Int J Life Cycle Assess (2017) 22:2018–2029
DOI 10.1007/s11367-017-1281-3

UNCERTAINTIES IN LCA

Interpretation of comparative LCAs: external normalization and a method of mutual differences

Valentina Prado[1] · **Ben A. Wender**[2] · **Thomas P. Seager**[3]

Received: 23 November 2015 / Accepted: 8 February 2017 / Published online: 27 February 2017

Abstract
Purpose Identification of environmentally preferable alternatives in a comparative life cycle assessment (LCA) can be challenging in the presence of multiple incommensurate indicators. To make the problem more manageable, some LCA practitioners apply external normalization to find those indicators that contribute the most to their respective environmental impact categories. However, in some cases, these results can be entirely driven by the normalization reference, rather than the comparative performance of the alternatives. This study evaluates the influence of normalization methods on interpretation of comparative LCA to facilitate the use of LCA in decision-driven applications and inform LCA practitioners of latent systematic biases. An alternative method based on significance of mutual differences is proposed instead.
Methods This paper performs a systematic evaluation of external normalization and describes an alternative called *the overlap area approach* for the purpose of identifying relevant issues in a comparative LCA. The overlap area approach utilizes the probability distributions of characterized results to assess significant differences. This study evaluates the effects in three LCIA methods, through application of four comparative studies. For each application, we call attention to the category indicators highlighted by each interpretation approach.
Results and discussion External normalization in the three LCIA methods suffers from a systematic bias that emphasizes the same impact categories regardless of the application. Consequently, comparative LCA studies that employ external normalization to guide a selection may result in recommendations dominated entirely by the normalization reference and insensitive to data uncertainty. Conversely, evaluation of mutual differences via the overlap area calls attention to the impact categories with the most significant differences between alternatives. The overlap area approach does not show a systematic bias across LCA applications because it does not depend on external references and it is sensitive to changes in uncertainty. Thus, decisions based on the overlap area approach will draw attention to tradeoffs between alternatives, highlight the role of stakeholder weights, and generate assessments that are responsive to uncertainty.
Conclusions The solution to the issues of external normalization in comparative LCAs proposed in this study call for an entirely different algorithm capable of evaluating mutual differences and integrating uncertainty in the results.

Keywords Comparative life cycle assessment · Decision support · Interpretation · Normalization bias

Responsible editor: Sangwon Suh

Electronic supplementary material The online version of this article (doi:10.1007/s11367-017-1281-3) contains supplementary material, which is available to authorized users.

✉ Valentina Prado
v.prado@cml.leidenuniv.nl

[1] Institute of Environmental Sciences CML, Leiden University, Einsteinweg 2, 2333CC Leiden, The Netherlands

[2] The National Academies of Sciences, Engineering, and Medicine, Washington D.C, USA

[3] Arizona State University, Tempe, AZ, USA

1 Introduction

Research in life cycle assessment (LCA) methods focus predominantly on building life cycle inventory (LCI) databases

(Frischknecht et al. 2004; Suh and Huppes 2005; Miller and Theis 2006; Dones et al. 2007; Verbeeck and Hens 2010; Jungbluth et al. 2012), calculating new midpoint characterization factors (Koellner and Scholz 2007; Pfister et al. 2009; Van Zelm et al. 2009; Gallego et al. 2010; Saad et al. 2011; Hauschild et al. 2013), and improving end-point damage modeling (Hayashi et al. 2006; Boulay et al. 2011; Motoshita et al. 2014). Less emphasis has been placed on normalization and weighting, which are optional practices in life cycle impact assessment (LCIA).

Nonetheless, normalization and weighting remain crucial in comparative LCA to provide decision support in the face of uncertain environmental tradeoffs—such as when one alternative performs best in some areas and worse in others. In problems of comparative technology assessment, characterized results alone seldom result in a definitive environmental choice, leaving decision-makers to confront complex environmental tradeoffs largely unaided in examples critical to sustainability (Rowley et al. 2012). These environmental tradeoffs exist regardless of the completeness of characterization factors or LCI databases. Thus, there is a critical need for analogous research efforts focused on normalization and weighting as tools to improve decision support in LCA.

There are numerous impact assessment methods available to LCA analysts that apply to any LCI, each with their own external normalization references. These tools provide alternative methods of characterizing and interpreting environmental impacts from the myriad and disparate chemical releases reported in a LCI. Some of the most widely applied LCIA methods are as follows:

1. the Tool for Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI) developed by the US Environmental Protection Agency (Bare 2011),
2. the Institute for Environmental Sciences (CML) impact assessment tool developed at the University of Leiden in the Netherlands (Guinée et al. 2002), and
3. ReCiPe, an impact assessment methodology developed in partnership between four leading institutions (Goedkoop et al. 2009).

According to ISO standards, normalization provides context to characterized results by relating results to a reference information (ISO 2006). Typically, as is the case with the main LCIA methods, these normalization references represent a community such as Europe, USA, or the world. The reference information can also represent another system, or an internal baseline such as the largest or smallest alternative. There are two distinct approaches to normalization known as external (when the reference is outside the study) or internal (when the reference is within the study). While both approaches are mentioned in the ISO guidelines, external normalization approaches dominate current practice, with the exception of the comparative bar charts typically produced by LCA software packages that scale results via division by a maximum.

1.1 External normalization

The main goal of external normalization is to provide an understanding of the relative importance of category indicator results of a single product system (Guinée et al. 2002). Externally normalized results show the relative significance of category indicators and thus can help guide improvement efforts within a single product system (Heijungs et al. 2007). Note the emphasis in *single product system* as these results should not be used to make comparisons across impact categories and multiple product systems. Other uses of external normalization are for checking inconsistencies, communication of the relative significance of category indicators (i.e., hot spot identification) and as a procedure for weighting.

External normalization is done by dividing characterized results by an estimate of the total or per capita equivalent emissions in that impact category associated with an entire geographical region (Eq. (1)). LCIA methods have options of normalizing midpoint characterized results according to external references. For example, ReCiPe midpoint H has a European and a World normalization reference, which will compare results according to estimations of annual European or World per capita emissions (Goedkoop et al. 2009).

$$NI_{a,i} = \frac{CI_{a,i}}{NR_i} \tag{1}$$

where

$NI_{a,i}$ is the normalized impact per year of alternative a in impact category i.

$CI_{a,i}$ is the characterized impact of alternative a in impact category i.

NR_i is the normalization reference representing a specific geographical region for impact category i in the physical units (per year) corresponding characterized impact $CI_{a,i}$.

The Handbook on LCA (Guinée et al. 2002) limits applicability of externally normalized results to identify issues within one single product system, yet the use of externally normalized results to identify relevant aspects in comparative LCA (thus multiple product systems) is seen recently in the literature (Van Hoof et al. 2013; Laurent and Hauschild 2015). To compare between product systems and across impact categories, externally normalized results must be weighted, which provides the basis for aggregation to a single score (Heijungs et al. 2007; Lautier et al. 2010; Prado et al. 2012). This practice, although included in the ISO guidelines and the Handbook on LCA, can have misleading recommendations as it is subject to the same biases of external normalization (Prado et al. 2012; Prado-Lopez et al. 2014).

