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Uncertainty caused by life cycle impact assessment methods: Case studies in process-based LCI databases

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ABSTRACT

Life cycle impact assessment (LCIA) transforms inventories of environmental flows to environmental impacts in life cycle assessment (LCA) studies. Many impact assessment methods have been developed for impact categories such as global warming, acidification, and ecotoxicity. These impact assessment methods provide different characterization factor values and impact units for the same impact category. LCA studies often report results for one or at most a few impact assessment methods and overlook the uncertainty caused by selecting and using different methods. In this study, we systematically evaluated uncertainties that result from considering different LCIA methods; cases from the US LCI and the ecoinvent database were used to demonstrate the uncertainties. Results showed that the discrepancies of the total impact results were caused by differences in 1) the total emission values included in the inventory; 2) the coverages of substances in methods, and 3) the differences in the characterization factor values of the substances. Case studies showed large uncertainties for all impact categories except for global warming. For most of the categories studied, the maximum values were 10,000 times larger than the minimum values. These results should be taken into consideration for impact assessments that involve categories with large uncertainties. The information provided by this paper can help researchers and software developers to understand the uncertainty caused by choosing different LCIA methods and the importance of communicating such information to LCA practitioners. The results can also help decision-makers to build guidance that is related to build and choose LCIA methods for various topics.

1. Introduction to LCIA and the comparison between LCIA methods

As regulated by the ISO 14040 standard, Life Cycle Impact Assessment (LCIA) seeks to evaluate the environmental impacts of a product system (ISO, 2006a). Since early 1990s, impact assessment methods have been developed for different purposes in LCA studies (Baumann and Rydberg, 1994). 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 the impact assessment framework, and principles of LCIA modeling have become widely accepted and implemented in LCIA. Currently, many LCIA methods exist and some are regularly updated. LCA practitioners often choose one impact method for all impact categories in their LCA studies. In some cases, a certain method or a combination of methods are recommended or required by an organization. For example, the European Commission's Research Joint Centre required the use of a set of impact categories under different impact methods for research of environmental performance (Pant et al., 2019). The United Nations Environmental Program also made an effort to reach a consensus on LCIA methods used to quantify impacts on climate change and other aspects (Jolliet et al., 2018). 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 difference between the methods is an interesting topic in the field of LCIA research (Dreyer et al., 2003; Owsianiak et al., 2014).

The comparison between different LCIA methods can be traced to the 1990s. The purpose of the comparison of these early studies was mainly to examine the differences between multiple impact assessment methods in relation to their models and methodologies (Baumann and Rydberg, 1994; Brent and Hietkamp, 2003; Pennington et al., 2004). These studies 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. Similar studies include (Guinée, 2015; Vilà

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et al., 2019)(Alyaseri and Zhou, 2019), these studies focused mostly on qualitative differences and did not elaborate on a quantitative comparison between LCIA methods.

More recently, LCA studies started to focus on the quantitative differences between various LCIA methods. According to the ISO standards, LCIA is the third stage of LCA (ISO, 2006a). In an LCIA method, the environmental issues are classified as impact categories, such as global warming, and elementary flows in an inventory that are considered to contribute to an impact category are defined as substances (e.g. CO_2 to air)(ISO, 2006b). The environmental impacts of a substance are quantified via each substance's corresponding characterization factors. Some researchers have been comparing different LCIA methods based on the numeric differences caused by different characterization indicators. For example, an early study by Dreyer et al. (2003) compared the LCIA results for particular materials using three methods: CML, Ecoindicator95, and EDIP. The authors examined the differences in impact results for a lacquer product system due to characterization factor values by calculating the contribution of impacts from each substance. The results showed that for some categories such as climate change and ozone depletion, the differences were very small; however, for aquatic ecotoxicity category, the result from CML2001 was 820 times larger than the result from EDIP97. In an LCIA study for polymer materials, (Bovea and Gallardo, 2006) showed that for the same polymer material, the differences between the minimum and maximum values in the impact results varied between 0 to more than 800 times; the highest values occurred in the photochemical oxidation category. More recently, 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 (Bovea and Gallardo, 2006; Landis and Theis, 2008; de Vries and de Boer, 2010; Cavalett et al., 2013; Martínez et al., 2015; Bueno et al., 2016; Cherubini et al., 2018). Apart from comparing case-study based LCIA results, there are a few studies that aim to systematically quantify differences in LCIA methods. A study conducted by Dong, Ng, and Kumaraswamy (2016) used a mathematical method to compare LCIA impact categories based on the differences in their characterization factor values. Wang et al., (2020) compared six commonly used LCIA methods quantifying human health impacts in biofuel production.

All of these studies demonstrate that for a product, different impact methods can lead to different LCIA results. However, the purposes of these studies were often to assist the users to select the most appropriate LCIA method for their LCA study. Few researchers paid attention to the LCIA methods and the impacts of using different LCIA methods in one LCA study. LCA is designed to support decision-making and strategic thinking. The potential of different results means there is potential for different decisions. However, some issues have not been addressed yet. First, previous comparisons often focused on providing guidelines of choosing a most appropriate impact assessment method for particular products. Systematic quantitative comparisons across impact methods have 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 often aimed to find uncertainty for a product, not focused on the underlying uncertainties in the methods. Here, we aim to study the variability in the impacts of many different products using an LCI dataset with inventories for many processes.

In this study, we perform a comprehensive comparison of uncertainties arising from the selection and use of different LCIA methods. Processes from the US LCI and the ecoinvent database are used to demonstrate the results. Our work considers three key sources of variability in LCIA results: 1) differences in the life cycle inventory, 2) differences in the number of substances included in the methods (i.e., coverage), and 3) differences in the characterization factor values for all commonly used impact assessment methods. Note that according to Huijbregts (Huijbregts, 1998), the variability between objects and sources is considered as one type of uncertainty in LCA. In this study, we followed this definition and classify the variability caused by the discrepancies in the impact methods as uncertainty.

