(i,1),1);
            num2=unique_num((l2(i,1)+1),1);
        end
       ImpactInR(i,1:length(num1:num2-1))=num1:num2-1;

    end
end

ImpactInR=unique(ImpactInR);
ImpactInR(any(ImpactInR==0,2),:)=[];

% LL returns the index number in unique A
% ImpactInR returns the index number in sort_meta_R
%% make R matrix that contains only traci processes
IMPACT_GWP_R=zeros(length(ImpactInR),size(sort_env_factors_norm,2));
for i = 1:length(ImpactInR)
    IMPACT_GWP_R(i,:)=sort_env_factors_norm(ImpactInR(i,1),:);
end

%%

% find (ind_GWP_R) index number of emissions (ref to sort_meta_R) for each
process
for i =1:size(IMPACT_GWP_R,2)
    midinx=find(IMPACT_GWP_R(:,i));
    num_GWP_R(1,i)=length(midinx);
end
ind_GWP_R=zeros(max(num_GWP_R),size(IMPACT_GWP_R,2));
for i =1:size(IMPACT_GWP_R,2)
    if num_GWP_R(1,i)>0
    midinx=find(IMPACT_GWP_R(:,i));
    ind_GWP_R(1:length(midinx),i)= midinx;
    end
end
for i = 1:size(ind_GWP_R,1)
    for j = 1:size(ind_GWP_R,2)
        if ind_GWP_R(i,j)>0
           ind_GWP_R(i,j)=ImpactInR(ind_GWP_R(i,j),1);
        end
    end
end



%%
L=inv(-norm_Atech_raw);
non_zero_num_L=zeros(size(L));
for i =1:length(L)
    test=find(L(:,i)>1e-5);
    for j =1:length(test)
        non_zero_num_L(j,i)=test(j,1);
    end
end
%%
```

```
% find (non_zero_num_R) index number of process (ref to the A matrix) that
% are connected to IMPACT_GWP_R (the R then the CF in the method)

R1=IMPACT_GWP_R';
non_zero_num_R=zeros(size(R1));
for i =1:size(R1,2)
    test=find(R1(:,i)~=0);
    for j =1:length(test)
        non_zero_num_R(j,i)=test(j,1);
    end
end
%%
% (num_GWP_L) numbers of processes (in A) that are connected to CF
num_GWP_L=zeros(size(non_zero_num_R,2),size(non_zero_num_R,1));

test_L_num=zeros(1471,1471);
%%
test2=zeros(1471,1471);
IMPACT_GWP_L=cell(size(equl_Eflow_in_R,1),1);
for n=1:size(equl_Eflow_in_R,1)
for i = 1:1471
    [test1,test2(:,i)]=ismember(non_zero_num_L(:,i),non_zero_num_R(:,n));
    for j= 1:length(non_zero_num_L)
        if non_zero_num_L(j,i)==0
            test2(j,i)=0;
        end
    end

    num_GWP_L(n,i)=nnz(test2(:,i));
end
IMPACT_GWP_L_1=zeros(1471,1471);
for i = 1:1471
    for j=1:1471
            if test2(j,i)>0
                if non_zero_num_R(test2(j,i),n)>0

IMPACT_GWP_L_1(non_zero_num_R(test2(j,i),n),i)=non_zero_num_R(test2(j,i),n);
                end
            end
    end
end
IMPACT_GWP_L{n,1}=IMPACT_GWP_L_1;
end



%%
%IMPACT_GWP_L_value_total: added value in L processes, compare it with
%IMPACT_GWP_R
IMPACT_GWP_L_value=IMPACT_GWP_L;
IMPACT_GWP_L_value_total=zeros(size(equl_Eflow_in_R,1),1471);
for n=1:size(equl_Eflow_in_R,1)
IMPACT_GWP_L_value{n,1}(IMPACT_GWP_L_value{n,1}~=0)=1;

R_value=IMPACT_GWP_R(n,:);
R_value=repmat(R_value,1471,1);
R_value=R_value';
```

```
IMPACT_GWP_L_value{n,1}=R_value.*(IMPACT_GWP_L_value{n,1}.*L);