A comparative LCA is usually decision driven with the goal of identifying the choice resulting in the least environmental burden. This requires a shift in assessment from *absolute impact of alternatives* (as done by external normalization) to *relative impact of the decision*. Here, the aspects most pertinent to the decision are those which differentiate the alternatives (Prado-Lopez et al. 2016). For example, alternatives A and B may both have large magnitudes for ozone depletion in comparison to a normalization reference. However, a decision between A and B can only impact on ozone depletion to the extent that they are differentiated. If A and B are identical in characterized ozone equivalents, the *decision* between them has no impact on eventual ozone levels, regardless of whether ozone depletion can be identified as a hotspot.

Another issue in external normalization is that of *inverse proportionality* where impact categories with larger regional emissions generate a smaller normalized impact and are thereby identified as less relevant (Rogers and Seager 2009; White and Carty 2010). This inverse proportionality effect between normalization references and normalized impacts can introduce systematic biases. In fact, when White and Carty (2010) evaluated externally normalized results of 800 processes taken from Ecoinvent using CML Global 1995 and TRACI US 2000 normalization references, authors found a bias where each normalization approach repeatedly highlights the same set of impact categories regardless of the process inventory. Specifically, TRACI US 2000 normalization highlights human toxicity and terrestrial ecotoxicity, whereas CML Global 1995 references highlights marine ecotoxicity and to a lesser extent freshwater ecotoxicity. The impact categories highlighted at normalization were considerably larger than the rest. To reduce this bias, White and Carty (2010) propose application of external normalization in combination with internal normalization by division within a dataset. However, regardless of the reference value and dataset, external normalization and internal normalization by division exclude uncertainty and apply a linear function that is fully compensatory (Prado et al. 2012). This means that it is possible for a favorable performance in a single impact category to entirely drive results, hiding multiple poor performances in other areas of the environment and promoting burden shifting when aggregating to a single score. Moreover, when normalized results are dominated by a few or a single impact category, weights will have little influence in the final aggregation, thus generating scores that may contradict stakeholder preferences.

1.2 Weighting and weight sensitivity

Weighting in LCA reflects stakeholder or decision-maker values regarding the relative importance of each impact category and enables the ranking of alternatives (Huppes et al. 2012; Cortés-Borda et al. 2013). Similar to normalization, weighting is an optional stage in LCIA that is avoided in most LCA studies. Given subjectivity concerns, and a general lack of information regarding decision-maker preferences, most LCAs truncate results at characterization, at external normalization, or apply "equal weights" (Prado-Lopez et al. 2016). However, where analysis continues beyond these stages, weight values can be derived from a panel of experts in a professional field (Gloria et al. 2007), through surveys (Schmidt et al. 2002), monetization or willingness-to-pay techniques (Finnveden 1999), linear programming (Cortés-Borda et al. 2013), and distance-to-target approaches (Seppälä and Hämäläinen 2001). Alternatively, in the absence of preference information, novel stochastic approaches in LCA provide a useful way to sample all possible weight values without favoring any single impact category thus enabling an inclusive view of the problem (Rogers and Seager 2009; Prado-Lopez et al. 2014). However, regardless of the elicitation process, weighting can remain ineffective given a linear normalization step (Stewart 2008). When the effects of the normalization step are too strong, the effects of weighting become negligible, leading to recommendations that are independent of stakeholder values. Previous LCA studies have already identified instances of weight insensitivity in external normalization (Rogers and Seager 2009; White and Carty 2010; Cortés-Borda et al. 2013; Myllyviita et al. 2014; Castellani et al. 2016). For instance, Myllyviita et al. (2014) evaluates different weight elicitation approaches and finds that most weights have little influence on the results given external normalization. This is evidence that weights are subject to the biases of the previous normalization step. Decision support in LCA should guide the decision making process, not replace human judgment entirely. A method that provides a recommendation irrespective of stakeholder input is inadequate for transparent decision-making. In particular, weight insensitivity represents a major issue for environmental decision-making because it can yield results that are unsatisfactory for problems involving multi-stakeholder groups.

1.3 Overlap area approach

An alternative approach to identify the category indicators relevant to a decision in a comparative LCA is the overlap area approach (Prado-Lopez et al. 2016). The overlap area approach applies to probabilistic characterized results of comparative LCAs in any of the LCIA methods. It refers to the common area between two probability distributions at characterization. It ranges from 0 when alternatives are evidently different from one another, to 1 when the characterized results of alternatives are identical. The overlap area focuses on mutual differences and favors those aspects where alternatives are the most distinguishable from one another. Therefore, the overlap area does not identify hotspots for improvement assessment; rather it is aimed exclusively at supporting selection in comparative assessments.

The overlap area approach is concerned with finding differences among alternatives. The premise being that when faced with a comparison, distinctions drive selection. For example, given a comparative LCA where all alternatives have the same climate change impact, selection of any alternative results in the same impacts to climate change regardless of stakeholder weights. Alternatively, if alternatives have different impacts in eutrophication, then eutrophication plays a larger role in the decision as the selection here does matter for eutrophication. Therefore, these differences, or *tradeoffs* between alternatives, measure the *impact of the decision*. We can measure tradeoff significance by incorporating the uncertainty of characterized results and identify the issues where we have the most evidence that an alternative may be in fact better or worse than another. That way, the decision is informed by the aspects with the best resolution and we can save data refinement efforts for those aspects where uncertainties are the largest. Tradeoff significance in a comparative LCA does not necessarily correlate to hotspots as identified by external normalization since each approach describes different aspects of the data (Prado-Lopez et al. 2016). Uncertainties included in the overlap area can be propagated from inventory and characterization via Monte Carlo analysis. As more studies provide ways of estimating these uncertainties (Henriksson et al. 2014; Mendoza Beltran et al. 2016; Wender et al. 2016), it becomes important to incorporate them in the interpretation phase.

Besides the overlap area approach, there are other alternatives to incorporate uncertainty when evaluating mutual differences in LCA. For instance, discernibility analysis (Heijungs and Kleijn 2001) counts the times in which one alternative is greater than another in each Monte Carlo run. Following the same basis, but illustrating a more extensive approach with sensitivity analysis is the approach shown in Gregory et al. (2016). The relevance parameter as introduced in Prado-Lopez et al. (2014) evaluates the ratio of the differences in means to the standard deviations. This approach is relatively simple, but one limitation is that it assumes normal distributions. Another example can be found in Henriksson et al. (2015), where authors perform dependent sampling in uncertainty analysis and test hypotheses to evaluate comparative performances. Finally, the use of reliability theory from engineering science has also been incorporated to LCA for the purposes of evaluating the superiority of an alternative with respect to another given probabilistic results (Wei et al. 2016). However, illustrations of these methods are limited to two alternatives and implementation of these methods to comparisons involving additional alternatives generates increasingly complicated results. That is, a comparison with four alternatives (for instance, A, B, C, D), generates six sets of results (corresponding to AB, AC, AD, BC, BD, CD) per impact category, making the interpretation challenging in larger comparative problems. Unlike these approaches, the overlap area approach can generate one result per impact category regardless of the number of alternatives and thus facilitating communication of results (Prado-Lopez et al. 2016). Therefore, the overlap area serves as a good example to illustrate a fundamentally distinct approach to that of external normalization.

