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Abstract

The process-based life cycle assessments (LCA) of goods and services are calculated using a bottom-up approach related to a functional unit. However, this does not provide any information regarding the scale of the environmental impacts. Therefore, the normalization allows to relate the impacts to a reference system (specific countries, regions or even the whole world). These references are usually obtained from top-down approach. The different data sources introduce inconsistencies on results and raise doubts on their adequacy and representativity. This paper proposes a novel approach for determining the data for the reference in order to ensure consistency about boundaries, data sources and modelling hypotheses describing the system. For this purpose, normalization is applied as an expression of the result relative to the average component of the reference system, instead of the sum of all the components. The reference values are determined from the geometric means of the datasets of the inventory database, used for assessing the studied systems. The exemplary application to the ecoinvent databases provides normalization references for 878 versions of the impacts categories listed by ecoinvent and for the 2077 involved substances. For eight impact assessment methods, the results are compared with 16 normalization sets from the literature and point out highly significant correlations.

Keywords

Life Cycle Assessment; normalization; bottom-up reference; geometric mean;

1. Introduction

The purpose of Life Cycle Assessment (LCA) is to assess and quantify the environmental interventions of human activities. All introduction chapters in books and lectures concerning LCA present the well-known ISO standard (ISO, 2006a) diagram. This schematic highlights the importance of interpretation: within the sequence of goal and scope, inventory, impact assessment and interpretation, the latter visually takes up the half of the diagram. The reason for this is that LCA results are often difficult to decipher and interpret.

LCA is a relative and multicriteria approach (Finkbeiner et al., 2006). When the environmental impacts of a given system are calculated, the output often comprises a set of results expressed with different units (such as global warming in $kg_{CO2\text{-}Eq}$, freshwater ecotoxicity in Comparative Toxic Unit, CTUe.m^3.yr, or resource depletion in $kg_{Sb\text{-}Eq}$). To put the results into context and for understanding the magnitude of the impacts compared with one another, the results are related to a common reference system. This removes the different units and brings the quantitative results in similar orders of magnitude. A normalization procedure, an optional step in the LCA, addresses this issue.

Normalization is the calculation of the magnitude of the category indicator results, relative to some reference information (ISO, 2006b). Typically, external normalization references are chosen, i.e. the data for the reference system are independent from the environmental profile of the study and as a consequence also do not vary according to the system under study (Laurent and Hauschild, 2015). External normalization data require ideally a complete inventory of emissions and resource consumptions for the reference area during the reference time period (e.g. regional or world emissions over one year). It allows for the plausibility check of the order of magnitude of results and facilitates communication of results by expressing them with a commensurable unit, such as person equivalents for example (Pizzol et al., 2017). Normalization is also recommended as a preliminary step for a potential weighting of environmental impacts and assembling all impacts into a single reference system.

The quantification of the reference system and associated data raises the issue of system boundaries in terms of space (region, country or worldwide) and duration. According to these limits, consumption- or production-based inventories can be used (Laurent and Hauschild, 2015). In all situations, the reference is intended to be exhaustive, but this is obviously never fully achieved and introduces bias. The use of different background data sources for the study results and the normalization data introduce inconsistencies. Especially for regional normalization, there is a tendency to over-interpret the results. As an example, normalization to European reference values is often interpreted as the share of the product under study to emissions in Europe, whereas depending on the product systems a significant share of emissions occurs outside Europe and as such are not part of the reference value.

The Life Cycle Initiative, hosted by UN environment, recently published a state of the art of current works and issues with normalization in LCA (Pizzol et al., 2017). In this document, the potential biases of an external normalization approach have been highlighted as well as in other references (Benini and Sala, 2016; Cucurachi et al., 2017; Heijungs et al., 2007). They result from the discrepancies between the life cycle inventory (LCI) of a system studied and the LCI of normalization references, in terms of involved processes (the perimeter), modelling choices and inventoried substances. It recommends the definition of methods providing consistent and sufficiently complete inventories of emissions and resource consumptions at a global scale.

In line with previous works (Esnouf et al., 2019, 2018) where the principle was used in another context, the purpose of this paper is to define a generic approach for establishing an appropriate normalization reference, using the same representation (i.e. modelling) of the world, both for the system under study and the reference system. The method can be applied based on the inventory databases used by LCA practitioners, i.e. it does not rely on any other data sources than the ones which are used in the study itself. The approach is exemplarily applied to ecoinvent (Wernet et al., 2016) to test its applicability and to compare it with existing external normalization references.

2. Material and methods

For matters of convenience, all the notations in the article are detailed in Table 1. The matrices are in bold and their elements in italic. See Heijungs and Suh (2002) for details about matrix products to compute the Life Cycle Impact Assessment (LCIA) result. Note that pre-calculated inventories $\widetilde{\mathbf{B}}$ (Broadbent et al., 2011; Lesage et al., 2018) are used (known as "system" datasets in ecoinvent).

[Insert Table 1 here]

2.1. Normalization principle.

A normalized result h_k^{N} is defined as follows:

$$h_k^{\mathrm{N}} = \frac{h_k}{h_k^{\mathrm{REF}}} \quad (1)$$

According to LCA principles, the normalization references h_k^{REF} result from the multiplications of emissions (or resource consumptions) of the reference system by the associated characterization factors. The elementary flows of the reference system are commonly determined from statistics provided by international agencies and institutions, with a structured collection and aggregation work (Crenna et al., 2019; Sala et al., 2015). This is defined here in a different way but similar to other LCA results, i.e. with the intervention matrix and the final demand:

$$h_k^{\mathrm{REF}} = \sum_{j=1}^{n} q_j \sum_{i=1}^{m} \tilde{b}_{j,i} f_i^{\mathrm{REF}} \tag{2}$$

The definition of an external normalization reference implies the estimation of the overall emissions. Considering $\tilde{\mathbf{B}}$ as representative of all the processes involved in the reference system (i.e. the inventory database is sufficiently complete to represent what is happening at a global scale), the computing of $\mathbf{h}^{\mathrm{REF}}$ only requires the determination of $\mathbf{f}^{\mathrm{REF}}$ (the f_i^{REF} values). The difficulty in defining normalization references resides in the quantification of the final demand of the reference system.

As the system under study is the part of the reference system, consistent normalization implies the use of the same intervention datasets for both. Therefore, only the final demands $\mathbf{f}$ and $\mathbf{f}^{\mathrm{REF}}$ differ between h_k and h_k^{REF}. By defining the reference system in this manner, the same perimeter, data sources and list of inventoried elementary flows are used.