IMPACT_GWP_L_value_total(n,:)=sum(IMPACT_GWP_L_value{n,1});
end
%%
%separte processes (cutoff, Cradle-to-gate, non-cradle-to-gate
IMPACT_GWP_L_value_total_cutoff=IMPACT_GWP_L_value_total(:,89:613);
IMPACT_GWP_R_cutoff=IMPACT_GWP_R(:,89:613);
IMPACT_GWP_L_value_total_CTG=IMPACT_GWP_L_value_total(:,CTG_Num_alphabeta(:,1)
);
IMPACT_GWP_R_CTG=IMPACT_GWP_R(:,CTG_Num_alphabeta(:,1));
IMPACT_GWP_L_value_total_GTG=IMPACT_GWP_L_value_total(:,GTG_Num_alphabeta(:,1)
);
IMPACT_GWP_R_GTG=IMPACT_GWP_R(:,GTG_Num_alphabeta(:,1));
%%
GWP_All_CF_value_all=duplicate_names_2(:,7:end);
GWP_All_CF_value_all = cell2mat(GWP_All_CF_value_all);
%%
GWP_L_cl=cell(length(IMPACT_GWP_L),1);
for n = 1:1
[GWP_L_cl{n,1}(:,1),GWP_L_cl{n,1}(:,2)]=find(IMPACT_GWP_L{n,1});
end
%%
% impact values (kg CO2 eq) for 21 methods
IMPACT_final_CTG=cell(size(GWP_All_CF_value_all,2),1);
for i = 1:size(GWP_All_CF_value_all,2)

a=repmat(GWP_All_CF_value_all(:,i),1,size(IMPACT_GWP_L_value_total_CTG,2));
    IMPACT_final_CTG{i,1}=a.*IMPACT_GWP_L_value_total_CTG;
end

IMPACT_final_GTG=cell(size(GWP_All_CF_value_all,2),1);
for i = 1:size(GWP_All_CF_value_all,2)

a=repmat(GWP_All_CF_value_all(:,i),1,size(IMPACT_GWP_L_value_total_GTG,2));
    IMPACT_final_GTG{i,1}=a.*IMPACT_GWP_L_value_total_GTG;
end
%%
num_sub_4_process=sum(IMPACT_GWP_R_GTG~=0);
num_sub_4_process=num_sub_4_process';
[B,index_sort_1]=sort(num_sub_4_process,'descend');
for i = 1:size(IMPACT_GWP_R_GTG,2)
    IMPACT_GWP_R_GTG_sorted(:,i)=IMPACT_GWP_R_GTG(:,index_sort_1(i,1));

IMPACT_GWP_L_value_total_GTG_sorted(:,i)=IMPACT_GWP_L_value_total_GTG(:,index_
sort_1(i,1));

end

num_methods_4_sub=sum(IMPACT_GWP_R_GTG~=0,2);
num_methods_4_sub_2=sum(IMPACT_GWP_L_value_total_GTG~=0,2);

[B,index_sort_2]=sort(num_methods_4_sub_2,'descend');
%%
% non_zero_num_R:none zero numbers in GWP R matrix
```

```
% non_zero_num_L:none zero numbers in GWP L matrix that linked to R
% num_GWP_L: each row link to each GWP elementary flow, each column is each
% process
% num_GWP_R:number of process that linked to all GWP elementary flows
% IMPACT_GWP_R: the length is "number in R", which means the how many
% elementary flows in the selected method
% equl_CF_in_R: strict equlities
% equl_Eflow_in_R: soft equlities
num_GWP_R=num_GWP_R';
num_GWP_R_GTG=num_GWP_R(GTG_Num_alphabeta);
%%
[lia_in_USLCI,in_USLCI]=ismember(TARGET1(:,3),duplicate_names_2(:,3));
lia_in_USLCI=lia_in_USLCI+1-1;
in_USLCI=find(in_USLCI);
USLCI=TARGET1(in_USLCI,:);
[lia_du,in_USLCI_du]=ismember(equl_Eflow_in_R(:,1),USLCI(:,3));

%%
GTG_names=meta_info_A_updated(GTG_Num_alphabeta,:);
CTG_names=meta_info_A_updated(CTG_Num_alphabeta,:);