2. Methods

In this section, we provide the methodologies that were used in understanding uncertainty caused by using different impact assessment methods. First, in Section 2.1 and Section 2,2 we provide a brief summary of the impact assessment methods, impact categories, and inventory data used in this study. Then in Section 2.3, we explain the method used to calculate impact results. For some impact categories, different impact units were used by different impact methods, unit conversion was necessary to make a fair comparison. Therefore, in Section 3.4, we explain the method for the unit conversion. To understand how inventory can affect the impact results, we matched elementary flows with impact substances. The method of matching is discussed in Section 3.5

2.1. Impact assessment methods

In this study, we used a practitioner's perspective. We chose to use methods provided by the SimaPro software (version 8.5) because the software included most of the commonly used LCIA methods and LCA practitioners often choose to use such LCA software to perform their studies. SimaPro 8.5 supports 37 active and 38 inactive impact assessment methods. The type and number of categories included in each method varies (Table 1). Single issue methods were developed for a specific purpose, such as IPCC and Cumulative Energy Demand (CED), which have only one impact category. Other methods such as ReCiPe and TRACI, cover around 10 categories. Some methods provide multiple sub-categories with a different focus on compartments and year-spans. For example, there are four different sub-categories under the global warming category in the Greenhouse Gas Protocol method: Fossil CO_2 Equivalent, Carbon Uptake, CO_2 from land transformation, and CO_2 uptake. Some categories are used in most of the methods, such as global warming and acidification; while others are given in only a few methods.

We focused on the latest version of each distinct method (version numbers shown in Table 1). Eight impact categories, namely global warming, acidification, eutrophication, ozone depletion, human health air (HH air), human health carcinogenics (HH cancer), human health noncarcinogenics (HH noncancer), and ecotoxicity were chosen. These categories were chosen based on two reasons. First, these categories were available in most of the impact assessment methods. This was not the case for all impact categories, for instance, "smog" was available only in a few methods. Second, the number of characterized substances was different across different categories. The acidification category had the least number of substances (31) while ecotoxicity had the largest number of substances (26,700). This coverage of substances enabled comparison with a sufficient amount of data.

2.2. Life cycle inventory used for case study

First, we chose a representative process to visualize the uncertainty caused by the choice of an LCIA method. We chose to analyze the 100-year global warming category for the 1 kg *Aluminum, primary, ingot, at plant* process in the US LCI database. The 100-year global warming category was chosen due to its usage and significance. The aluminum ingot process was chosen because it had a more compete inventory than most of other similar processes in the USLCI database.

To show the uncertainties in LCI results due to the LCIA methods, we used 99 electricity processes (all electricity processes provided) in the USLCI database as case studies. In the analysis, for each impact category,

Table 1
Types of 37 active impact assessment methods and their numbers of sub-categories (full table is shown in Table S1 in the SI).

Name	Type	Version	Number of Sub-categories in Each Impact Category					
			Global Warming	Energy Resource	Natural Resource	Human Toxicity	Eco-toxicity	Ozone Depletion
Boulay et al 2011 (Human Health)	Endpoint	1,2				2		
Pfister et al 2009 (Eco-indicator 99)	Endpoint	1,2			sa1		1	
Pfister et al 2010 (ReCiPe)		1,2			1		1	
Cumulative Energy Demand	Midpoint	1,10		6				
Cumulative Exergy Demand	Midpoint	1,5		10				
Greenhouse Gas Protocol	Midpoint	1,2	4					
IPCC 2013 GWP 100a	Midpoint	1,3	1					
IPCC 2013 GWP 20a	Midpoint	1,3	1					
USEtox 2 (recommended + interim)	Midpoint	1,0				2		
USEtox 2 (recommended only)	Midpoint	1,0				2	1	
BEES+	Midpoint	4,7	1	1		3	1	1
TRACI 2.1	Midpoint	1,4	1	1		3	1	1
CML 1992	Midpoint	3,5	1		2	1	3	1
CML 2 baseline 2000	Midpoint/ Endpoint	3,4	5		1	4	19	8
Ecological Scarcity 2013		1,5	1	1	1	1		1
EDIP 2003		1,6	1		1	3	3	1
EPD (2013)		1,4	1		2			1
EPS 2015d		1,0			1	12	9	
EPS 2015dx		1,0			1	12	9	
ILCD 2011 Midpoint+	Midpoint	1,10	1	1		2	1	1
IMPACT 2002+	Midpoint/ Endpoint	2,14	1	2		4	2	1
ReCiPe 2016 Endpoint (E)	Endpoint	1,1		2		5	7	1
ReCiPe 2016 Endpoint (H)	Endpoint	1,1		2		5	7	1
ReCiPe 2016 Endpoint (I)	Endpoint	1,1		2		5	7	1
ReCiPe 2016 Midpoint (E)	Midpoint	1,1	1	2		3	4	1
ReCiPe 2016 Midpoint (H)	Midpoint		1	2		3	4	1
ReCiPe 2016 Midpoint (I)	Midpoint	1,1	1	2		3	4	1

we calculated the impact results for each of the 99 processes from all methods that were available for that category. The impact range for each process was then used to demonstrate the uncertainty caused by using different impact methods. Practitioners might choose one electricity as their electricity input and ignore the possible range caused by choosing an alternative electricity process. For example, a user might choose *Electricity, at grid, US, 2010* instead of *Electricity, at grid, US* process and ignore the uncertainty caused by the deterministic input. To understand the uncertainty caused by different LCIA methods, we aimed to consider the uncertainty in the inventory caused by scenario choices. Using these electricity processes could provide us both types of uncertainty and demonstrate the importance of uncertainty caused by choosing different LCIA methods. Another reason why electricity processes were chosen was that electricity processes had relatively similar attributes, such as upstream flows and downstream uses. Sometimes users need to choose between very similar processes as an input for an inventory and a choice based on assumptions would introduce uncertainty in the inventory data. These electricity processes were good examples of such similar processes.