2.2. External normalization as an average intervention.

The overall emissions are proportional, with the factor *m,* to $M_1(\tilde{b}_{j,i} f_i^{\mathrm{REF}}, \forall i) = \frac{1}{m}\sum_{i=1}^{m} \tilde{b}_{j,i} f_i^{\mathrm{REF}}$, defined as the arithmetic mean of all $\tilde{b}_{j,i} f_i^{\mathrm{REF}}$

$$h_k^{\mathrm{REF}} = m \sum_{j=1}^{n} q_j M_1(\tilde{b}_{j,i} f_i^{\mathrm{REF}}, \forall i) \tag{3}$$

m does not depend on j and is therefore identical for all impact categories. The use of $\frac{h_k^{\mathrm{REF}}}{m}$ instead of h_k^{REF} as normalization factor does not modify the ratios between normalized impact categories. The conclusions on the results should be identical. A parallel can be made with a normalization concerning either an average citizen or a whole population: between both references, the normalized impacts differ by a factor equal to the population size, but the interpretation of the outcome remains identical for both normalizations.

Normalization references correspond to the sum of all associated interventions; however, their average could be easily taken into account instead. The normalization procedure could thus be defined by the expression of the result as a function of the impact of the arithmetic mean of interventions in the reference system.

2.3. From the arithmetic mean to the geometric mean.

The arithmetic mean is the most commonly used mean. It is the expected value of data distributed according to the well-known normal law. For the normalization process, the distribution of $\tilde{b}_{j,i} f_i^{\mathrm{REF}}$ cannot be described because, unlike the $\tilde{b}_{j,i}$ values, the values of f_i^{REF} are unknown. Let us focus on $\tilde{b}_{j,i}$ values. The shapes of flow distributions in inventory databases rather seem to resemble log-distribution laws, with values spreading over several orders of magnitude. This has been demonstrated by Qin and Suh (2017) who observed that the main part of the technology and intervention flows in ecoinvent follows lognormal laws. Log-distributions are not well described by the arithmetic mean but rather by the geometric mean (i.e. the exponential of the arithmetic mean of logarithm-transformed values)

$$M_0\left(\widetilde{\mathbf{B}}_j\mathbf{f}^{\mathrm{REF}}\right) = \exp\left(\frac{1}{m}\sum_{i=1}^{m}\log\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}\right)\right) = \sqrt[m]{\prod_{i=1}^{m}\tilde{b}_{j,i}f_i^{\mathrm{REF}}} \tag{4}$$

It is therefore relevant to use it in eq (3) with the hypothesis of a constant proportion between the means

$$c\, M_0\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}, \forall i\right) \approx M_1\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}, \forall i\right) \tag{5}$$

then

$$h_k^{\mathrm{REF}} \approx m\, c \sum_{j=1}^{n} q_j M_0\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}, \forall i\right) \tag{6}$$

$M_0\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}, \forall i\right)$ can be split into $M_0\left(\tilde{b}_{j,i}, \forall i\right) = M_0\left(\widetilde{\mathbf{B}}_j\right)$ and $M_0\left(f_i^{\mathrm{REF}}, \forall i\right) = M_0\left(\mathbf{f}^{\mathrm{REF}}\right)$

$$M_0\left(\tilde{b}_{j,i}f_i^{\mathrm{REF}}, \forall i\right) = M_0\left(\widetilde{\mathbf{B}}_j\right) \times M_0\left(\mathbf{f}^{\mathrm{REF}}\right) = \sqrt[m]{\prod_{i=1}^{m}\tilde{b}_{j,i}} \times \sqrt[m]{\prod_{i=1}^{m}f_i^{\mathrm{REF}}} \tag{7}$$

Then, with eq (6)

$$h_k^{\mathrm{REF}} \approx m\, c\, M_0\left(\mathbf{f}^{\mathrm{REF}}\right)\sum_{j=1}^{n} q_j M_0\left(\widetilde{\mathbf{B}}_j\right) \tag{8}$$

2.3.1. Inventory-based normalization references

As previously stated for the term m in eq (3), the constant term $m\, c\, M_0\left(\mathbf{f}^{\mathrm{REF}}\right)$ can be neglected without consequences on the interpretation of results. The normalized reference is defined as

$$h_k^{\mathrm{REF},\widetilde{\mathbf{B}}} = \sum_{j=1}^{n} q_j M_0\left(\widetilde{\mathbf{B}}_j\right) \tag{9}$$

$$h_k^{\mathrm{REF},\widetilde{\mathbf{B}}} \approx \frac{1}{m\ c\ M_0(\mathbf{f}^{\mathrm{REF}})} h_k^{\mathrm{REF}} \tag{10}$$

which should produce the same results, in terms of interpretation, as h_k^{REF}, without the need to know $\mathbf{f}^{\mathrm{REF}}$.

The obtained normalization reference is based on characterization factors and on the inventory database only, without necessary external data collection. The approach implies two assumptions: (1) The reference system is defined by the inventories listed in the used LCI database. These inventories ensure consistency with the system under study. (2) The geometric mean is used instead of the arithmetic mean. This is a coherent choice for representing a variability spread over several orders of magnitude.

Similar reasoning can be carried out with the intervention matrix $\mathbf{B}$ instead of $\widetilde{\mathbf{B}}$ and so with $M_0(\mathbf{B}_j) \times M_0(\mathbf{A}^{-1}\mathbf{f}^{\mathrm{REF}})$ instead of $M_0(\widetilde{\mathbf{B}}_j) \times M_0(\mathbf{f}^{\mathrm{REF}})$. However, the geometric mean estimations with $\mathbf{B}$ are more difficult (see below).

2.3.2. Zero and negative values for interventions

While the arithmetic mean can be calculated with all true values, the geometric mean strictly requires positive values. This constraint has to be considered for eqs (4) to (10), for $M_0(\mathbf{f}^{\mathrm{REF}})$ to allow the simplification (note that the value of $M_0(\mathbf{f}^{\mathrm{REF}})$ does not need to be calculated, but only its existence should be taken into account), and for eq (4) to (9) to compute $M_0(\widetilde{\mathbf{B}}_j)$.

For $M_0(\mathbf{f}^{\mathrm{REF}})$, this seems quite simple to achieve. If $f_i^{\mathrm{REF}} < 0$, the avoided quantity is higher than its production in the final demand. This case should not be encountered when the whole system is taken into account for the reference. It is possible to have $f_i^{\mathrm{REF}} = 0$; however, for a given process, it indicates that its use is exactly equal to the sum of its calls by the other processes, without any additional final demands for the normalization reference. To ensure that $f_i^{\mathrm{REF}} > 0, \forall i$, the non-existence of zero values can be considered by assuming that there will always be a very small amount (e.g. 1 µg of a product or 1 µWh of electricity) missing in calls and thus at least required for the final demand of the reference.

For $M_0(\widetilde{\mathbf{B}}_j)$, the issue is more challenging. Most processes directly induce a few numbers of elementary flows, usually less than one hundred, while the total number of elementary flows amounts to a thousand. Therefore, matrix $\mathbf{B}$ is particularly sparse, but this appears less problematic for $\widetilde{\mathbf{B}}$: a high number of elementary flows are involved because a pre-calculated intervention encompasses the whole system associated to the corresponding process (the complete process tree). Not many zeros are observed in $\widetilde{\mathbf{B}}$, although some do obviously occur.