2 Methods

This paper presents a methodological evaluation of life cycle impact assessment (LCIA) that isolates the effect of normalization across multiple LCIA methods and comparative LCA applications. Three current practices, CML EU25 2006 and World 2000 (Sleeswijk et al. 2008), ReCiPe midpoint H version 1.10 European and World (Goedkoop et al. 2009), and TRACI US 2008 (Bare 2011; Ryberg et al. 2014) are compared to the overlap area approach in application to four comparative LCA studies, and patterns in the results are examined for evidence of systematic biases. The findings help inform LCA practitioners of the implications in the choice of normalization methods in comparative assessments.

2.1 Representative applications

Four comparative LCA applications serve as variables to evaluate *how* each approach handles characterized data. These applications represent broad sectors such as centralized and distributed energy, construction materials and paper pulp production (Table 1). Inventory data for each process included in these comparative LCA applications derives directly from the Ecoinvent 3.01 database (Wernet et al. 2016). Refer to the Electronic Supplementary Material for detailed information on the inventory.

Probability distributions at characterization used in the overlap area calculations, derive from an uncertainty analysis using the Pedigree Matrix coefficients available in Ecoinvent 3.01 (Lewandowska et al. 2004; Lloyd and Ries 2007; Muller et al. 2016). Issues particular to the estimation of uncertainty parameters and issues in implementation in LCA software packages are out of the scope of the paper. Rather, we focus on *how* to take quantitative uncertainty into account in the interpretation of comparative results. This procedure consisted of 1000 Monte Carlo runs done separately for each alternative within each comparative LCA application using the three LCIA methods and the goodness-of-fit test implemented in Simapro 8.0 PhD version. Thus, sampling is done independently per alternative where it is assumed there are no shared processes between them. For illustration purposes, uncertainty in this case derives from the inventory, but it could also be propagated from characterization factors and methodological choices as shown in Mendoza Beltran et al. (2016).

Table 1 Comparative LCA applications

Comparative LCA application	Description	Alternatives	Functional unit
Photovoltaic technologies (PV)	Electricity production of 5 PV technology alternatives in a 3-kWp slanted-roof installation	Single crystalline silicon cells (single-Si) Multi crystalline silicon cells (multi-Si) Thin film cadmium telluride (CdTe) Amorphous cells (a-Si) Ribbon silicon (ribbon-Si)	MJ
US electric grid mixes (eGrid)	High voltage electricity production from the 10 regions in the USA as classified by the North American Electric Reliability Corporation (NERC)	Alaska Systems Coordinating Council (ASCC) Florida Reliability Coordinating Council (FRCC) Hawaiian Islands Coordinating Council (HICC) Midwest Reliability Organization (MRO) Northeast Power Coordinating Council (NPCC) Reliability First Corporation (RFC) SERC Reliability Company (SERC) Southwest Power Pool (SPP) Texas Regional Entity (TRE), and Western Electricity Coordinating Council (WECC)	MWh
Concrete	Production of five different lightweight concrete block materials	Expanded clay Expanded perlite Expanded vermiculite Polystyrene Pumice	kg
Paper pulp	Paper pulp production with five different processes	Chemi-thermomechanical pulp Stone groundwood pulp Sulfate pulp Bleached sulfite pulp Thermomechanical pulp	kg

The more uncertainty sources are included, the larger they become in the overall result. However, this enhances rather than limits the importance of comparative uncertainty analysis. After uncertainty analysis, characterized results consist of lognormal distributions per impact category (mean and arithmetic standard deviation), rather than a single value (refer to the Electronic Supplementary Material for complete set of results at characterization). Fitting of results to a lognormal distribution is performed by Simapro. Evaluation of the overlap area is done via a standalone Java tool, as illustrated in Prado-Lopez et al. (2016).

We isolate the effect of each interpretation approach by applying each LCIA method to a set of four comparative LCA applications (Table 1). In this manner, the inventory and characterization factors remain constant while the interpretation step changes. Here, the independent variable is the interpretation approach and the results, broken down by impact category, represent the dependent variable (Fig. 1). For each representative application, we call attention to the category indicators most salient in each interpretation approach.

2.2 Salient aspects in external normalization

In external normalization, the most influential impact categories are those with the largest normalized values. If the same impact categories continue to be highlighted across the set of representative examples examined, this may provide evidence of systematic bias driving interpretation of the results. For instance, it may be that human toxicity represents 80 and 70% of the total normalized score of alternatives A and B, respectively. We represent the overall contribution of the human toxicity category by the average, Θ_i, in this case, 0.75. Calculations of overall contributions per category indicator are given by Eqs. (2) and (3). The contribution of each category indicator, Θ_i describes the extent that each normalized impact category is highlighted by the normalization reference across all alternatives in each comparative LCA application.

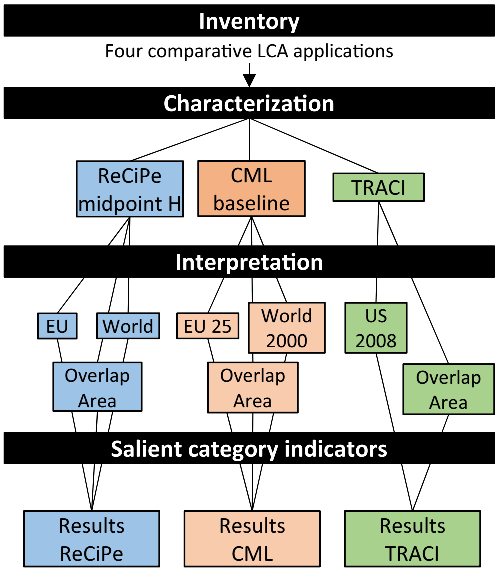

Fig. 1 Schematic of the methodology evaluating the effects of external normalization and the overlap area approach in three LCIA methods. Evaluation starts with four comparative LCA applications; then this inventory is characterized by three methods: ReCiPe midpoint H, CML baseline, and TRACI. Each of these methods already contain normalization references. Within ReCiPe, we evaluate EU and World normalization references, in CML baseline we evaluate EU25 and World 2000, and in TRACI we evaluate the US 2008 normalization reference. In addition, the overlap area approach applies for each set of characterized results. Results are evaluated per LCIA method to see if there are any patterns indicative of a bias

Note that externally normalized results are scaled from 0 to 1 when dividing individual result by the sum as shown in Eq. (2). Although aggregation of externally normalized results without explicit weighting is not recommended, we do it to illustrate the effects of normalization. We plot individual normalized contributions with respect to data uncertainty by arranging category indicators in the x-axis according to the coefficient of variation (details in the Electronic Supplementary Material). The evaluation of external normalization was performed using the mean values of characterized results and the normalization references without uncertainty estimation to illustrate current practice. Values of externally normalized results can be found in the Electronic Supplementary Material. The order of magnitude of externally normalized results tend to be a miniscule fraction of the normalization reference, thus, can be considered realistic. However, our critique pertains to the relative values and how the normalized values of impact categories can be order of magnitudes apart.

$$\beta_{a,i} = \frac{NI_{a,i}}{\sum_i NI_{a,i}} \tag{2}$$

$$\Theta_i = \frac{\sum_a \beta_{a,i}}{n} \tag{3}$$

where

$\beta_{a,i}$ is the fraction of each normalized impact to the sum of the normalized results. This is calculated per impact category i, per alternative.