2.3. Calculate life cycle impact assessment (LCIA) results

In LCIA, environmental effects are converted to environmental impacts through characterization factor values provided by an impact method (Matthews et al., 2014). This concept can be expressed as a function shown in Eq. (1). In Eq. (1), vector $\boldsymbol{g}$ represents environmental effects calculated from an LCA inventory; $\boldsymbol{q}_i^k$ is the characterization row vector for the impact method $\boldsymbol{k}$ and category $\boldsymbol{i}$; each entry in the $\boldsymbol{q}_i^k$ vector is the characterization factor corresponding to the respective elementary flows in vector $\boldsymbol{g}$. 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 $\boldsymbol{g}$ in an LCA study includes the results from two global warming substances: carbon dioxide and methane. 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.

$$\boldsymbol{h}_i^k = \boldsymbol{q}_i^k \circ \boldsymbol{g} \tag{1}$$

In this study, we calculated multiple $\boldsymbol{h}$ values for the same inventory $\boldsymbol{g}$ and impact category $\boldsymbol{i}$ and used these $\boldsymbol{h}$ values to represent uncertainty caused by using different impact assessment methods. We used a practitioner's perspective in this analysis. Impact assessment methods were obtained from the SimaPro software (version 8.5) (PRé, 2013). We focused on distinct methods from the latest versions and chose eight impact categories for the analysis. Details are presented in the Results section.

2.4. Unit conversion

For each impact category, many impact methods use the same units. For example, mid-point global warming methods all use CO_2-equivalents (CO_2eq). However, some categories present a diversity of impact units. For the purpose of comparison in these cases, similar to the methods introduced by Horvath et al (1995) and Landis (2008), we used one unified default impact unit for each category. For two methods using two different impact units, the values with the non-default unit were converted to values with the default unit. The conversion factor was calculated using the ratio of two characterization factor values of a selected mutual substance. Default units and mutual substances were decided and selected on a case-by-case basis; different mutual substances will be chosen for different impact categories. The mutual substance was selected based on 1) the most commonly used unit and 2) characterization factor availability for the selected mutual substance.

For example, TRACI and ILCD use different units (g SO_2eq and H+mmole eq, respectively) to evaluate acidification impacts. Because eight out of 11 methods used gSO_2/g as the unit and both TRACI and ILCD methods cover SO_2 as a substance, SO_2 is selected as the default mutual substance. Because SO_2 was the base substance for TRACI, which used gSO_2/g as its unit, its characterization factor value was 1g SO_2eq/g in TRACI. In ILCD, the characterization factor value for SO_2 was 1.31 H+mmole eq/g. Based on these two values with different units for the same substance, the conversion factor between methods can be assumed as 1.31 H+mmole eq/g SO_2. When characterization factor values are in H+mmole eq/g, they can be converted to g SO_2eq/g by dividing by 1.31. In some other cases, the selection depended on the availability of characterization factors for the mutual substance. For example, for the human health carcinogenics (HH cancer) category, kg 1,4-DCB eq/kg was chosen as the unified unit because all nine methods provided characterization factor values for *1,4-dichloro-benzene*, which then was

Table 2
Excerpt of characterization factor values for substances from 10 mid-point global warming impact methods (100-year time horizon).