The computation of geometric means using zero values is an issue often encountered in data processing, as for example, in biology with microbial counting or in chemistry, with concentrations below detection limits. The most common approach is to add 1 to the values, compute the product and remove 1 afterwards. In this work, a recent algorithm, based on this principle, was used (de la Cruz and Kreft, 2018). It determines the smallest value to be added and then removed in order to compute a consistent estimation of geometric means involving zero values.

The intervention matrix $\widetilde{\mathbf{B}}$ contains negative values. This can be due to the intrinsic properties of the represented process, such as plant growth removing CO_2 from atmosphere through photosynthesis. Negative emissions are found in system models involving substitution (i.e. avoided processes, then avoided elementary flows) or partition/allocation (e.g. negative flows ensuring the carbon balance consistency between products and coproducts, see for example Weidema (2018) for details).

When the whole dataset is negative, the computation of a geometric mean is generally carried out with absolute values after multiplication by minus one. Unfortunately, this is not feasible when both negative and positive values are in the dataset. To overcome this issue, two new matrixes $\widetilde{\mathbf{B}}^{+}$ and $\widetilde{\mathbf{B}}^{-}$ are defined, where the elements $\tilde{b}_{j,i}^{+}$ and $\tilde{b}_{j,i}^{-}$ are described as follows

$$\tilde{b}_{j,i}^{+} = \begin{cases} \tilde{b}_{j,i}, & \tilde{b}_{j,i} > 0 \\ 0, & \tilde{b}_{j,i} \leq 0 \end{cases}, \qquad \tilde{b}_{j,i}^{-} = \begin{cases} 0, & \tilde{b}_{j,i} \geq 0 \\ -\tilde{b}_{j,i}, & \tilde{b}_{j,i} < 0 \end{cases} \tag{11}$$

The LCIA result does not change with the following equation

$$\mathbf{h} = \mathbf{Q}\widetilde{\mathbf{B}}\mathbf{f} = [\mathbf{Q} \quad -\mathbf{Q}] \begin{bmatrix} \widetilde{\mathbf{B}}^{+} \\ \widetilde{\mathbf{B}}^{-} \end{bmatrix} \mathbf{f} \tag{12}$$

$\widetilde{\mathbf{B}}^{+}$ and $\widetilde{\mathbf{B}}^{-}$ only contain positive or null values, as the negative sign is represented by $-\mathbf{Q}$. It is therefore possible to compute the corresponding estimation of geometric means $M_0(\widetilde{\mathbf{B}}_{j}^{+})$ and $M_0(\widetilde{\mathbf{B}}_{j}^{-}), \forall j$. The normalization reference $h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}$ is thus

$$h_k^{\mathrm{REF},\widetilde{\mathbf{B}}} \approx \sum_{j=1}^{n} q_j M_0(\widetilde{\mathbf{B}}_{j}^{+}) - \sum_{j=1}^{n} q_j M_0(\widetilde{\mathbf{B}}_{j}^{-}) = \sum_{j=1}^{n} q_j \left(M_0(\widetilde{\mathbf{B}}_{j}^{+}) - M_0(\widetilde{\mathbf{B}}_{j}^{-}) \right) \tag{13}$$

2.4. Intervention databases and associated impacts.

Inventories $\mathbf{B}$ and pre-calculated inventories $\widetilde{\mathbf{B}}$ are used. They are provided by ecoinvent (Wernet et al., 2016) 3.5 version released in august 2018. Ecoinvent edits three system models: At Point Of Substitution (APOS), Cut-off and Consequential; all three were run in the present work to assess the effect of modelling choices at the inventory level.

Ecoinvent also provides characterization factors ($\mathbf{Q}$) for several LCIA methods. Among these, the LCIA methods are selected when normalization references are easily available: CML 2000 (Guinée et al., 2002) (named CML 2001 by ecoinvent), EDIP 2003 (Hauschild and Potting, 2005), ILCD 2016 (EC-JRC, 2011), EF 2.0 (Fazio et al., 2018) (European Environmental Footprint, named ILCD2018 by ecoinvent), ReCiPe midpoint 2008 (Goedkoop et al., 2013) (Egalitarian (E), Hierarchist (H) and Individualist (I) versions, named ReCiPe V1.13 by ecoinvent, unfortunately 2016 version is not available on the ecoinvent website and the use of the Simapro® software values would require a parser to match the substance names) and TRACI (Bare, 2002) (first version). For CML 2000, EDIP 2003 and ILCD 2016, and ReCiPe 2008, normalization reference factors are extracted from Simapro software (Pré Consultant, 8.5.2 version). EF 2.0 factors are downloaded from JRC website (EC-JRC, 2018) and TRACI factors from the dedicated article (Bare et al., 2006).

Ecoinvent provides characterization factors with and without long term emission (Hellweg and Frischknecht, 2004) for CML 2000, EDIP 2003, ILCD 2016 and EF 2.0 and ReCiPe (E and H versions). Both sets were used here for comparison.

Several normalization sets can be provided for some methods, according to the perimeters of the inventories. Thus, normalization reference factors could be compared, based on ecoinvent ($h_k^{\mathrm{REF},\tilde{\mathbf{B}}}$), with those found in the literature (h_k^{REF}) for six methods (eight methods considering ReCiPe I, H, and E versions as different methods) with a total of 12 normalization sets. Four are available for CML 2000 (The Netherlands 1997, Europe 1995, World 1995, World 1990) one for EDIP 2003, three for ILCD 2016 (EU-27 2010, EC-JRC Global, PROSUITE Global), one for EF 2.0 (only global factors are provided on JRC website), two for ReCiPe (Eur 2000, World 2000) and one for TRACI. Normalization set names are those used in Simapro.

3. Results and discussions

3.1. Overview of intervention matrices

An overview of intervention matrices is provided in supplementary information (see Table SI.1). The zeros values are spread over a large number of elementary flows for both $\mathbf{B}$ and $\widetilde{\mathbf{B}}$. Matrix $\mathbf{B}$ is sparse, with 98 or 99% zero values, according to the system model. This amount substantially decreases with the pre-calculated intervention matrix $\widetilde{\mathbf{B}}$. The smallest percentage of zero values is observed for the APOS system model (3.6%). These observations justify the choice for dealing with $\widetilde{\mathbf{B}}$ instead of $\mathbf{B}$ for the approach, as the estimations of geometric means are more accurate, with fewer zero values.