$NI_{a,i}$ is the dimensionless normalized impact in impact category i of alternative a, given by Eq. (1).

Θ_i is the average contribution per impact category i across all alternatives within each comparative LCA application.

n is the number of alternatives within each comparative LCA application. For example, for the PV comparative LCA application, n = 5 (Table 1).

2.3 Salient aspects according to the overlap area approach

The most influential impact categories according to the overlap area approach are those with the most significant tradeoffs between alternatives (Prado-Lopez et al. 2016). Tradeoff significance is defined as the mutual differences between the alternatives at characterization relative to data uncertainty. Tradeoff significance, Ψ_i, of each impact category is a function of the pairwise overlap areas between alternatives (Eq. (4)). An impact category with a high tradeoff significance indicates a significant difference between alternatives. Impact categories with larger tradeoff significance become more influential in the assessment. Values for the overlap area results can be found in the Electronic Supplementary Material.

$$\Psi_i = 1-\left(\frac{2}{n(n-1)}\right)\sum\nolimits_{\alpha \in C} A_\alpha \tag{4}$$

where

Ψ_i is defined as 1 minus the average overlap area of impact category i. The "1 minus" ensures that a higher number correlates with tradeoff significance. An alternative mode of visualization can be found in Prado-Lopez et al. (2016).

n is the number of alternatives within each comparative LCA application used here to calculate the number of possible pairs.

A_α is the overlap area of all pairs where $G = \{1,2,\ldots,n\}$ represents the set of alternatives and C is the 2 subset of G ($\{\{1, 2\}, \{1, 3\}, \ldots, \{n-1, n\}\}$). Individual overlap areas are a function of the mean and standard deviations of characterized results. Calculation details are available in Prado-Lopez et al. (2016).

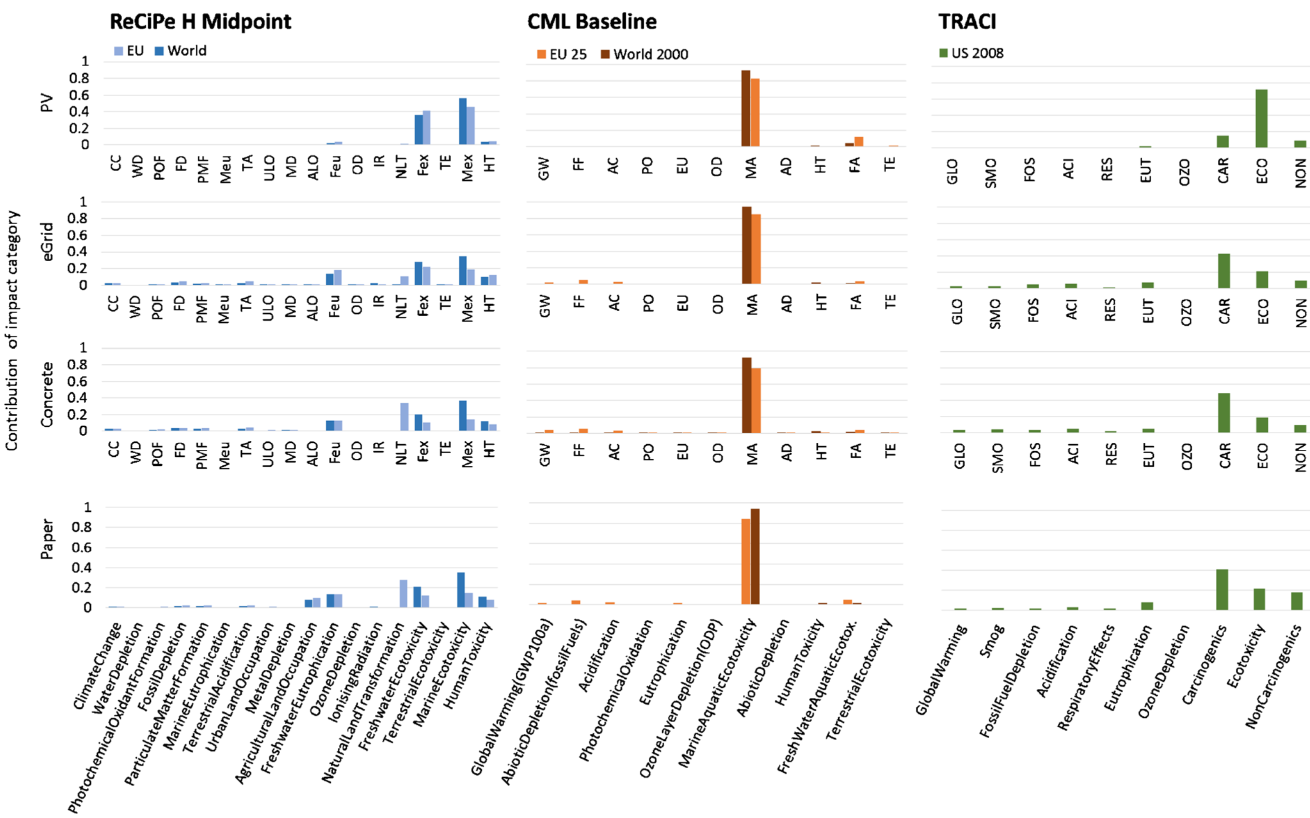

Fig. 2 The contribution per impact category, Θ_i, according to normalization references across the four comparative LCA applications (*top to bottom*: PV, eGrid, concrete, and paper pulp) using ReCiPe midpoint H, CML Baseline, and TRACI LCIA methods (*left to right*). The impact categories in the x-axis correspond to each LCIA method and are arranged according to the average coefficient of variation

3 Results

Results show the systematic effects of external normalization and the overlap area in ReCiPe, CML, and TRACI. Figure 2 highlights the impact categories most influential in each LCIA across all four comparative LCA applications. The x-axis represents the impact categories within each LCIA method organized according to the coefficient of variation so that the impact categories to the right have the largest uncertainty. The y-axis shows the contribution according to Eq. (3). Depending on the LCIA, there can be two series in the graphs, corresponding to a European and global normalization reference.

Within ReCiPe H Midpoint, EU and World normalization references highlight toxicity and eutrophication-related impact categories with the exception of natural land transformation, which is larger when using the EU reference. Impact categories most salient in EU and World references replicate across the four LCA applications indicating the possibility of a systematic bias in the normalization approach. With the exception of Kasah (2014), this same pattern in ReCiPe externally normalized results was found in recent LCA applications such as concentrated solar power (Corona et al. 2014), structural beams (Ibbotson and Kara 2013), industrial cleaning products (Kapur et al. 2012), diapers (Mirabella et al. 2013), laundry detergents (Prado-Lopez et al. 2014), energy recovery from rice husks (Prasara-A and Grant 2011), and dishwashing soap (Van Hoof et al. 2013).