Compartment	Methods / Unit / Name	BEES+ (g/gCO2)	ILCD 2011 Midpoint+ (kg/kgCO2)	IMPACT 2002+ (kg/kgCO2)	IPCC100a (2013) (kg/kgCO2)	ReCiPe 2016 Midpoint (E) (kg/kgCO2)	TRACI 2.1 (kg/kgCO2)	Range (kg/kgCO2)
Air	Carbon dioxide	1	1	1	1	1	1	1
Air	Carbon dioxide, biogenic	NA	1	NA	NA	NA	NA	1
Air	Carbon dioxide, fossil	1	1	1	1	1	1	1
Air	Carbon dioxide, land transformation	1	1	1	1	1	1	1
Air	Carbon monoxide	NA	NA	1.57	NA	NA	NA	1.57
Air	Carbon monoxide, fossil	NA	NA	1.57	NA	NA	NA	1.57
Air	Chloroform	30	31	9	16	2.74	31	2.74 - 31
Air	Dimethyl ether	NA	1	1	NA	NA	1	1
Air	Dinitrogen monoxide	296	298	156	265	78.8	298	78.8 - 298
Air	Ethane, 1,1-difluoro-, HFC-152a	NA	124	37	138	23	124	23 - 138
Air	Ethane, 1,1,1-trichloro-, HCFC-140	140	146	42	160	26.8	146	26.8 - 160
Air	Ethane, 1,1,1,2-tetrafluoro-, HFC-134a	NA	1430	400	1300	218	1430	218 - 1430
Air	Ethane, 1,1,2-trichloro-1,2,2-trifluoro-, CFC-113	NA	6130	2700	5820	1410	6130	1410 - 6130
Air	Ethane, 1,1,2-trifluoro-, HFC-143	NA	353	100	328	54.9	353	54.9 - 353
Air	Ethane, 1,2-dichloro-	NA	NA	NA	0.898	0.15	NA	0.15 - 0.898
Air	Ethane, 1,2-dichloro-1,1,2-trifluoro-, HCFC-123a	NA	NA	NA	370	61.9	NA	61.9 - 370
Air	Ethane, 1,2-dichloro-1,1,2,2-tetra-fluoro-, CFC-114	NA	10000	8700	8590	3490	10000	3490 - 10000
Air	Ethane, 2-chloro-1,1,1,2-tetrafluoro-, HCFC-124	NA	609	190	527	88.2	609	88.2 - 609
Air	Ethane, 2,2-dichloro-1,1,1-trifluoro-, HCFC-123	NA	77	36	79	13.3	77	13.3 - 79
Air	Ethane, hexafluoro-, HFC-116	NA	12200	18000	11100	17800	12200	11100 - 18000
Air	Ethane, pentafluoro-, HFC-125	NA	3500	1100	3170	546	3500	546 - 3500
Air	Hydrocarbons, chlorinated	NA	NA	NA	NA	1.97	NA	1.97
Air	Methane	23	25	7.6	30.5	4.76	25	4.76 - 30.5
Air	Methane, biogenic	20	25	4.85	27.75	4.8	22.25	4.8 - 28
Air	Methane, bromo-, Halon 1001	5	5	1	2	0.394	5	0.394 - 5
Air	Methane, bromochlorodifluoro-, Halon 1211	NA	1890	390	1750	293	1890	293 - 1890
Air	Methane, bromotrifluoro-, Halon 1301	6900	7140	2700	6290	1340	7140	1340 - 7140
Air	Methane, chlorodifluoro-, HCFC-22	1700	1810	540	1760	296	1810	296 - 1810
Air	Methane, chlorotrifluoro-, CFC-13	NA	14400	16300	13900	12700	14400	12700 - 16300
Air	Methane, dichloro-, HCC-30	10	8.7	3	9	1.49	8.7	1.49 - 10
Air	Methane, dichlorodifluoro-, CFC-12	10600	10900	5200	10200	2710	10900	2710 - 10900
Air	Methane, dichlorofluoro-, HCFC-21	NA	151	65	148	24.6	151	24.6 - 151
Air	Methane, difluoro-, HFC-32	NA	675	170	677	113	675	113 - 677
Air	Methane, fossil	23	25	10.35	30.5	4.9	25	4.9 - 30.5
Air	Methane, monochloro-, R-40	16	13	5	12	2.04	13	2.04 - 16
Air	Methane, tetrachloro-, CFC-10	1800	1400	580	1730	296	1400	296 - 1800
Air	Methane, tetrafluoro-, CFC-14	5700	7390	8900	6630	11000	7390	5700 - 11000
Air	Methane, trichlorofluoro-, CFC-11	NA	4750	1600	4660	875	4750	875 - 4750
Air	Methane, trifluoro-, HFC-23	NA	14800	10000	12400	5660	14800	5660 - 14800
Air	Nitrogen fluoride	NA	17200	NA	16100	12800	17200	12800 - 17200
Air	Propane, 1,1,1,3,3-pentafluoro-, HFC-245fa	NA	1030	300	858	144	1030	144 - 1030
Air	Sulfur hexafluoride	NA	22800	32400	23500	34400	22800	22800 - 34400
Raw	Carbon dioxide, in air	NA	-1	NA	NA	NA	NA	-1
Water	Methane, dichloro-, HCC-30	NA	8.7	NA	NA	NA	NA	8.7
Water	Methane, tetrachloro-, CFC-10	NA	1400	NA	NA	NA	NA	1400

used as the base value of all characterization factor values. Other HH cancer impact units such as cases/kg could not be used as the common unit because “case” was not a substance, therefore there was no base value for that unit, making the conversion from other units to case/kg impossible. The mutual substance used for the unit conversion for all categories are shown in Table S2 in the SI.

2.5. Matching inventory with LCIA substances

The third source of variability was from differences in inventories. An impact substance could only be captured in LCIA results when it was included in the life cycle inventory. We matched elementary flows in the USLCI and ecoinvent database (ecoinvent 3.4) with substances that were covered in various LCIA methods and categories to understand the connection between LCIA methods and inventories provided by different LCI databases. The substances/elementary flows were categorized into Raw, Water, Air, Soil, and Social compartment. Within each compartment, there were several sub-compartments, such as unspecified, low population, and in ground. The matching was based on the same substance name, CAS number, compartments and sub-compartments.

3. Results and Discussion

3.1. Uncertainties due to different LCIA methods

This study only focuses on comparing the methods that include any of these eight categories. In this paper, we show results from the global warming category as examples, the results from other impact categories can be seen in the data file in SI.

Table 1 shows an excerpt of the characterization factors available for the global warming category from ten mid-point LCIA methods that are on a 100-year time horizon. The complete data set is provided in the datafile in SI. Global warming is an impact category where most practitioners would presume that there is little uncertainty in estimated impacts given the maturity of the underlying science. The estimation method for the global warming category was assumed to be developed from one research agency, the Intergovernmental Panel on Climate Change (IPCC), and accepted by most methods. Thus, the methods can be expected to be identical or at least very similar, and the choice of method would seem irrelevant. However, while the characterization factor values and the time horizon are the same in all methods, there are notable discrepancies in the coverage of substances and characterization factors values for other substances. First, the coverage of substances shows the methods’ comprehensiveness. For an impact category, ideally a method should cover as many substances as possible to convert all necessary environmental effects to environmental impacts (not doing so implies zero impact for uncovered substances). In the example shown in Table 2, the BEES+ method only covers 17 substances whereas other methods cover at least 36; no method includes all substances. The IMPACT 2002+ method includes *carbon monoxide* that is not included in any other methods; yet it does not include *nitrogen fluoride*, a substance that is included in all other methods. In addition to substance coverages, the characterization factor values also vary significantly across different methods. There are only a few substances that have one unified value while the discrepancies are often large. For example, the maximum characterization factor value for *methane, difluoro-, HFC-32* is 677 kg CO_2eq/kg in four different methods (CML 2, EDP, GHG Protocol, and IPCC100), 6 times larger than the minimum value of 113 kg CO_2eq/kg in the ReCiPe method.