Negative values remain an exception for $\mathbf{B}$ and $\widetilde{\mathbf{B}}$, except for the pre-calculated matrix of the Consequential model where 15% of the interventions are negative. Note that negative values mainly concern certain elementary flows for APOS and Cut-off models (between 7 and 12 for 95% of negative values to be attained) but the Consequential model has many, whether for $\mathbf{B}$ or for $\widetilde{\mathbf{B}}$ (1403 and 1547 to have 95% negative values respectively). Hence, for the both first system models, $\widetilde{\mathbf{B}}$ is almost completely positive with $M_0\left(\widetilde{\mathbf{B}}_{\boldsymbol{j}}\right) \approx M_0\left(\widetilde{\mathbf{B}}_{\boldsymbol{j}}^{+}\right)$ and $M_0\left(\widetilde{\mathbf{B}}_{\boldsymbol{j}}^{-}\right) \approx 0$. Nevertheless, this is less applicable to the Consequential system model where $M_0\left(\widetilde{\mathbf{B}}_{\boldsymbol{j}}^{-}\right)$ cannot be neglected.

3.2. Geometric means of interventions.

The estimation of geometric means of the pre-calculated intervention of ecoinvent databases are all available online for download from https://doi.org/10.5281/zenodo.2598037*[NOTE TO THE REVIEWERS: this link will be activated for the accepted version of the article, the file is available for the review process here https://www.dropbox.com/s/9wfgmmqo60i9elj/mu0%28Btild%29.xlsx?dl=0 (anonymous download).].* Scatterplots are provided in supplementary material of the article (see Figure SI.1). The estimations of geometric means from the three system models reveal significant correlations. The highest is found between APOS and Cut-off models with log-log Pearson coefficients of positive values equal to 0.91 (p-value $\ll$ 0.001). The Consequential model is also correlated but to a lesser extent: 0.79 (p-value $\ll$ 0.001) with the APOS model and 0.89 (p-value $\ll$ 0.001) with the Cut-off model. These correlations make sense with respect to modelling principles, as APOS and Cut-off models are both based on allocation procedures whereas the Consequential model involves substitutions.

3.3. Ecoinvent-based normalization reference

Using the characterization factors provided by ecoinvent, 878 impacts have been assessed. The corresponding normalization references $h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}$ are downloadable at https://doi.org/10.5281/zenodo.2598035 *[NOTE TO THE REVIEWERS: this link will be activated for the accepted version of the article, the file is available for the review process here https://www.dropbox.com/s/wx7dt43ds7abi90/allHref.xlsx?dl=0 (anonymous download).]* From this table, entries associated to the selected methods with normalization references provided from the literature (i.e. h_k^{REF}) have been extracted to determine normalization references based on ecoinvent (i.e. $h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}$) according to system models, involving long-term emissions or not.

3.4. Relevance of the estimates

In a first approach, the log-log Pearson coefficients are provided in the supplementary materials (see Figure SI.2). Generally, high correlations between normalization sets from ecoinvent and from literature were observed. The correlation coefficients vary between 0.77 (TRACI method versus APOS or Cut-off models) and 0.98 (various methods). All are significant with p-values < 0.001, except for ReCiPe E and I vs the Consequential system model that have p-values < 0.01 and TRACI (all system models) where p-values < 0.05.

The log-log Pearson coefficient indicates a linear correlation between $h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}$ and h_k^{REF}, but eq (10) presents a more restricted relationship: $\log\left(h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}\right) \approx \log\left(h_k^{\mathrm{REF}}\right) - \log\left(c\,M_0(\mathbf{f}^{\mathrm{REF}})\right) - \log(m)$. The parameter m is known and constant for a given system model, whatever the impact. $c\,M_0(\mathbf{f}^{\mathrm{REF}})$ is also constant but unknown. To address the latter, $c\,M_0(\mathbf{f}^{\mathrm{REF}})$ average values are calculated in the log-space for each comparison. Values are provided in supplementary materials (Table SI.2). The average values are similar for APOS (4.9×10^{-9} with, and 2.7×10^{-9} without long-term emissions) and Cut-off (5×10^{-9} and 2.7×10^{-9}) models, but the Consequential model presents values ten-fold smaller (0.5×10^{-9} and 0.3×10^{-9}). Values with long-term emissions are about twice higher than those without long-term emissions except for EF 2.0 where values are comparable.

The coefficient of variation of the estimated $c\,M_0(\mathbf{f}^{\mathrm{REF}})$ (see Figure 1) describes the accuracy of eq (10). The lower the coefficient of variation, the better eq (10) is validated. The match between normalization sets from the literature and those built from datasets excluding long-term emissions seems improved: the coefficient of variation decreases when long-term emissions are not taken into account (average value 3%). Only an exception remains for EF 2.0 normalization set vs the Consequential model, describing a slight 0.1% increase. Regarding the estimation of $c\ M_0(\mathbf{f}^{\mathrm{REF}})$, results are similar between APOS and Cut-off models. The coefficient of variation is higher for Consequential models except for the CML 2000 and TRACI methods.

When normalization sets are available for methods at both European and global levels (ILCD 2016, ReCiPe 2008, CML 2000) the best fit with ecoinvent-based references is found at the European level. Although ecoinvent inventories now cover the whole world, the database was originally essentially focused on the Swiss and European contexts. The global level is being increasingly addressed thanks to the addition of new inventories; nevertheless, it is still frequently represented by extrapolations of European technologies. Consequently, the large proportion of European inventories in ecoinvent accounts for the better match amongst European normalization references.

[Insert Figure 1 here]

For a more detailed analysis of the adequacy between $h_k^{\mathrm{REF},\tilde{\mathbf{B}}}$ and h_k^{REF}, a log-log scatterplot can be drawn for each comparison. This was done for EF 2.0 without long-term emissions in Figure 2. Scatterplots for EF 2.0 with long-term emissions and for the other methods are available in supplementary materials. The reader can refer to them during the following discussion.

These scatterplots indicate that a perfect adequacy between the reference system traced out in the normalization literature and the reference determined by the inventory database would be an alignment of all impact results (circles in Figure 2) along a single line. This line represents the relationship with the average value for $c\, M_0(\mathbf{f}^{\mathbf{REF}})$ estimation.

Beyond the gap between $c\, M_0(\mathbf{f}^{\mathbf{REF}})$ and $M_1(\mathbf{f}^{\mathbf{REF}})$ and its consequences on the relationship, a higher value either implies that the normalization literature underestimates the impact or that the associated flows are overestimated in the inventory database. Intuitively, this second possibility seems unlikely (since the main issue with inventory data rather concerns data gaps) but can occur when obsolete processes with high impacts are represented in the database. A lower value reflects the opposite situation: either an overestimation of the impact in the normalization literature or an underestimation of the involved intervention flows in the inventory database. This second explanation appears to be more realistic, as the inventory data may well be incomplete.