Normalization references within CML baseline, EU 25 and World 2000, reveal that a single impact category, marine aquatic ecotoxicity, as the most and only dominant impact category (Fig. 2). Here, the selection of alternatives in each example (PV, eGrid, concrete, and paper pulp) is determined by single impact category. A survey of recent publications from the *International Journal of Life Cycle Assessment* reporting normalized impacts from CML supports the finding that marine aquatic ecotoxicity is the most influential category in evaluations of water services (Barjoveanu et al. 2014), diapers (Mirabella et al. 2013), exterior household walls (Monteiro and Freire 2012), packing tape (Navajas et al. 2014), thermal insulation (Struhala et al. 2014), and an entire inventory data library (White and Carty 2010). These results were also reproduced by Sim et al. (2007) in a food sourcing application where authors excluded marine aquatic ecotoxicity from normalized results due to masking of other aspects. Alternatively, some exceptions can be found in soil remediation processes (Busset et al. 2012) and pad-dyeing technology (Yuan et al. 2013).

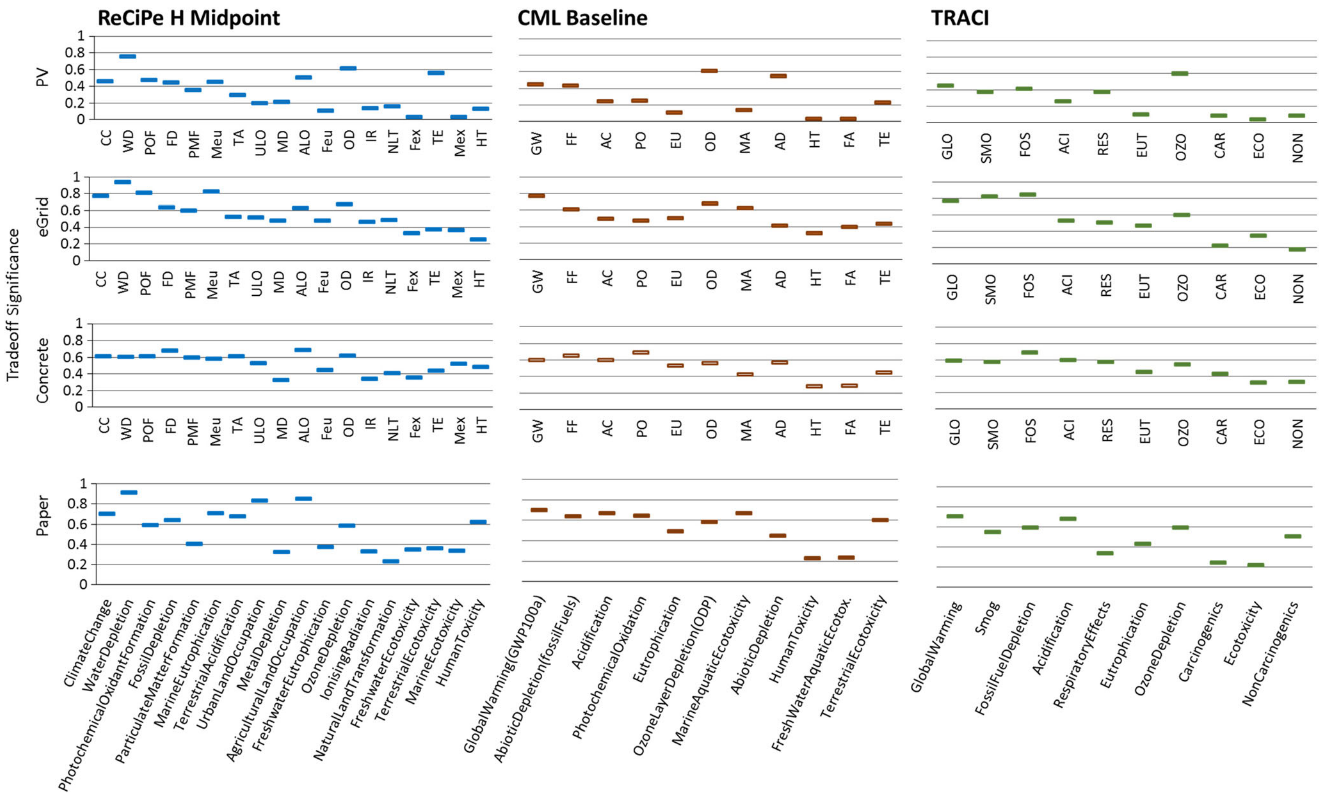

Fig. 3 Tradeoff significance (*y*-axis) per impact category in each application (PV, eGrid, concrete, and paper) and LCIA method (ReCiPe, CML, and TRACI) according to the overlap area approach. Tradeoff significance correlates to significant differences between alternatives. Impact categories in the *x*-axis correspond to each LCIA method and are arranged in ascending order according to the average coefficient of variation (same as in Fig. 2). Thus, the uncertainty in characterized impacts relative to mean values increases as the impact categories move right

The US 2008 normalization reference within TRACI highlights carcinogenics, non-carcinogenics, and ecotoxicity impact categories (Fig. 2). These externally normalized results are also replicated by Rostkowski et al. (2012) in a bioplastic example and again by White and Carty (2010) in 800 different processes.

Alternatively, application of the overlap area to the four comparative LCA application is shown in Fig. 3. The *x*-axis represents the impact categories as characterized by ReCiPe, CML, and TRACI arranged according to the coefficient of variation. The *y*-axis measures the tradeoff significance, Ψ_i, in each application ranging from 0 to 1 according to Eq. (4). For example, in the PV comparative LCA application (individual graph in the top left corner of Fig. 3), the performances at characterization of alternatives (CdTe, A-Si, Single-Si, Multi_Si, and Ribbon-Si) are most different in water depletion (high Ψ) and nearly undistinguishable in freshwater and marine ecotoxicity (low Ψ) when using ReCiPe characterization factors. For each application, the overlap area calls attention to the most significant differences, the tradeoffs, to guide the selection process. Unlike in external normalization, the overlap area results show no clear pattern across applications. More importantly, the relative scales of tradeoff significance across impact categories lies within the same order of magnitude. Thus, avoiding an assessment where a few or a single impact category dominates results.