Results from other impact categories show much larger variances across methods. For each category, we compared the differences between the minimum and maximum characterization factor value for each substance. Results showed that the largest difference was from the HH cancer category, the maximum value was 1.3×10^{24} times larger than the minimum value (5.86×10^{-21} and 7600 kg/kg 1,4-DCB as the minimum and maximum value, respectively). The HH noncancer and ecotoxicity categories also showed large discrepancies, with maximum values 1.05×10^{24}, and 7.76×10^{13} times larger than the minimum values, respectively. The details of the characterization factor values for the 8 categories are shown in data file in SI.

Figure 1 shows the results of applying different LCIA methods focusing on the 100-year global warming category for the 1 kg *Aluminum, primary, ingot, at plant* process in the US LCI database (data used for the visualization is shown in Table S3 in the SI). Results show that the total global warming impact ranged from 41.4 to 71.8 kg CO_2eq. The result also highlights the two most important reasons for the nearly two times difference in estimated impact: the number of substances covered and the values of characterization factors. First, only the IMPACT 2002+ method classifies *carbon monoxide* as having a global warming impact. All other methods assume that *carbon monoxide* is carbon neutral. Second, the ReCiPe (H), CML2, GHG Protocol, and IPCC methods have higher characterization factors for methane than the other methods. IMPACT 2002+ method has a much higher characterization factor for *HFC-116*. The impact value from *HFC-116* was the largest in IMPACT 2002+, however, because of the small value for methane, the total impact became the second smallest.

The discrepancies of the total impact results are caused by differences in 1) the total emission values included in the inventory; 2) the coverages of substances in methods, and 3) the differences in the characterization factor values of the substances. The first difference lays in the inventory. If an inventory is not complete, it could miss important impact substances and therefore affect the total impact results. We will discuss this matter later in this paper. The other two differences are caused by impact assessment methods. Some methods do not cover as many substances as other methods due to their focuses. For example, BEES+ covers only four substances in this example, while most of the other methods cover 10 substances. The excluded substances cannot be simply treated as zero because zero values indicate active measurement but untested results; substances with no measurement should be listed differently in the inventory or impact results. Differences in the characterization factor values are the main sources of uncertainty in this particular case. We can see that most of the methods disagreed on the characterization factor values for *HFC-116*, and that was the main source of uncertainty. However, sometimes the inclusion of certain unusual substances in a particular method can result in outliers in the impact results. For example, for 1 kg of the *Crude palm kernel oil, at plant* process, the global warming impact ranged from 0.5 to 4.2 kg CO_2eq. The maximum value (kg CO_2eq) was the result from the GHG Protocol method, which was the only method that included “Carbon dioxide, biogenic” as a substance. The impact value only from this substance *was 3.3 kg CO_2eq, causing an outlier in the total global warming impact values. If this substance was not included, the global w*arming impacts calculated from the GHG Protocol method would be 0.914 kg CO_2eq, in the lower end of the impact range.

In LCA studies, results in Fig. 1 can help to improve the understanding of the impact results by showing the main sources of discrepancies and help practitioners with more informed decision-making. It can also help LCA software developers to provide more guidance to the users on how to select one or more LCIA methods. We recognize that some methods such as BEES+, are relatively old and unpopular; however, since they continue to be included in software, they can be chosen by practitioners, which could lead to spurious impact results.

Fig. 2 (at the end of this manuscript) compares the results for all eight impact categories of the 99 electricity processes. In Fig. 2, the x-axis represents the 99 electricity sectors, and the y-axis shows the total impact values for each category (these eight Fig.s use different scales and units, some Fig.s use a base 10 log scale). We used a round mark with a unique color to represent a value calculated by one impact method, and a triangle mark replaced the round mark when the characterization factor values for that method were converted to match the default unit (data for the Fig.s are provided in the data file in the SI). In some cases, one method provides more than one set of characterization