[Insert Figure 2 here]

3.4.1. EF 2.0 method

Most of the impacts are in the vicinity of the average line. According to Figure 2, the APOS and Cut-off models have same result, whereas the Consequential model is different. No substantial changes occur between system models involving or not long-term emissions (see supplementary materials Figure SI.2) while the values of the coefficients of variation are similar. This is a particular situation, as the other methods present an increasing quality of the relationship excluding long-term emissions but it is easily explained because EF 2.0 method is stated without long-term emission for human toxicity and ecotoxicity impacts (Fazio et al., 2018). Between ILCD 2016 and EF 2.0 (the latter being an update of the former), the impact characterization model for human toxicities (both cancer and non-cancer effects) and for freshwater ecotoxicity is the same USEtox® model (Rosenbaum et al., 2008). In ILCD 2016, two types of characterization factors are considered: inclusion and exclusion of long-term emissions. This directly affects the results (see below). In EF 2.0, values without long-term emissions are also used for assessment with long-term emissions. There is therefore no difference between them.

For APOS and Cut-off, the two most distant impacts situated beneath the line are Ozone depletion and Land use. The first could be explained by incomplete inventories in the databases rather than by an overestimation of the reference in the literature: ozone depleting gases have been quantified for decades and estimations of country level emissions seem robust. It is noteworthy that a similar result is reached for all other methods (see below). For land use, there is most likely a lack of hindsight regarding the application of the LANCA method (Bos et al., 2016) aggregated indicator to ecoinvent datasets. This indicator has been selected for the latest version of the environmental footprint. However, the normalization set for this impact is recent (Faragò et al., 2019) and is characterized by global and spatialized data. Consequently, incomplete inventories could influence this impact rather than an overestimation of the global flows of the normalization reference (see discussion below about land transformation in the ReCiPe 2008 method).

For the Consequential model, three other impacts deviate from the line: "ecotoxicity, freshwater" and "ionizing radiation human health" are situated beneath the line; "resource use, minerals and metals" are significantly above. The latter explains the high coefficient of variation value for this system model (see Figure 1). Similar results for resources with the Consequential model are found for ReCiPe methods (I, H and E) where fossil and mineral resources are assessed separately. This similarity is not observed when they are not differentiated (ILCD 2016 and CML 2000 methods). Indeed, as the fossil resources seem less affected by the system model, they probably conceal the effect of the latter on the mineral resources.

The "Ionizing radiation human health" impact is strongly correlated to the electricity mix. For a rising market (i.e. electricity), products issued from modern and competitive technologies, instead of established ones, are to be avoided in the Consequential model. The Consequential electricity demand (having a low nuclear contribution) thus strongly differs from the current electrical mix, which uses normalization sets from the literature. It is therefore obvious that the match between ecoinvent-based and literature-based normalization is not satisfactory with this system model, as it reveals an overestimation due to the literature-based reference.

3.4.2. ILCD 2016

The comparison of database-based normalization references with sets from literature for the ILCD 2016 method show, as a general tendency, similar results as the EF 2.0 method. The main difference is a decrease in the coefficient of variation of about 3% without long-term emissions. This is particularly significant for human toxicity (both cancer, non-cancer effects) and freshwater ecotoxicity impacts: they do not deviate in large proportion from the line without long-term emissions, whereas normalization sets from the literature underestimate them when all emissions are considered. The global inventories proposed in the literature thus seem to reflect best the inventories without long-term emissions.

3.4.3. ReCiPe 2008.

Three versions of the ReCiPe 2008 method are available, the egalitarian (E) with a 1000-year time horizon for the impacts, the hierarchist (H) with a 100-year time horizon and the individualist (I) with 20 years. The short time horizon of the latter justifies the absence of characterization sets without long-term emissions. However, the results for the I version are closest to those of the E and H versions which are assessed with long term emissions. The I version only takes into account short-term impacts, although these are also related to short- and long-term emissions. Consequently, the ReCiPe I cannot be interpreted as a method without long-term emissions for normalization.

Some results are similar to those of previously discussed methods: a decrease in the coefficient of variation excluding long-term emissions, an ozone depletion beneath the average line and underestimations of toxicity and ecotoxicity impacts by literature when all emissions are considered. A further underestimation by the normalization references has been observed for freshwater eutrophication.

Land transformation impacts are characterized by positive (from the previous occupation) and negative (towards the subsequent occupation) characterization factors. The ecoinvent based normalization references for natural land transformation are negative with APOS and Cut-off models (this is never encountered elsewhere). They are therefore not represented in the logscale scatterplots provided in supplementary materials. As previously mentioned, ecoinvent has mainly been built using European inventories. For this continent, natural land transformations are very low as they have already been made during the previous millennials, sometimes with re-naturalization, with afforestation and with abandoned land (Fuchs et al., 2015). This situation is taken into account in ecoinvent. The normalization references from literature are quite different, with a world value two orders of magnitude higher than the European reference. Therefore, concerning this type of impact, the database does not seem representative at a global scale (in agreement with the conclusion on land use in the EF 2.0 method). Ecoinvent-based references are positive for this impact using the Consequential model. The change in land use, introduced by agricultural avoided co-products, leads to a good fit with the world reference set.

3.4.4. EDIP 2003

The list of impacts assessed here differs from previous methods but similar results are found: The coefficients of variation decrease from the "with" to "without" long-term emission situations, but within a lower range (−1.8%), with a better fit for toxicity and ecotoxicity impacts. Ozone depletion sits beneath the line. With the Consequential system model, radioactive wastes, associated to ionizing radiation impacts in the other methods, are overestimated, as previously observed.

3.4.5. CML 2000

The main difference found between results from CML 2000 and from the other methods is the increase in the coefficients of variation of the Consequential model. This can be explained by (1) the association of mineral and fossil resource depletion into a unique impact and (2) the lack of ionizing radiation in this method. The literature-based normalization references for these two impacts poorly match the Consequential system model for the other methods and increase the coefficients of variation; due to their absence, this is not observed for CML 2000.

3.4.6. TRACI

The coefficients of variation are among the worst in Figure 1. Nevertheless, the scatterplots available in supplementary materials provide insights for understanding this result. Two subsets can be distinguished: the "carcinogenics", "non-carcinogenics" and "ecotoxicity" impacts are found well above the line with similar gap sizes, whereas the other impacts apparently seem to follow the same line. As the TRACI reference values are about 20 years old, toxic emissions are undoubtedly underestimated due to lack of data at that time. In order to be aligned with the others, the normalization values should be greater by almost three orders of magnitude. This range for deviations corresponds to a proposed update for TRACI normalization (Kim et al., 2013), which suggests values that are two (ecotoxicity) to four (carcinogenic) orders of magnitude higher.

3.5. Hypotheses needed for this approach

3.5.1. Modelling and limits of the reference system

With eq (2), the reference system for the normalization is defined as a result of an LCA. The functional unit would then be for example the one-year life for the world population, or for a citizen. Conceptually, this is not an issue. The use of the same modelling approach for both the studied system and the reference system can only be expected. However, that differs from common normalisation practices where the reference is established from external datasets, as national or regional statistics.