4 Discussion

The normalization references evaluated in this study show a systematic bias where the same impact categories are highlighted regardless of the LCA application, uncertainty or geographical coverage of the normalization reference. In all four applications, the use of global or regional normalization references had little influence in the outcome of the results as both point out to the same impact categories. Therefore, previous recommendations on the choice of a normalization reference fail to avoid bias. Within ReCiPe H midpoint, the highest normalized contributions in the EU and World normalization references come from freshwater ecotoxicity, marine ecotoxicity, and human toxicity (Fig. 2). Similarly, both EU25 and World 2000 normalization references within CML baseline consistently identify marine aquatic ecotoxicity as the largest contributor to normalized scores across all four applications (Fig. 2). Finally, TRACI US 2008 normalization reference identifies carcinogenics, ecotoxicity, and non-carcinogenics the most influential impact categories in all four comparative LCA applications (Fig. 2). Consistently, the external normalization approaches in the three LCIA methods highlight toxicity-related impacts. This may be due to the underestimation of toxicity impacts in the area of coverage in the normalization reference dataset because of the lack of emission data and characterization factors. Previous studies comparing LCIA methods shed light on gaps in characterization factors and explain how that may influence the outcome of results (Huijbregts et al. 2003; Cavalett et al. 2012; Castellani et al. 2016). For instance, the issue of characterization of impacts of metals has been an issue in impact assessment that leads to an overestimation of ecotoxicity impacts as seen in CML-IA (Ligthart et al. 2004; Heijungs et al. 2007). Given the consistency of results over diverse applications, it is unlikely this bias is due to an overestimation at inventory level in the product system (as newer inventory libraries become available, this type of evaluation could help point out biases early on). These and other conceptual issues in normalization have been discussed extensively in the literature (Bare and Gloria 2006; Bare et al. 2006; Sleeswijk et al. 2008; Finnveden et al. 2009; Bare 2009), but what is most concerning is that these gaps can have such strong influence on the results. It is also concerning that the results obtained in this study are shown repeatedly in the recent literature across a wide range of applications with different temporal and geographical scales including water systems, steel beams, cleaning products, and bioenergy.

It is important to have these limitations in mind when interpreting externally normalized results in improvement assessment. One recommendation is to include hotspot analysis from outside of LCA and call attention to flows not characterized to complement the analysis and obtain more robust conclusions (Castellani et al. 2016). Solving issues in data completion requires extensive and constant data compilation efforts to achieve a complete and up-to-date normalization reference (Kim et al. 2013). These efforts, although theoretically plausible, suffer from great practical challenges as achieving data completion is an endless, laborious task. Ideally, a perfect normalization reference will not have such biases but rather show a more balanced result that varies across inventories. The questions are then, “How will we know when we have an adequate normalization reference? How can we obtain unbiased results?” Previous studies have arbitrarily attempted to scale down normalized data “peaks” as in White and Carty (2010), but such repair efforts lack a fundamental basis.

Alternatively, the use of planetary boundaries or carrying capacity based normalization references has been proposed as a way to provide a better measure of absolute impacts (Bjørn et al. 2015; Bjørn and Hauschild 2015; Fang et al. 2015). This can function as some sort of “threshold” that rejects alternatives exceeding such planetary boundaries following a strong sustainability approach (Janeiro and Patel 2015). The use of the planetary boundaries can also help prioritize areas for improvement and set reduction goals (Sandin et al. 2015). However, there are some issues remaining with planetary boundaries that hinder its application in LCA. For instance, reaching consensus over the planetary boundary per impact category and scaling to a relevant geographical and/or product scale. It is also unclear how to deal with impact categories that exceed established planetary boundaries. With advancements in these areas, planetary boundaries could serve as a basis for narrowing down alternatives and complementing existing interpretation approaches for comparative and improvement assessment.

In contrast to improvement assessment, external normalization remains wholly unsatisfactory for the purposes of comparative LCAs, even in the case of complete datasets. The issues highlighted in the paper concern the practice of external normalization in any impact assessment beyond the illustrated three LCIA methods. While more up-to-date inventories, characterization factors and external normalization reference datasets may produce slightly different results (Owsianiak et al. 2014), the fact is that when evaluating competing alternatives, any form of external normalization will by definition fail to evaluate mutual differences. So, while there are more up-to-date LCIA methods available (such as the ILCD method), the interpretation approach for comparative LCAs remains limited. Thus, the problem identified in this paper goes beyond data completion solutions and rather it calls for a *paradigm shift in the way we approach interpretation of comparative LCAs.*

Even in the case of an ideal normalization reference, external normalization does not evaluate mutual differences with respect to uncertainty. Thus, it does not highlight the tradeoffs in a particular decision and changes in information that may increase or decrease uncertainty ranges will not influence the results. Currently, the level of uncertainty that is propagated up to characterization does not determine whether an impact category is highlighted or not. For instance, the normalization references in ReCiPe and TRACI highlight the impact categories with the largest coefficient of variation (Fig. 2), so they can lead to recommendations driven by the aspects of largest uncertainties. In addition, in the case of preparing for weighting, external normalization applies a linear function that allows for a single, or few, impact categories to dominate the assessment, as seen in previous cases of weight insensitivity and studies describing compensation in aggregation methods (Rowley et al. 2012).

Instead, this study calls for *decision-driven* (Stern and Fineberg 1996) approaches that evaluate mutual differences and incorporate data uncertainty in the interpretation of comparative results. As shown here, the overlap area uses quantitative uncertainty information, which can derive from inventory, characterization, and/or methodological choices (Mendoza Beltran et al. 2016). We can identify relevant aspects of a comparison with the overlap area between probability distributions or other approaches that evaluate mutual differences (Heijungs and Kleijn 2001; Prado-Lopez et al. 2014; Henriksson et al. 2015; Gregory et al. 2016; Wei et al. 2016). These results do not suffer from the systematic biases of external normalization, as the outputs vary for each LCA application (Fig. 3). Unlike external normalization, overlap area results adapt to changes in uncertainty information and can guide the decision towards those aspects where we have the most knowledge. Aspects with larger uncertainties that make alternatives indistinguishable from each other can then be identified as areas that benefit the most from data refinement efforts (Prado-Lopez et al. 2016).

The overlap area does not serve as a basis for weighting but it does help illustrate key properties required in alternative methods of aggregation. Previously, outranking has been proposed as an alternative method of normalization that can serve as preparation for weighting (Cinelli et al. 2014). Along with weighting, it allows aggregation of to an overall (probabilistic) score as shown in Prado-Lopez et al. (2014) and Rogers and Seager (2009). Outranking evaluates pairwise mutual differences with respect to uncertainty data of characterized results and applies a nonlinear function that avoids full compensation between good and poor performances. Compared to external normalization, outranking generates results that are more sensitive to different weight ranges (Rogers and Seager 2009).

5 Conclusions

This study shows that the effects of external normalization may overwhelm differences in inventory and technology applications. In ReCiPe, CML, and TRACI, external normalization highlights the same set of impact categories across four diverse representative applications even if they utilize distinct inventories. The same results were found in multiple other studies in the literature, thus providing further evidence of these systematic biases. As a consequence, results of external normalization can lead to recommendations based entirely in the normalization approach. Therefore, when using external normalization references for hotspot identification, it should be done with care and it may be useful to perform some complementary analysis. However, when dealing with multiple alternatives and tradeoffs between them, as in a comparative LCA, these systematic biases are an issue that is not resolved by better data or a different geographical coverage area (as both regional and global references had biases). External normalization is not suitable for comparative LCA, as the normalization step imposes a linear aggregation among impact categories that can dominate most weight schemes. In fact, any type of division by an external reference, whereas it pertains to total per capita impacts of a community or a particular aspect such as average per capita nutrition, mobility or energy use, will by definition fail to evaluate mutual differences and integrate uncertainty in the results. Rather, comparative LCA calls for a decision-driven approach for evaluation of relevant differences that is consistent with internal normalization.