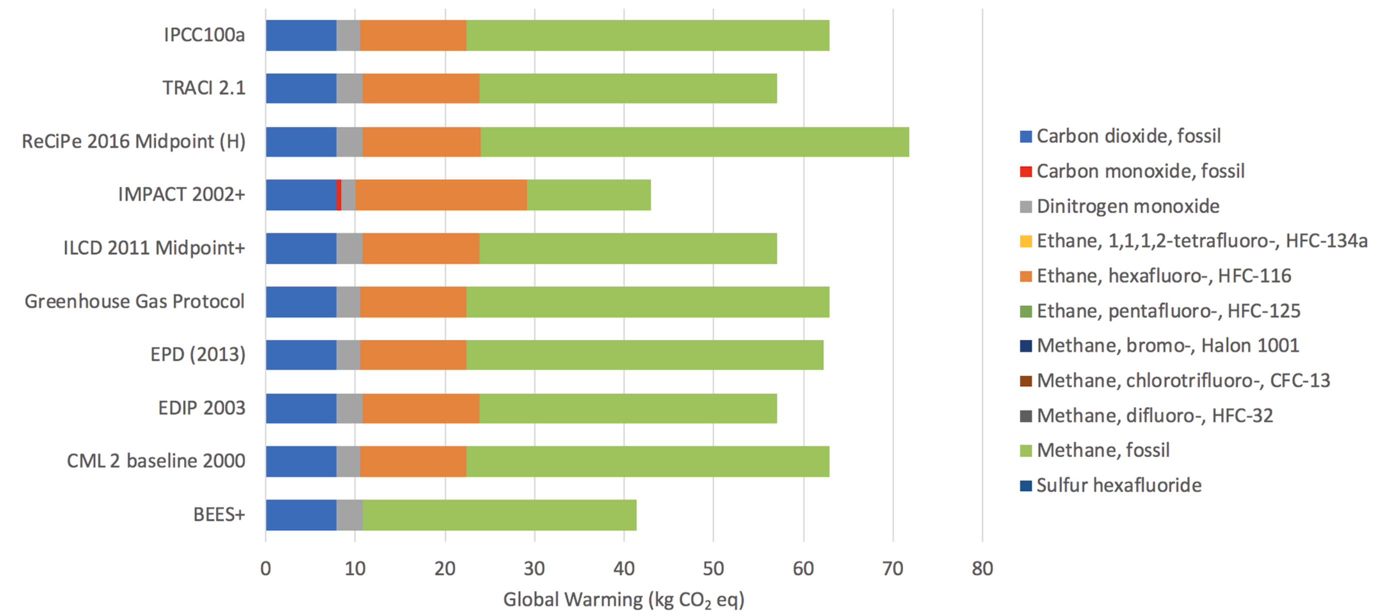


Fig. 1. substance-based Mid-point global warming (100-year) impact values for the "Aluminum, primary, ingot, at plant" process from 9 impact methods. Only 100-year global warming methods are shown.

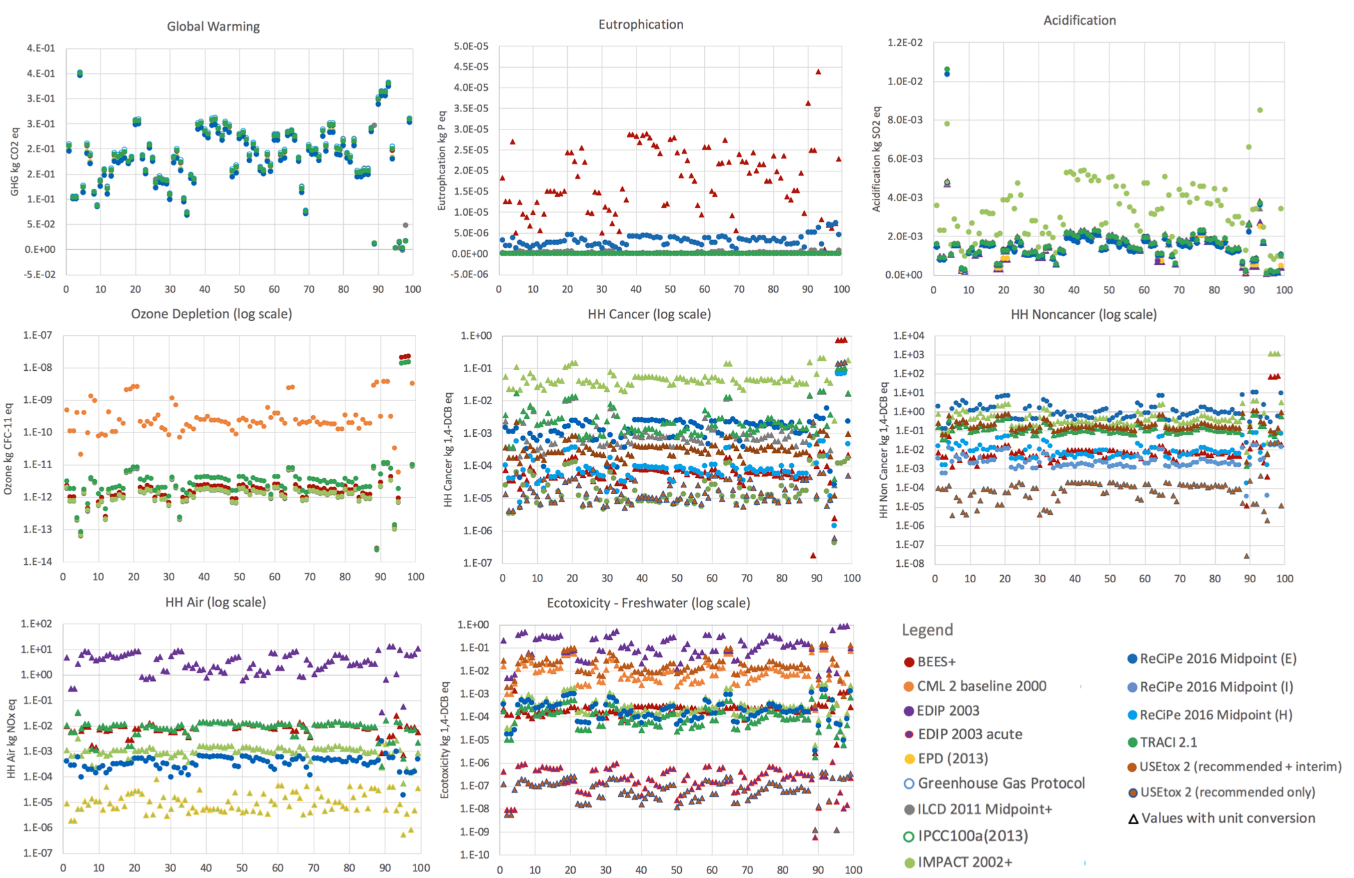


Fig. 2. Impact values for eight impact categories for 99 electricity processes in the US LCI database. The x-axis represents the 99 electricity sectors, and the y-axis shows the total impact values for each category. A round mark with a unique color represents a value calculated by one impact method, and a triangle mark replaced the round mark when the characterization factor values for that method were converted to match the default unit. Note that the eight Fig.s use different scales and units, the Fig.s use a base 10 log scale are marked in their captions.

factor values for the same impact category. For example, the US ecotoxicity 2 method provides two sets of characterization factor values (recommended + interim, and recommended only) for ecotoxicity - freshwater category. We used marks with the same color but a different border to separate the two sets in the Fig.. The first 5 and last 12 sectors in the Fig.s are different types of electricity generation, such as coal-fired power plant generation, nuclear generation, and biomass generation; the 82 sectors in the middle are US regional electricity mixes or e-grid mixes. The inventoried differences between these generation scenarios are more significant, inducing larger uncertainty. As shown in the Fig.s, the trend of the first 5 and last 12 processes' results are not as consistent as the other 82 processes, there are more variances in the data than the uncertainty caused by impact assessment method used. For example, for the global warming and acidification categories, fossil fuel electricity processes always have the largest impact despite the impact method used. For the ozone depletion category, electricity generated from on-site boiler processes always return much larger impact values.