Consequently, the comparisons between the present approach and the references from the literature (i.e. eq (10)) deal with the relevance of the approach, but also with the completeness of the LCI database with respect to the exhaustivity of the method reference sets. The first refers to the hypothesis on the means relationship (see below). For the second aspect, the results show relevant matches and the discrepancies have been discussed. Beyond proposing a new approach to normalization, this work is a way of checking the exhaustiveness of the or the representativeness of the databases relating to all human activities, at the same scale.

3.5.2. The geometric mean instead of the arithmetic mean

The constant difference between the geometric and the arithmetic means (eq. (5)) is the main hypothesis of the approach. As $\mathbf{f}^{\mathbf{REF}}$ is unknown, this cannot be verified but only partially addressed looking at the arithmetic and geometric means of $\widetilde{\mathbf{B}}_j$. Figure SI.11 illustrates the high correlation between these means with the APOS system model (log-log Pearson coefficients of positive values equal to 0.97 p-value <0.001), the Cut off system model (0.89, p-value <0.001) and the Consequential system model, to a lesser extent (0.70, p-value <0.001).

3.6. General discussion

The normalization step transforms results expressed at different scales to a common one, pursuing two purposes.

The first is to free the study of the units of impacts. The aggregation and the comparison of the result are then feasible. This aspect is not specific to LCA and can be found in most of statistical treatments where values (samples) are positioned in relation to a population (z-score, min-max normalisation, etc.). In LCA, the normalization is conventionally done with external information. However, in data processing, it is usually from the data that population descriptors are estimated. In line with this, the present approach consists of using all available LCA data (the inventory database) and describing the population in an adequate way (the geometric mean associated to the log-normal distribution).

The second purpose is to compare the result with a reference quantity, checking its consistency and facilitate its communication. The inventories-based normalization obviously cannot be used directly for that, since the reference quantities do not have a real meaning. This verification and communication work can be initiated by looking at how the impacts are distributed in relation to others, but the present approach deals more with the first aim.

This approach cannot produce relevant results if the database is not complete enough and then does not accurately represent all human activities. But in this case the LCA result itself, without normalization, is not relevant. The approach presented here makes it possible to assess the quality of the involved database before the study, checking the consistency with published normalization sets.

An LCA practitioner usually uses a pre-established inventory database for a given study. He modifies and adds only a very small number of processes. The reference should therefore not change significantly from one study to another and the same reference should be able to be used, by proposing a normalization adapted to each system model and corresponding to the same scope.

In addition to process-based LCA, Economic Input-Output LCA (EIO-LCA) allows an assessment with respect to economic data. The final demand of a process is replaced by the money spent in the associated economic sector, and the corresponding environmental impact is attributed to the product under study. EXIOBASE 3 (Stadler et al., 2018) is one of the most recent databases dedicated to. From a mathematical perspective, the EIO-LCA result is determined in the same way as the process-based LCA result. The approach can therefore be used. EIO databases contain only a few substances, but it will be relevant to compare the reference values obtained under this approach with cumulated impacts of all economic sectors, viewed as normalization values.

4. Conclusion

Normalisation is typically done within the LCA framework through external normalization references. They are related to the estimations of the sum of overall process interventions which occur within the reference perimeter. Using an LCI database to determine the reference values, the authors propose a normalization approach for LCA that involves expressing the study result in relation to the geometric average process. In this way normalization can be viewed as an approach for determining whether the impacts of the system under study have a higher or lower magnitude than for the other systems in the database. It compares the results with the most expected values, i.e. the mean process of the database used.

Intervention flows in LCA do not follow normal laws, but are close to a log-normal distribution. They spread out over several orders of magnitude and must be investigated in the log-space. The choice of the geometric mean instead of the arithmetic mean is therefore appropriate.

With this choice, it is not necessary to know how many times the processes are involved to represent the overall impact: only the process interventions are required, and these are currently described in LCI databases. This useful aspect of the geometric mean had previously been highlighted in the LCA context for uncertainty assessments (Ciroth et al., 2016).

Surprisingly good log-log matches are found between ecoinvent-based normalization references according to the proposed approach and the external references currently proposed in the literature. The main differences can be explained by examining the features of the impacts. Therefore, thanks to these comparisons, plausibility checks can be made to assess whether inventories are missing in the database or if the literature-based normalization references underestimate the impact. These results confirm that the proposed approach will not lead to completely different conclusions than the existing practice, while enhancing data quality and consistency between study results and normalization data.

The present approach proposes to define a normalization procedure where the same datasets are used to assess the system under study as well as the normalization reference. It avoids discrepancies between both in relation to the system model, to the system boundaries, to the data sources and to the considered environmental flows. It therefore provides a solution to all the potential limitations of normalization listed by Pizzol et al. (2017). However, the meaning of normalization in the present approach is slightly different. The result is no longer expressed in relation to the sum of interventions of the reference, as usually done, but according to the mean of intervention of the reference elements. Although the approach is not completely identical, the purpose remains nevertheless the same and the results are always expressed in relation to the reference. This can be seen even as an advantage of the more theoretically grounded proposal as over-interpretation of normalization results in the sense of "share in a certain region" are implicitly avoided.

This LCI database-based normalization approach is fully operational for all LCIA methods and databases. It allows therefore a broader coverage of studies than the existing external normalization references. Normalization references are provided here for ecoinvent, but this can be easily extended to other databases. The approach is transparent and ensures consistency of the normalized result. Practitioners are encouraged to test it and use it to compare, discuss and potentially aggregate environmental impacts in LCA.

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Table captions:

Table 1. List of notations

Figure Captions

Figure 1. Coefficient of variation in the log-space of $c\ M_0(\mathbf{f}^{\mathbf{REF}})$ estimations, determined according to methods with an associated normalization set and to the ecoinvent system models. Unaggregated values are depicted by blue histograms. The average coefficients of variation are in green for ecoinvent system models and for method normalization sets. The overall average is represented in red. When possible, differences in the coefficient of variation between methods with (All) and without long term emission (No LT) are indicated in square brackets.

Figure 2. Scatterplots for EF 2.0 method according to normalization sets from literature (h_k^{REF}, x-axis) and system models ($h_k^{\mathrm{REF},\widetilde{\mathbf{B}}}$, y-axis) without long-term emission. The lines show the relationship $h_k^{\mathrm{REF},\widetilde{\mathbf{B}}} = \frac{1}{mM_0(\mathrm{f}^{\mathrm{REF}})} h_k^{\mathrm{REF}}$, see supplementary materials for $c\ M_0(\mathbf{f}^{\mathbf{REF}})$ values.