%%
sss=SortR_mean_s(aws1:aws2,:);
num_R_total_1=sum(sss<0);
num_R_total_2=sum(sss>0);
num_R_total=num_R_total_1+num_R_total_2;
num_R_total_GTG=num_R_total(:,GTG_Num_alphabeta);
num_R_total_GTG=num_R_total_GTG';

num_R_total_CTG=num_R_total(:,CTG_Num_alphabeta);
num_R_total_CTG=num_R_total_CTG';
%%
load plotfeat.mat

fig=figure();
for i = 1:length(IMPACT_final_GTG)
    hold on
    z1 =
scatter(1,sum(IMPACT_final_GTG{i,1}(:,280)),'marker',marker{ni(i,1),1});
end
view(90,90);
xlim([0,2]);
% ylim([-3,3]);
title(['GWP value (kgCO2eq) from ',num2str(length(IMPACT_final_GTG)),'
methods']);

%%
fig=figure();
for i = 1:length(IMPACT_final_GTG)
    hold on
    z1 =
scatter(1,sum(IMPACT_final_GTG{i,1}(:,232)),'marker',marker{ni(i,1),1});
end
view(90,90);
xlim([0,2]);
```

```
% ylim([-3,3]);
title(['GWP value (kgCO2eq) from ',num2str(length(IMPACT_final_GTG)),'
methods']);

%%
fig=figure();
for i = 1:length(IMPACT_final_GTG)
    hold on
    k= 1:100;
    z1 =
scatter(k,sum(IMPACT_final_GTG{i,1}(:,k)),'marker',marker{ni(i,1),1});

end
view(90,90);
ylim([0,30]);
% ylim([-3,3]);
title(['GWP value (kgCO2eq) from ',num2str(length(IMPACT_final_GTG)),'
methods']);

fig=figure();
for i = 1:length(IMPACT_final_GTG)
    hold on
    k= 101:200;
    z1 =
scatter(k,sum(IMPACT_final_GTG{i,1}(:,k)),'marker',marker{ni(i,1),1});