Overall, the uncertainties of most grid mix processes within ozone depletion category can vary from -97% to 600% compared with the average value, while the uncertainties of some specific electricity generation method (No.96 – No.98, electricity generated from on-site boiler) within the same category vary only from -7% to 40%. The differences are due to the differences in the variety of outputs in the processes' inventories. As mentioned before, information in the life cycle inventory is one of the contributors to the uncertainty in the impact results. Due to different reasons, not all emissions from on-site generated electricity processes were captured, therefore affected the total impact results. When an inventory fails to include certain important impact substances, the impact results calculated would underestimate total impacts, causing uncertainty in the final results. For the same reason, similar uncertainty ranges can be observed for the grid mix electricity processes. Most of the regions in the US use similar electricity generation mixes, resulting in similar life cycle inventory results for these electricity mix processes. For instance, for the global warming, acidification, and eutrophication categories, we observed lower impacts from grid electricity mixes that had lower ratios of fossil fuel electricity, such as electricity from the NPCC region (New York state, the six New England states in the US; Ontario, Québec, New Brunswick and Nova Scotia in Canada (*NPCC*, 2020)).

Though inventory data can be a cause of uncertainty, results provided in Fig. 2 also show that the uncertainty caused by different methods varied across different impact categories. As expected, the variances for global warming are relatively small. For most of these 99 electricity processes, the maximum values are less than 10% larger than the minimum values. The rankings of impacts among all electricity processes are generally determined by electricity generation types as mentioned before. However, there are some exceptions. For example, biomass electricity often has the lowest global warming impact calculated from most of the methods; however, for the ILCD method, this value is much larger, almost the same as the impact from coal electricity.

Some other categories return larger uncertainty values. For example, for acidification and ozone depletion categories, the maximum values are generally around 1 to 1.5 times larger than the minimum values. For acidification, the IMPACT 2002+ method returns the largest values for all electricity types with the average value of 3.4 g SO_2 eq, compared with other methods with average values between 1.4 and 1.5 g SO_2 eq. For ozone depletion, the CML 2 baseline method has larger values for biomass, diesel, residual fuel oil electricity, and a few electricity mixes, while other methods return very similar results among all electricity processes.

The other five categories have a much larger variance. For most of the categories, the maximum values are 10,000 times larger than the minimum values. For the HH air and ecotoxicity category, the maximum value can be eight orders of magnitude larger than the minimum value. As shown in the Fig., unit conversion is not the most important contributor to the overall uncertainty. There was no unit conversion for the global warming and ozone depletion categories, yet the variances for ozone depletion are still around five orders of magnitude. For the HH noncancer and acidification category, the maximum values were original values without unit conversion; the HH cancer category's minimum values were also the result from original values. The impact from inventory is also insignificant in these categories, no electricity process dominates the impacts despite the method used. This shows the complexity of choosing an impact method and the importance of communicating all information with the users.

The unit conversion presented here were not used in LCIA because practitioners often choose only one impact assessment method, thus the comparisons between methods were not necessary. However, our results show that the uncertainty between impact assessment methods are significantly larger than the data uncertainty in the inventory. When researchers and practitioners focus on understanding and reducing data uncertainty in the inventory, they should also pay attention to the uncertainty caused by using different methods. This again could be improved through visualizations available in software.

There is no one single method that covered all maximum values or minimum values across all categories. For example, the BEES+ method provides the maximum values for the eutrophication category, but for most of the other categories, results from this method usually fall around average values. Similarly, results from IMPACT 2002+ are the largest values for the acidification and HH cancer category, but its results are the smallest values for ozone depletion. However, within categories, the maximum and minimum impact values are generally from the same impact methods, for example, BEES+ generally provides the largest eutrophication impact; US Ecotoxicity 2 (recommended only) often provides the smallest HH noncancer impact. This means that the coverages and characterization factor values provided by each method are critical to the overall uncertainty. Overall, results show that when LCA practitioners select an impact method, the results for different impact categories are unpredictable: one method can return larger results for one category but smaller results for another category. Without thorough knowledge of the differences between these impact assessment methods, practitioners might fail to understand the uncertainty due to the impact assessment method they choose.

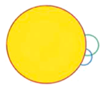
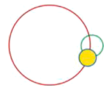
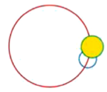
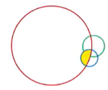
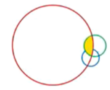
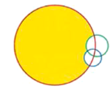
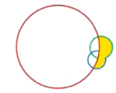
3.2. *Coverages of substances in the USLCI and ecoinvent databases*

Differences in the coverages from substances and differences in the characterization factors are two main sources for the variability in the LCIA results. The third source of variability is from differences in inventories. In this section, we provide a summary of the connection between LCIA methods and inventories provided by different LCI databases.

Table 3 provides a brief summary of coverages and matching results (full summary is provided in Table S4 in the SI). The first row of Table 3 has Venn diagrams (true to size) that represent the overlapping areas of the total substances between the databases and the LCIA methods. In each Venn diagram, the red circle on the left represents all substances provided by eight categories, the green circle at the top-right represents substances in the USLCI database, and the blue circle at the bottom-right represents substances in the ecoinvent database. The second row shows the logical relationship between the sets. For example, "USLCI AND LCIA" means substances covered by both USLCI and any of the LCIA methods. Each column shows the data for the substances in the overlapping area (shaded in yellow) of the corresponding Venn diagram; data for different compartments and sub-compartments are listed individually. The first three columns show the data for each of the three sets, and the remaining columns show the overlapping areas that were used to determine the coverages and matching results from the three sets.