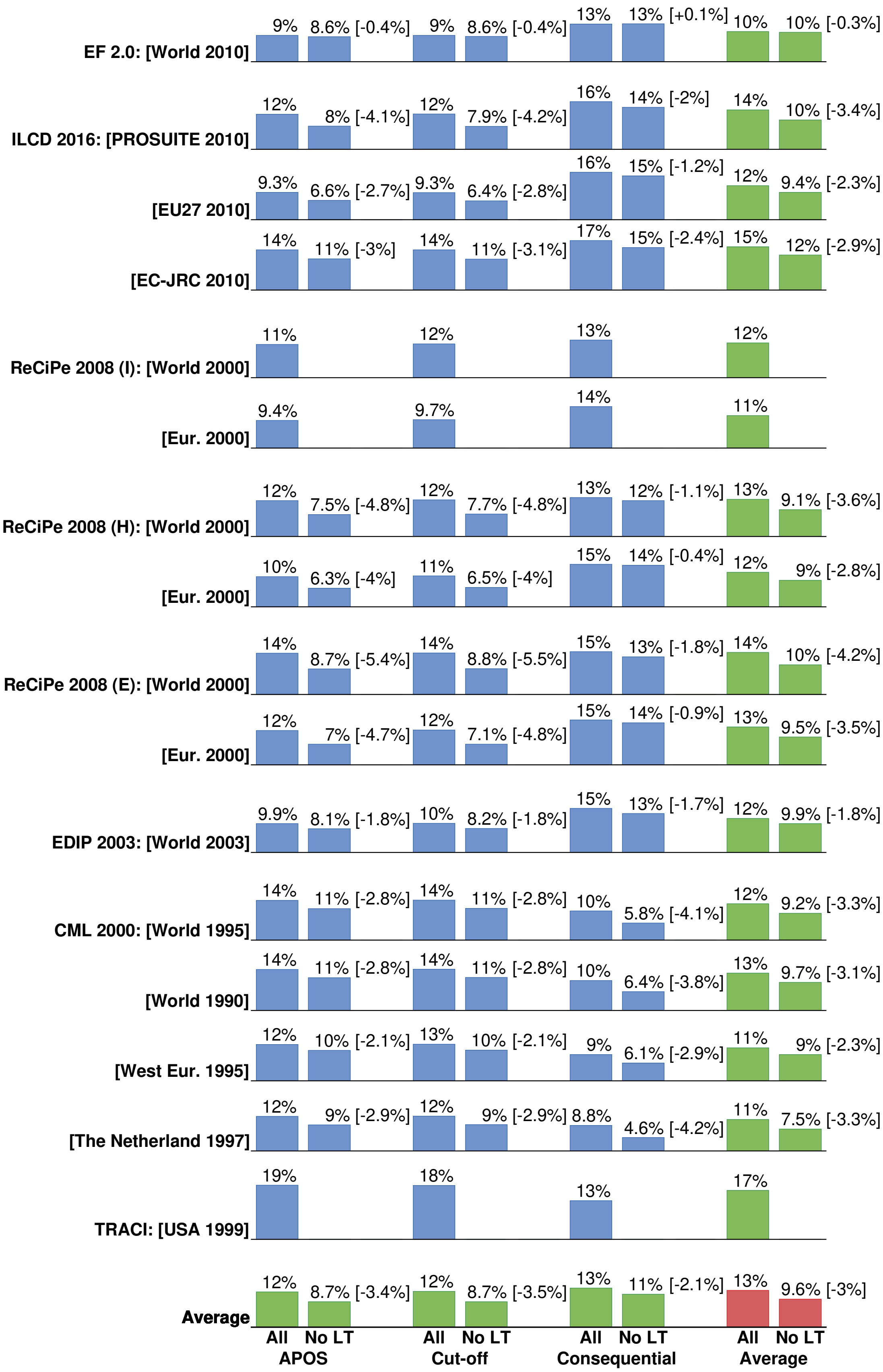
Table1

Notation	Description
m, i	Index: number of processes, i^{th} process ($i = 1, \dots, m$).
n, j	Index: number of elementary flows, j^{th} elementary flow ($j = 1, \dots, n$).
p, k	Index: number of impact categories, k^{th} impact category ($k = 1, \dots, p$).
$\mathbf{f}, f_i$	Final demand vector (m$\times$ 1), final demand of the i^{th} process.
$\mathbf{f}^{\text{REF}}, f_i^{\text{REF}}$	Final demand vector for the normalization reference system (m$\times$ 1), final demand of the i^{th} process for the normalization reference system.
$\mathbf{A}$	Technology matrix (m$\times$ m).
$\mathbf{B}, \mathbf{B}_j, b_{j,i}$	Intervention matrix ($n \times m$), intervention vector for the j^{th} elementary flow ($1 \times m$), intervention value of the j^{th} elementary flow for the i^{th} process.
$\widetilde{\mathbf{B}}, \widetilde{\mathbf{B}}_j, \tilde{b}_{j,i}$	Pre-calculated intervention matrix ($n \times m$): $\widetilde{\mathbf{B}} = \mathbf{B}\mathbf{A}^{-\mathbf{1}}$, pre-calculated intervention vector for the j^{th} elementary flow ($1 \times m$): $\widetilde{\mathbf{B}}_j = \mathbf{B}_j\mathbf{A}^{-\mathbf{1}}$, pre-calculated intervention value of the j^{th} elementary flow for the i^{th} process.
$\widetilde{\mathbf{B}}^+, \widetilde{\mathbf{B}}_j^+, \tilde{b}_{j,i}^+$	Pre-calculated intervention matrix with only zeros and the positive values of $\widetilde{\mathbf{B}}$ ($n \times m$), pre-calculated intervention vector with only zeros and the positive values of $\widetilde{\mathbf{B}}_j$ (1$\times$ m), corresponding pre-calculated intervention value of the j^{th} elementary flow for the i^{th} process.

$\tilde{\mathbf{B}}^{-}, \tilde{\mathbf{B}}_j^{-}, \tilde{b}_{j,i}^{-}$	Pre-calculated intervention matrix with only zeros and the additive inverse of negative values of $\tilde{\mathbf{B}}$ $(n \times m)$, pre-calculated intervention vector with only zeros and the additive inverse of negative values of $\tilde{\mathbf{B}}_j$ $(1\times m)$, corresponding pre-calculated intervention value of the j^{th} elementary flow for the i^{th} process.
$\mathbf{Q}, \mathbf{Q}_{\boldsymbol{k}}, q_{k,j}$	Characterization matrix $(p \times n)$, characterization vector of the k^{th} impact $(1 \times n)$, characterization factor of the k^{th} impact category for the j^{th} elementary flow.
$\mathbf{h}, h_k$	LCIA result $(p \times 1)$ $\mathbf{h} = \mathbf{Q}\tilde{\mathbf{B}}\mathbf{f}$, LCIA result on the k^{th} impact category.
$\mathbf{h}^{\text{REF}}, h_k^{\text{REF}}$	LCIA result of the normalization reference system $(p \times 1)$ $\mathbf{h}^{\text{REF}} = \mathbf{Q}\tilde{\mathbf{B}}\mathbf{f}^{\text{REF}}$, LCIA result of the normalization reference system on the k^{th} impact category.
$\mathbf{h}^{\text{REF},\tilde{\mathbf{B}}}, h_k^{\text{REF},\tilde{\mathbf{B}}}$	Normalization reference value based on $\tilde{\mathbf{B}}$ and $\mathbf{Q}$ only $(p \times 1)$, normalization reference value based on $\tilde{\mathbf{B}}$ and $\mathbf{Q}_{\boldsymbol{k}}$ only for the k^{th} impact category.
$\mathbf{h}^{\text{N}}, h_k^{\text{N}}$	Normalized LCIA result $(p \times 1)$, normalized LCIA result of the k^{th} impact category.
$M_1(\dots)$	Arithmetic means of all elements in brackets, mean of a vector has to be interpreted as the mean of all elements of the vector.
$M_0(\dots)$	Geometric means of all elements in brackets, mean of a vector has to be interpreted as the mean of all elements of the vector.