end
view(90,90);
ylim([0,10]);
% ylim([-3,3]);
title(['GWP value (kgCO2eq) from ',num2str(length(IMPACT_final_GTG)),'
methods']);
```

References

Ali, J. and J.R. Santos. 2014. Stochastic Input-Output Analysis and Extensions: A Case Study of the United States. In *22nd International Input-Output Conference & 4th Edition of the International School of I-O Analysis, 14-18 July 2014, Lisbon, Portugal*.

Bare, J., G.A. Norris, and D.W. Pennington. 2003. TRACI - The Tool for the Reduction and Assessment of Chemical and Other Envrionmental Impacts. *Journal of Industrial Ecology* 6(3): 49–78.

Bare, J.C., P. Hofstetter, D.W. Pennington, and H. a. U. Haes. 2000. Midpoints versus endpoints: The sacrifices and benefits. *The International Journal of Life Cycle Assessment* 5(6): 319–326.

Baumann, H. and T. Rydberg. 1994. Life cycle assessment. A comparison of three methods for impact analysis and evaluation. *Journal of Cleaner Production* 2(1): 13–20.

Bawden, K.R., E.D. Williams, and C.W. Babbitt. 2015. Mapping Product Knowledge to Life Cycle Inventory Bounds:A Case Study of Steel Manufacturing. *Journal of Cleaner Production* doi: 10.10. http://linkinghub.elsevier.com/retrieve/pii/S0959652615013955.

BEA. 2002. *Bureau of Economic Analysis. Benchmark Input-Output Accounts of the United States, 1997.* http://www.bea.gov/scb/pdf/2002/12December/1202I-OAccounts2.pdf.

Beynon, M.J. and M. Munday. 2006. The elucidation of multipliers and their moments in fuzzy closed Leontief input-output systems. *Fuzzy Sets and Systems* 157(18): 2482–2494.

Bovea, M.D. and A. Gallardo. 2006. The influence of impact assessment methods on materials selection for eco-design. *Materials and Design* 27(3): 209–215.

Brent, A.C. and S. Hietkamp. 2003. Comparative Evaluation of Life Cycle Impact Assessment Methods with a South African Case Study. *International Journal Of Life Cycle Assessment* 8(1): 27–38. http://ovidsp.ovid.com/ovidweb.cgi?T=JS&PAGE=reference&D=emed6&NEWS=N&AN=2003059434.

Brook, R.D., B. Franklin, W. Cascio, Y. Hong, G. Howard, M. Lipsett, R. Luepker, et al. 2004. Air pollution and cardiovascular disease: A statement for healthcare professionals from the expert panel on population and prevention science of the American Heart Association. *Circulation* 109(21): 2655–2671.

Buckley, J.. 1989. Theory and Methodology Fuzzy input-output analysis. *European Journal of Operational Reserach* 39(November 1987): 54–60.

Bullard, C.W., A. V Sebald, S. The, N. Nov, C.W. Bullard, and A. V Sebald. 1988. Monte Carlo Sensitivity Analysis of Input-Output Models. *The Reviiew of Economics and Statistics* 70(4): 708–712.

Cavalett, O., M.F. Chagas, J.E.A. Seabra, and A. Bonomi. 2013. Comparative LCA of ethanol versus gasoline in Brazil using different LCIA methods. *International Journal of Life Cycle Assessment* 18(3): 647–658.

CBECS. 2003. *Commercial buildings energy consumption survey (CBECS)."United States Energy Information Agency (EIA) (2003).* http://www.eia.gov/consumption/commercial/data/2003/.

Census. 2007a. *2002 Economic Census Industry Series Reports-Mining*.

Census. 2007b. *US Census Bureau. 2002 Economic Census Industry Series Reports-Mining*. https://www.census.gov/econ/census02/guide/INDRPT21.HTM.

Chen, X., H.S. Matthews, and M. Griffin. 2016. *ESTIMATION OF DATA USED IN THE 2002 US BENCHMARK VERSION OF THE ECONOMIC INPUT- OUTPUT LIFE CYCLE ASSESSMENT (EIO-LCA) MODEL WITH CONSIDERATION OF UNCERTAINTY*. http://www.eiolca.net/docs/full-document-2002-uncertainty-040716.pdf.

Chester, M. V and A. Horvath. 2009. Environmental assessment of passenger transportation should include infrastructure and supply chains. *Environmental Research Letters* 4(2): 24008.

Chevalier, J.-L. and J.-F. Le Téno. 1996. Life cycle analysis with ill-defined data and its application to building products. *The International Journal of Life Cycle Assessment* 1(2): 90–96.

Consultants, Pr. 2008. SimaPro LCA software." Amersfoort, Netherlands: PRé Product Ecology Consultants.

Cruze, N., P.K. Goel, and B.R. Bakshi. 2012. On the “rigorous proof of fuzzy error propagation with matrix-based LCI.” *The International Journal of Life Cycle Assessment* 18(2): 516–519. http://link.springer.com/10.1007/s11367-012-0475-y. Accessed November 14, 2014.