Decision support in a comparative LCA must focus on evaluating the impact of the decision (e.g., elucidating tradeoffs) rather than the impact of individual alternatives (such as hotspot identification). This is achieved by evaluating mutual differences relative to uncertainty—a practice that has been adopted in several approaches. This practice is sensitive to changes in uncertainty of information, frees studies from issues of data completion in normalization references, enables prioritization of data refinement, and is sensitive to stakeholder and decision-maker values. This study illustrates the overlap area as one of the approaches to identify relevant aspects of a decision and proposes a paradigm shift in the way we approach interpretation of comparative LCAs.

Acknowledgments This material is based upon work supported by the National Science Foundation (NSF) under Grants No. 1140190 and No. 0937591, by the NSF and Department of Energy (DOE) Quantum Energy and Sustainable Solar Technologies (QESST) Engineering Research Center at Arizona State University under Grant No. 1041895. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the NSF or DOE. Finally, the authors would like to thank Jeoren Guinée, Reinout Heijungs, and the three anonymous reviewers for their valuable feedback.

References

Bare JC (2009) Life cycle impact assessment research developments and needs. Clean Techn Environ Policy 12:341–351

Bare J (2011) TRACI 2.0: the tool for the reduction and assessment of chemical and other environmental impacts 2.0. Clean Techn Environ Policy 13:687–696

Bare J, Gloria T (2006) Critical analysis of the mathematical relationships and comprehensiveness of life cycle impact assessment approaches. Environ Sci Technol 40:1104–1035

Bare J, Gloria T, Norris G (2006) Development of the method and U.S. normalization database for life cycle impact assessment and sustainability metrics. Environ Sci Technol 40:5108–5115

Barjoveanu G, Comandaru IM, Rodriguez-Garcia G et al (2014) Evaluation of water services system through LCA. A case study for Iasi City, Romania. Int J Life Cycle Assess 19:449–462

Bjørn A, Hauschild MZ (2015) Introducing carrying capacity based normalization in LCA: framework and development of references at midpoint level. Int J Life cycle Assess 1005–1018

Bjørn A, Diamond M, Owsianiak M et al. (2015) Strengthening the link between life cycle assessment and indicators for absolute sustainability to support development within planetary boundaries. Environ Sci Technol 150522103758006. doi: 10.1021/acs.est.5b02106

Boulay A, Bulle C, Deschênes L, Margni M (2011) LCA characterisation of freshwater use on human health and through compensation. Towards Life Cycle Sustain Manags 193–204

Busset G, Sangely M, Montrejaud-Vignoles M et al (2012) Life cycle assessment of polychlorinated biphenyl contaminated soil remediation processes. Int J Life Cycle Assess 17:325–336

Castellani V, Sala S, Benini L (2016) Hotspots analysis and critical interpretation of food life cycle assessment studies for selecting eco-innovation options and for policy support. J Clean Prod 140(Part 2):556–568

Cavalett O, Chagas MF, Seabra JEA, Bonomi A (2012) Comparative LCA of ethanol versus gasoline in Brazil using different LCIA methods. Int J Life Cycle Assess 18:647–658

Cinelli M, Coles SR, Kirwan K (2014) Analysis of the potentials of multi criteria decision analysis methods to conduct sustainability assessment. Ecol Indic 46:138–148

Corona B, San Miguel G, Cerrajero E (2014) Life cycle assessment of concentrated solar power (CSP) and the influence of hybridising with natural gas. Int J Life Cycle Assess 19:1264–1275

Cortés-Borda D, Guillén-Gosálbez G, Esteller LJ (2013) On the use of weighting in LCA: translating decision makers' preferences into weights via linear programming. Int J Life Cycle Assess 18:948–957

Dones R, Bauer C, Bolliger R et al. (2007) Life cycle inventories of energy systems: results for current systems in Switzerland and other UCTE countries. Ecoinvent report No. 5

Fang K, Heijungs R, De Snoo GR (2015) Understanding the complementary linkages between environmental footprints and planetary boundaries in a footprint–boundary environmental sustainability assessment framework. Ecol Econ 114:218–226

Finnveden G (1999) A critical review of operational valuation/weighting methods for life cycle assessment

Finnveden G, Hauschild MZ, Ekvall T et al (2009) Recent developments in life cycle assessment. J Environ Manag 91:1–21

Frischknecht R, Jungbluth N, Althaus H-J et al (2004) The Ecoinvent database: overview and methodological framework. Int J Life Cycle Assess 10:3–9

Gallego A, Rodríguez L, Hospido A et al (2010) Development of regional characterization factors for aquatic eutrophication. Int J Life Cycle Assess 15:32–43

Gloria TP, Lippiatt BC, Cooper J (2007) Life cycle impact assessment weights to support environmentally preferable purchasing in the United States. Environ Sci Technol 41:7551–7557

Goedkoop M, Heijungs R, Huijbergts M, et al. (2009) ReCiPe 2008. Report 1: characterisation

Gregory J, Noshadravan A, Olivetti E, Kirchain R (2016) A methodology for robust comparative life cycle assessments incorporating uncertainty. Environ Sci Technol 50:6397–6405

Guinée JB, Gorrée M, Heijungs R, Huppes G, Kleijn R, de Koning A, van Oers L, Wegener Sleeswijk A, Suh S, Udo de Haes HA, de Bruijn H, van Duin R, Huijbregts MAJ (2002) Handbook on life cycle assessment operational guide to the ISO standards. Kluwer Academic Publishers, Dordrecht

Hauschild MZ, Goedkoop M, Guinée J et al (2013) Identifying best existing practice for characterization modeling in life cycle impact assessment. Int J Life Cycle Assess 18:683–697

Hayashi K, Nakagawa A, Itsubo N, Inaba A (2006) Expanded damage function of stratospheric ozone depletion to cover major endpoints regarding life cycle impact assessment. Int J Life Cycle Assess 11: 150–161

Heijungs R, Kleijn R (2001) Numerical approaches towards life cycle interpretation five examples. Int J Life Cycle Assess 6:141–148

Heijungs R, Guinée J, Kleijn R, Rovers V (2007) LCA methodology bias in normalization: causes, consequences, detection and remedies. Int J Life Cycle Assess 12:211–216

Henriksson PJG, Guinée JB, Heijungs R et al (2014) A protocol for horizontal averaging of unit process data—including estimates for uncertainty. Int J Life Cycle Assess 19:429–436

Henriksson PJG, Heijungs R, Dao HM et al (2015) Product carbon footprints and their uncertainties in comparative decision contexts. PLoS One 10:1–11. doi:10.1371/journal.pone.0121221

Huijbregts MAJ, Breedveld L, Huppes G et al (2003) Normalisation figures for environmental life-cycle assessment: the Netherlands (1997/1998), Western Europe (1995) and the world (1990 and 1995). J Clean Prod 11:737–748

Huppes G, van Oers L, Pretato U, Pennington D (2012) Weighting environmental effects: analytic survey with operational evaluation methods and a meta-method. Int J Life Cycle Assess 17:876–891

Ibbotson S, Kara S (2013) LCA case study. Part 1: cradle-to-grave environmental footprint analysis of composites and stainless steel I-beams. Int J Life Cycle Assess 18:208–217