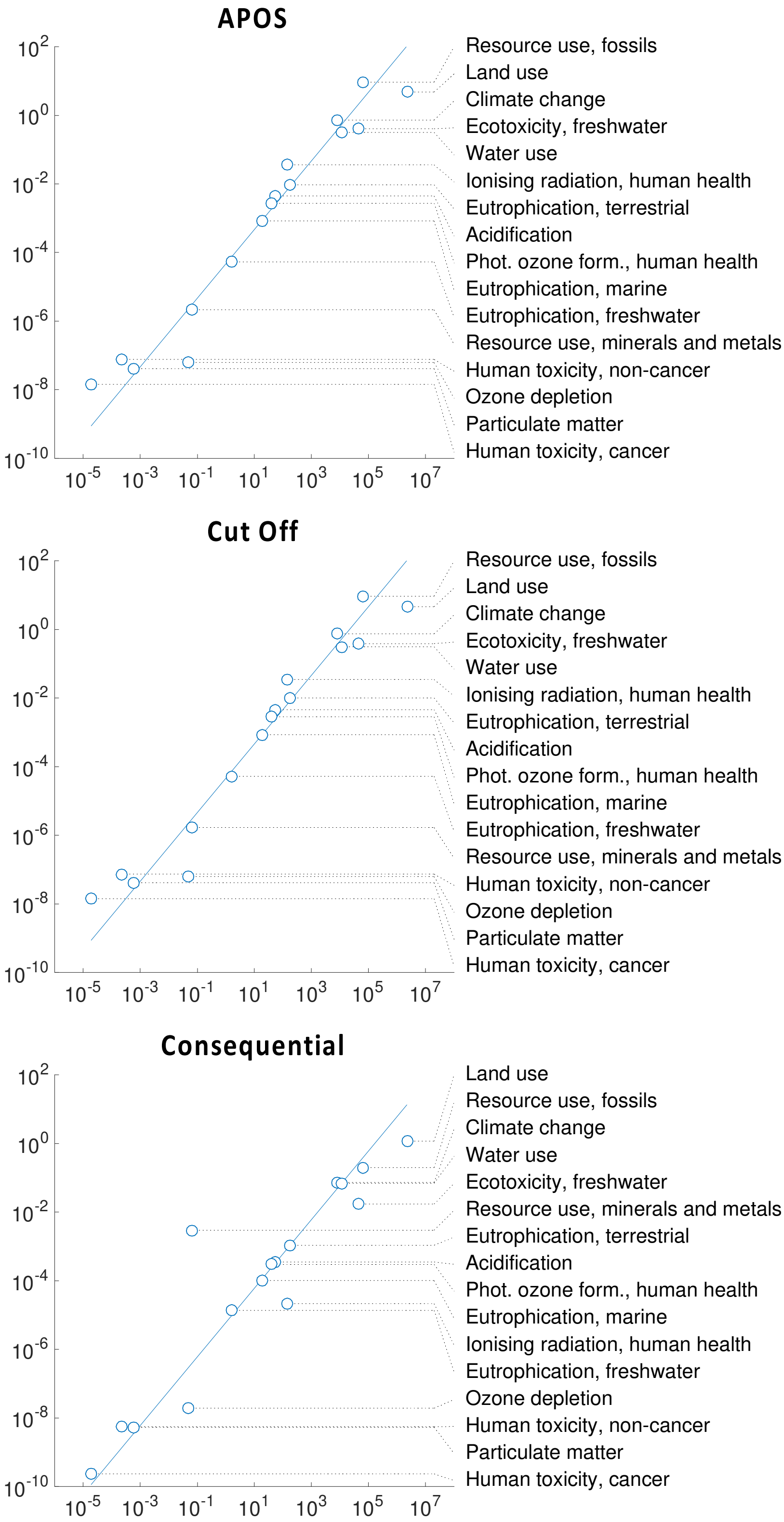
c	Stated constant for the relationship between geometric mean and arithmetic mean.

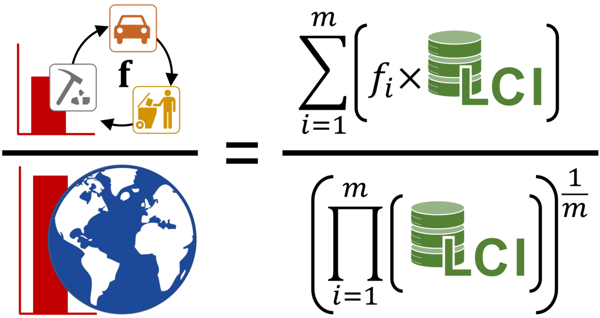
701 Figure 1



702

Figure 2


APOS
Resource use, fossils
Land use
Climate change
Ecotoxicity, freshwater
Water use
Ionising radiation, human health
Eutrophication, terrestrial
Acidification
Phot. ozone form., human health
Eutrophication, marine
Eutrophication, freshwater
Resource use, minerals and metals
Human toxicity, non-cancer
Ozone depletion
Particulate matter
Human toxicity, cancer
Cut Off
Resource use, fossils
Land use
Climate change
Ecotoxicity, freshwater
Water use
Ionising radiation, human health
Eutrophication, terrestrial
Acidification
Phot. ozone form., human health
Eutrophication, marine
Eutrophication, freshwater
Resource use, minerals and metals
Human toxicity, non-cancer
Ozone depletion
Particulate matter
Human toxicity, cancer
Consequential
Land use
Resource use, fossils
Climate change
Water use
Ecotoxicity, freshwater
Resource use, minerals and metals
Eutrophication, terrestrial
Acidification
Phot. ozone form., human health
Eutrophication, marine
Ionising radiation, human health
Eutrophication, freshwater
Ozone depletion
Human toxicity, non-cancer
Particulate matter
Human toxicity, cancer
10^{2} 10^{0} 10^{-2} 10^{-4} 10^{-6} 10^{-8} 10^{-10}
10^{-5} 10^{-3} 10^{-1} 10^{1} 10^{3} 10^{5} 10^{7}


f
m
i=1
f_i ×
LCI
m
i=1
LCI
1/m