Deng, L., C.W. Babbitt, and E.D. Williams. 2011. Economic-balance hybrid LCA extended with uncertainty analysis: Case study of a laptop computer. *Journal of Cleaner Production* 19(11): 1198–1206. http://dx.doi.org/10.1016/j.jclepro.2011.03.004.

Dreyer, L.C., A.L. Niemann, and M.Z. Hauschild. 2003. Comparison of Three Different LCIA Methods: EDIP97, CML2001 and Eco-indicator 99. *The International Journal of Life Cycle Assessment* 8(4): 191–200.

EIA. 2004. *Commercial Building Energy Consumption Survey*.

EPA. 2014. *US Environmental Protection Agency, Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990–2012*.

Finnveden, G., M.Z. Hauschild, T. Ekvall, J. Guinée, R. Heijungs, S. Hellweg, A. Koehler, D. Pennington, and S. Suh. 2009. Recent developments in Life Cycle Assessment. *Journal of Environmental Management* 91(1): 1–21. http://www.ncbi.nlm.nih.gov/pubmed/19716647. Accessed July 10, 2014.

Franklin Associates. 2010. Cradle-to-gate life cycle inventory of nine plastic resins and four polyurethane precursors: 572.

Geisler, G., S. Hellweg, and K. Hungerbühler. 2005. Uncertainty Analysis in Life Cycle Assessment (LCA): Case Study on Plant-Protection Products and Implications for Decision Making. *The International Journal of Life Cycle Assessment* 10(3): 184–192.

GmbH, I.U. of S. and P.E. 2006. GaBi 4: the software for environmental process and product. http://www.gabi-software.com/index.html.

Guinee, J.B. 2002. Handbook on life cycle assessment operational guide to the ISO standards. *The International Journal of Life Cycle Assessment* 7(5): 311–313. http://link.springer.com/10.1007/BF02978897. Accessed December 9, 2014.

Heijungs, R. 2010. Sensitivity coefficients for matrix-based LCA. *International Journal of Life Cycle Assessment*.

Heijungs, R., J.B. Guinée, G. Huppes, R.M. Lankreijer, H.A. Udo de Haes, A. Wegener Sleeswijk, A.M.M. Ansems, P.G. Eggels, R. van Duin, and H.P. de Goede. 1992. *Environmental life cycle assessment of products: guide and backgrounds*. CML, Leiden.

Heijungs, R. and S. Suh. 2006. Reformulation of matrix-based LCI: from product balance to process balance. *Journal of Cleaner Production* 14(1): 47–51. http://linkinghub.elsevier.com/retrieve/pii/S095965260500137X. Accessed December 12, 2014.

Hellweg, S. and L.M.I. Canals. 2014. Emerging approaches, challenges and opportunities in life cycle assessment. *Science* 344(6188): 1109–1113.

Hendrickson, C., A. Horvath, S. Joshi, and L. Lave. 1998. Peer Reviewed: Economic Input - Output Models for Environmental Life-Cycle Assessment. *Environmental Science & Technology* 32(7): 184A–191A.

Hertwich, E.G. 2005. Life Cycle Approaches to Sustainable Consumption: A Critical Review. *Environmental Science & Technology* 39(13): 4673–4684. http://dx.doi.org/10.1021/es0497375. Accessed December 11, 2014.

Hocking, M.B. 1991. Paper Versus Polystyrene : A Complex Choice. *Science* 251(4993): 504–505.

Horvath, A. and C. Hendrickson. 1998. Steel versus steel-reinforced concrete bridges: environmental assessment. *Journal of Infrastructure Systems* 4(3): 111–117.

Huijbregts, M.A. 1998. Application of Uncertainty and Variability in LCA Part I: A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment. *The International Journal of Life Cycle Assessment* 3(5): 273–280.

Huijbregts, M.A.J., W. Gilijamse, A.M.J. Ragas, and L. Reijnders. 2003. Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling. *Environmental Science & Technology* 37(11): 2600–2608. http://pubs.acs.org/doi/abs/10.1021/es020971%2B.

ISO. 2006a. *ISO 14040:2006 - Environmental management -- Life cycle assessment -- Principles and framework*. http://www.iso.org/iso/catalogue_detail%3Fcsnumber%3D37456. Accessed December 9, 2014.

ISO. 2006b. *ISO 14040: Environmental management-Life cycle assessment-Principles and framework*. *ISO*. Vol. 2006.

Kagawa, S., S. Okamoto, S. Suh, Y. Kondo, and K. Nansai. 2013. Finding environmentally important industry clusters: Multiway cut approach using nonnegative matrix factorization. *Social Networks* 35(3): 423–438. http://dx.doi.org/10.1016/j.socnet.2013.04.009.