Two important messages are found in this analysis. First, most of the substances covered by LCIA methods are not included in any of the inventories. There are around 35,000 substances found in all eight impact categories, only 4% are included by either the ecoinvent or the USLCI

Table 3
Summary of coverage of substances in the USLCI and ecoinvent databases. Red, green and blue circles in the Venn diagrams represent the set of substances in all eight categories, the USLCI database, and the ecoinvent database, respectively. Each column in the table show the data in the shaded area in each corresponding Venn diagram

	Venn Diagram							
	Sub-Com	All LCIA methods	USLCI	Ecoinvent	USLCI AND LCIA	Ecoinvent AND LCIA	LCIA NOT (USLCI OR Ecoinvent)	(USLCI OR Ecoinvent) NOT LCIA
Raw	unspedified	1	285	0	1		0	284
	in ground	0	54	152			0	179
	biotic		4	6				
	in air		2	8				
	land		18	109				
	in water		2	203				
Water	unspedified	3287	443	212	267	80	3004	277
	river	0	0	327			0	327
	groundwater	968	0	127		38	930	89
	ocean	3239	62	102	40	38	3188	67
	gw, long-term	970	0	46		21	949	25
Air	unspedified	3851	528	181	365	139	3482	176
	high. pop.	3140		225		118	3022	107
	low. pop.	3150	9	260	3	131	3018	131
	low. pop., long-term	3112		45		22	3090	23
	stratosphere + troposphere	3151		22		12	3139	10
	indoor	3109	12		3		3106	9
Soil	unspedified	3256	135	41	103	24	3149	35
	agricultural	3213	1	309	1	239	2974	70
	industrial	1	31	29			1	39
	forestry	0		2			0	2
Social	unspecified	0		5			0	5
Total		**34448**	**1586**	**2406**	**783**	**862**	**33052**	**1850**

database. Second, many elementary flows are also not all covered by LCIA methods. It can be seen that among 3,394 ecoinvent or USLCI elementary flows, more than 50% are not covered by any of the LCIA methods included in this study. Considering all impact categories, 51% of the US LCI elementary flows are not substances in any of these eight categories, resulting in zero impacts. Because the flows are not substances for any impact categories, they would not be included in the LCIA results. Similarly, for the ecoinvent database (ecoinvent 3.4), 64% of elementary flows in the database are not substances of any impact category. These results show that though there are comprehensive studies in life cycle impacts on different compartments caused by individual substances, most of these substances are not reflected in life cycle inventories. On the other hand, some elementary flows in inventories are not covered by any impact method, which means these elementary flows would not be converted in life cycle impact results. In both cases, the life cycle impact information is not efficiently used. Overall, this suggests there continues to be a large gap between coverage of substances in inventories and the number of substances available in impact assessment models.

It is reasonable that there are more substances included in impact assessment methods than the numbers of substances emitted from production, because data came from many individual processes, each of which could in fact not have emissions of such substances. Yet, there might be different reasons for the exclusion of substances in LCI databases. Possible cutoff criteria can cause neglects of emissions; the emissions smaller than the cutoff value were not reported in the inventory. This lack of information caused potential neglects of impact values in the LCA results.

4. Conclusion and future work

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 eight impact categories, around 50% of the US LCI elementary flows were not substances in the impact methods and this number was even larger in the ecoinvent database. These results could help LCA practitioners better understand current situations in LCIA analyses.

The uncertainty caused by using different LCIA methods could be significantly large. Taking the most unified categories, global warming as an example, the uncertainty was generally within 10% with some outliers. For some other impact categories, the maximum value was as big as eight orders of magnitude larger than the minimum value. The sources of discrepancies were from either the LCIA method or the inventory results. In LCIA methods, different coverages of substance and characterization factors values provided by different methods were the main contributors to the uncertainty. In inventory results, the exclusion of important elementary flows could lead to smaller impacts.

In LCIA studies, 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 their particular analysis, they could accidentally choose an inappropriate method. The inappropriate choice of a method may influence decisions. For example, a method with inappropriate global warming 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 and the decisions made according to the results can be problematic. To overcome these issues, we recommend LCA researchers and software developers to provide a rich description of the LCIA methods and show results comparing different impact methods. This can help users with selecting the appropriate LCIA methods that account for the LCI data and align with the goal and scope of their studies. It might also benefit organizations such as the United Nations Environmental Program in developing guidelines of LCA studies or other environmental footprint assessments.

Because the comprehensiveness of inventory data can affect the impact results, LCI data providers should consider impact results when generating or collecting LCI data. Currently, mass-based cutoff criteria were used to determine the minimum reported value in an inventory. As such, inventory reporters could potentially ignore substances with small mass emission values but which comprised large unit impact values (characterization factor values). Therefore, we believe that cutoff criteria based on impact assessment results rather than should be introduced to better capture inventory data that are eventually converted to impacts. This will also help reduce the model uncertainty introduced by using different impact methods. In our future work, we aim to promote a set of impact-based cutoff criteria for building LCI inventories.

Overall, raising awareness of uncertainties due to LCIA is important but often ignored. This paper provides an overview of the origins of the uncertainties and possible solutions to reduce these uncertainties. LCA practitioners and researchers should always be aware of possible uncertainties and make decisions accordingly.

CRediT authorship contribution statement

Xiaoju Chen: Data curation, Conceptualization, Methodology, Software, Validation, Writing - original draft, Visualization, Writing - review & editing. **H. Scott Matthews:** Supervision, Conceptualization, Methodology, Writing - original draft. **W. Michael Griffin:** Supervision, Writing - review & editing.

Declaration of Competing Interest

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

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2021.105678.

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