Kuczenski, B. 2015. Partial ordering of life cycle inventory databases. *The International Journal of Life Cycle Assessment* 20(12): 1673–1683. http://link.springer.com/10.1007/s11367-015-0972-x. Accessed December 12, 2016.

Lashof, D. a and D.R. Ahuja. 1990. Relative Contributions of Greenhouse Gas Emissions to Global Warming. *Nature*. http://www.nature.com/doifinder/10.1038/344529a0%5Cnpapers3://publication/doi/10.1038/344529a0.

Lave, L.B., E. Cobas-Flores, and C.T. Hendrickson. 1995. Using Input-Output Analysis to Estimate Economy-wide Discharges. *Environmental Policy Analysis* 29(9): 0–6.

Lenzen, M. 2001. Errors in Conventional and Input-Output-based Life-Cycle Inventories. *Journal of Industrial Ecology* 4(4): 127–148.

Lenzen, M., R. Wood, and T. Wiedmann. 2010. Uncertainty Analysis for Multi-Region Input - Output Models - a Case Study of the Uk'S Carbon Footprint. *Economic Systems Research* 22(1): 43–63. http://www.tandfonline.com/doi/abs/10.1080/09535311003661226. Accessed September 23, 2014.

Leontief, W. 1970. Environmental repercussions and the economic structure: an input-output approach. *The Review of Economics and Statistics*: 262–271.

Lloyd, S.M. and R. Ries. 2007. Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *Journal of Industrial Ecology* 11(1): 161–179.

Lucas, A., C. Alexandra Silva, and R. Costa Neto. 2012. Life cycle analysis of energy supply infrastructure for conventional and electric vehicles. *Energy Policy* 41: 537–547. http://dx.doi.org/10.1016/j.enpol.2011.11.015.

Martinez, E., J. Blanco, E. Jimenez, J.C. Saenz-Diez, and F. Sanz. 2015. Comparative evaluation of life cycle impact assessment software tools through a wind turbine case study. *Renewable Energy* 74: 237–246.

Matthews, H.S., C.T. Hendrickson, and D. Matthews. 2014. *Life Cycle Assessment: Quantitative Approaches for Decisions that Matter*. http://www.lcatextbook.com/. http://www.lcatextbook.com/.

MECS. 2002. *2002 MECS Survey Data*.

National Renewable Energy Laboratory. 2012. U.S. Life Cycle Inventory Database. https://www.lcacommons.gov/nrel/search.

NIST. 2009. BEES 2.0--Building for Environmental and Economic Sustainability. the Building and Fire Research Laboratory, National Institute of Standards and Technology.

NREL. 2012. U.S. Life Cycle Inventory Database. *National Renewable Energy Laboratory, 2012.* https://www.lcacommons.gov/nrel/search. Accessed November 19, 2016.

NREL, ASMI, and Franklin Associates. 2004. U.S. LCI Database Project – User's Guide. *Contract*(February): 1–21. http://www.nrel.gov/lci/pdfs/users_guide.pdf.

NTRC. 2014. *Transportation Energy Data Book. Edition 33*.

Nuss, P., W.-Q. Chen, H. Ohno, and T.E. Graedel. 2016. Structural Investigation of Aluminum in the U.S. Economy using Network Analysis. *Environmental Science & Technology* 50(7): 4091–4101. http://pubs.acs.org/doi/abs/10.1021/acs.est.5b05094. Accessed December 13, 2016.

Ong, S.., T.. Koh, and A.Y.. Nee. 2001. Assessing the environmental impact of materials processing techniques using an analytical hierarchy process method. *Journal of Materials Processing Technology* 113(1–3): 424–431. http://linkinghub.elsevier.com/retrieve/pii/S0924013601006185.

Owens, J.W. 1997. Life-Cycle Assessment: Constraints on Moving from Inventory to Impact Assessment. *Journal of Industrial Ecology* 1(1): 37–49. http://public.eblib.com/choice/publicfullrecord.aspx?p=774299%5Cnhttp://www.blackwell-synergy.com/doi/abs/10.1162/jiec.1997.1.1.37.

Owsianiak, M., A. Laurent, A. Bjørn, and M.Z. Hauschild. 2014. IMPACT 2002+, ReCiPe 2008 and ILCD's recommended practice for characterization modelling in life cycle impact assessment: A case study-based comparison. *International Journal of Life Cycle Assessment* 19(5): 1007–1021.

Pairotti, M.B., A.K. Cerutti, F. Martini, E. Vesce, D. Padovan, and R. Beltramo. 2014. Energy consumption and GHG emission of the Mediterranean diet: a systemic assessment using a hybrid LCA-IO method. *Journal of Cleaner Production*. http://www.sciencedirect.com/science/article/pii/S0959652614000079. Accessed December 11, 2014.

Pennington, D.W., J. Potting, G. Finnveden, E. Lindeijer, O. Jolliet, T. Rydberg, and G. Rebitzer. 2004. Life cycle assessment Part 2: Current impact assessment practice. *Environment International* 30(5): 721–739.

Raa, T. ten and M.F.J. Steel. 1994. Revised stochastic analysis of an input-output model. *Regional Science and Urban Economics* 24(3): 361–371.

Sharrard, A.L. 2007. Green construction processes using an input-output-based hybrid life cycle assessment.

Singh, S. and B.R. Bakshi. 2011. Insights into sustainability from complexity analysis of life cycle networks: A case study on gasoline and bio-fuel networks. In *Proceedings of the 2011 IEEE International Symposium on Sustainable Systems and Technology*, 1–6. IEEE, May. http://ieeexplore.ieee.org/document/5936854/. Accessed December 13, 2016.

Suh, S., M. Lenzen, G.J. Treloar, H. Hondo, A. Horvath, G. Huppes, O. Jolliet, et al. 2004. System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. *Environmental Science and Technology* 38(3): 657–664.

Tan, R.R. 2008. Using fuzzy numbers to propagate uncertainty in matrix-based LCI. *The International Journal of Life Cycle Assessment* 13(7): 585–592. http://link.springer.com/10.1007/s11367-008-0032-x. Accessed October 2, 2014.

TEDB. 2014. *Transportation Energy Data Book. Edition 33.* http://cta.ornl.gov/data/index.shtml.

Turconi, R., A. Boldrin, and T. Astrup. 2013. Life cycle assessment (LCA) of electricity generation technologies: Overview, comparability and limitations. *Renewable and Sustainable Energy Reviews* 28: 555–565. http://dx.doi.org/10.1016/j.rser.2013.08.013.

Udo de Haes, A.H., O. Jolliet, G. Finnveden, M. Hauschild, W. Krewit, and R. Muller-Wenk. 1999. Best available practice regarding impact categories and category indicators in life cycle impact assessment. *The International Journal of Life Cycle Assessment* 4(3): 167–174. http://link.springer.com/10.1007/BF02979453.

Ukidwe, N.U. and B.R. Bakshi. 2008. Resource intensities of chemical industry sectors in the United States via input-output network models. *Computers and Chemical Engineering* 32(9): 2050–2064.

UN. 2008. *The International Standard Industrial Classification of All Economic Activities (ISIC), Rev.4*.

UNEP. 2011. Global Guidance Principles for Life Cycle Assessment Databases: 156.

US EIA. 2003. Rough crosswalk of CBECS PBAs to 2002 NAICS codes (3 digit). *Commercial Building Energy Consumption Survey*. http://www.eia.gov/consumption/commercial/faq.cfm.

USDA. 2002a. *Census Volume 1, Chapter 1: U.S. National Level Data, Table 59*.

USDA. 2002b. *Census Volume 1, Chapter 1: U.S. National Level Data, Table 59,*. http://www.agcensus.usda.gov/Publications/2002/Volume_1,_Chapter_1_US/.

USDOT. 2002. *PRICE TRENDS for FEDERAL – AID HIGHWAY CONSTRUCTION 1987 BASE, 2002*.

USGS. 2002. *Mineral Commodity Summaries 2002*.

Vries, M. de and I.J.M. de Boer. 2010. Comparing environmental impacts for livestock products: A review of life cycle assessments. *Livestock Science* 128(1–3): 1–11. http://dx.doi.org/10.1016/j.livsci.2009.11.007.

Wang, R. and D. Work. 2014. Application of robust optimization in matrix-based LCI for decision making under uncertainty. *The International Journal of Life Cycle Assessment* 19(5): 1110–1118. http://link.springer.com/10.1007/s11367-013-0685-y. Accessed December 9, 2014.

Weidema, B.P. and M.S. Wesnæs. 1996. Data quality management for life cycle inventories—an example of using data quality indicators. *Journal of Cleaner Production* 4(3–4): 167–174.

Williams, E.D., C.L. Weber, and T.R. Hawkins. 2009. Hybrid framework for managing uncertainty in life cycle inventories. *Journal of Industrial Ecology* 13(6): 928–944. http://www.scopus.com/inward/record.url?eid=2-s2.0-75649136159&partnerID=40&md5=8ffe29cf0d688ea26e74f29550d0a3c6. Accessed August 6, 2014.

Xue, X. and A. Landis. 2010. Eutrophication Potential of Food Consumption Patterns. *Environmental Science & Technology* 44(16): 6450–6456.

Yamakawa, A. and G.P. Peters. 2009. Using Time-Series To Measure Uncertainty in Environmental Input - Output Analysis. *Economic Systems Research* 21(4): 337–362. http://www.tandfonline.com/doi/abs/10.1080/09535310903444766. Accessed September 23, 2014.

Zhang, Y., E.L. Gibbemeyer, and B.R. Bakshi. 2014. Empirical Comparison of Input-Output Methods for Life Cycle Assessment. *Journal of Industrial Ecology* 0(0): n/a-n/a. http://doi.wiley.com/10.1111/jiec.12133. Accessed September 23, 2014.