ISO (2006) International Standardization Organization 14044 (2006) Environmental management—life cycle assessment—requirements and guidelines

Janeiro L, Patel MK (2015) Choosing sustainable technologies. Implications of the underlying sustainability paradigm in the decision-making process. J Clean Prod 105:438–446

Jungbluth N, Stucki M, Flury K, Frischknecht R (2012) Life cycle inventories of photovoltaics

Kapur A, Baldwin C, Swanson M et al (2012) Comparative life cycle assessment of conventional and Green Seal-compliant industrial and institutional cleaning products. Int J Life Cycle Assess 17:377–387

Kasah T (2014) LCA of a newsprint paper machine: a case study of capital equipment. Int J Life Cycle Assess 19:417–428

Kim J, Yang Y, Bae J, Suh S (2013) The importance of normalization references in interpreting life cycle assessment results. J Ind Ecol 17: 385–395

Koellner T, Scholz RW (2007) Assessment of land use impacts on the natural environment. Part 1: an analytical framework for pure land occupation and land use change. Int J Life Cycle Assess 12:16–23

Laurent A, Hauschild MZ (2015) Normalisation. In: Hauschild MZ, Huijbregts MAJ (eds) Life cycle impact assessment. Springer Netherlands, Dordrecht, pp 271–300

Lautier A, Rosenbaum RK, Margni M et al (2010) Development of normalization factors for Canada and the United States and comparison with European factors. Sci Total Environ 409:33–42

Lewandowska A, Foltynowicz Z, Podlesny A (2004) Comparative lca of industrial objects part 1: LCA data quality assurance—sensitivity analysis and pedigree matrix. Int J Life Cycle Assess 9:86–89

Ligthart T, Aboussouan L, van de Meent D et al (2004) Declaration of Apeldoorn on LCIA of non-ferrous metals. SETAC Globe 5:46–47

Lloyd SM, Ries R (2007) Analyzing uncertainty in life-cycle assessment a survey of quantitative approaches. J Ind Ecol 11:161–181

Mendoza Beltran A, Heijungs R, Guinée J, Tukker A (2016) A pseudo-statistical approach to treat choice uncertainty: the example of partitioning allocation methods. Int J Life Cycle Assess 21:252–264

Miller SA, Theis TL (2006) Comparison of life-cycle inventory databases—a case study using soybean production. J Ind Ecol 10:133–147

Mirabella N, Castellani V, Sala S (2013) Life cycle assessment of bio-based products: a disposable diaper case study. Int J Life Cycle Assess 18:1036–1047

Monteiro H, Freire F (2012) Life-cycle assessment of a house with alternative exterior walls: comparison of three impact assessment methods. Energy Build 47:572–583

Motoshita M, Ono Y, Pfister S et al (2014) Consistent characterisation factors at midpoint and endpoint relevant to agricultural water scarcity arising from freshwater consumption. Int J Life Cycle Assess. doi:10.1007/s11367-014-0811-5

Muller S, Lesage P, Ciroth A et al (2016) The application of the pedigree approach to the distributions foreseen in Ecoinvent v3. Int J Life Cycle Assess 21:1327–1337

Myllyviita T, Leskinen P, Seppälä J (2014) Impact of normalisation, elicitation technique and background information on panel weighting results in life cycle assessment. Int J Life Cycle Assess 19:377–386

Navajas A, Bernarte A, Arzamendi G, Gandía LM (2014) Ecodesign of PVC packing tape using life cycle assessment. Int J Life Cycle Assess 19:218–230

Owsianiak M, Laurent A, Bjørn A, Hauschild MZ (2014) IMPACT 2002+, ReCiPe 2008 and ILCD's recommended practice for characterization modelling in life cycle impact assessment: a case study-based comparison. Int J Life Cycle Assess 19:1007–1021

Pfister S, Koehler A, Hellweg S (2009) Assessing the environmental impact of freshwater consumption in life cycle assessment. Environ Sci Technol 43:4098–4104

Prado V, Rogers K, Seager TP (2012) Integration of MCDA tools in valuation of comparative life cycle assessment. In: Life cycle assessment handbook: a guide for environmentally sustainable products. John Wiley and Sons, pp 413–431

Prado-Lopez V, Seager TP, Chester M et al (2014) Stochastic multi-attribute analysis (SMAA) as an interpretation method for comparative life-cycle assessment (LCA). Int J Life Cycle Assess 19:405–416

Prado-Lopez V, Wender BA, Seager TP et al (2016) Tradeoff evaluation improves comparative life cycle assessment: a photovoltaic case study. J Ind Ecol 4:710–718

Prasara-A J, Grant T (2011) Comparative life cycle assessment of uses of rice husk for energy purposes. Int J Life Cycle Assess 16:493–502. doi:10.1007/s11367-011-0293-7

Rogers K, Seager TP (2009) Environmental decision-making using life cycle impact assessment and stochastic multiattribute decision analysis: a case study on alternative transportation fuels. Environ Sci Technol 43:1718–1723. doi:10.1021/es801123h

Rostkowski KH, Criddle CS, Lepech MD (2012) Cradle-to-gate life cycle assessment for a cradle-to-cradle cycle: biogas-to-bioplastic (and back). Environ Sci Technol 46:9822–9829. doi:10.1021/es204541w

Rowley HV, Peters GM, Lundie S, Moore SJ (2012) Aggregating sustainability indicators: beyond the weighted sum. J Environ Manag 111:24–33. doi:10.1016/j.jenvman.2012.05.004

Ryberg M, Vieira MDM, Zgola M et al (2014) Updated US and Canadian normalization factors for TRACI 2.1. Clean Techn Environ Policy 16:329–339. doi:10.1007/s10098-013-0629-z

Saad R, Margni M, Koellner T et al (2011) Assessment of land use impacts on soil ecological functions: development of spatially differentiated characterization factors within a Canadian context. Int J Life Cycle Assess 16:198–211. doi:10.1007/s11367-011-0258-x

Sandin G, Peters GM, Svanström M (2015) Using the planetary boundaries framework for setting impact-reduction targets in LCA contexts. Int J Life Cycle Assess 20:1684–1700. doi:10.1007/s11367-015-0984-6

Schmidt W, Sullivan J, Strasse HF (2002) Weighting in Life Cycle Assessments in a Global Context EI = Eai Ri. 7:5–10

Seppälä J, Hämäläinen RP (2001) On the meaning of the distance-to-target weighting method and normalisation in life cycle impact assessment. Int J Life Cycle Assess 6:211–218. doi:10.1007/BF02979376

Sim S, Barry M, Clift R, Cowell SJ (2007) The relative importance of transport in determining an appropriate sustainability strategy for food sourcing. Int J Life Cycle Assess 12:422–431. doi:10.1007/s11367-006-0259-3

Sleeswijk AW, van Oers LFCM, Guinée JB et al (2008) Normalisation in product life cycle assessment: an LCA of the global and European economic systems in the year 2000. Sci Total Environ 390:227–240. doi:10.1016/j.scitotenv.2007.09.040

Stern PC, Fineberg HV (1996) Understanding risk: informing decisions in a democratic society. National Academies Press

Stewart TJ (2008) Robustness analysis and MCDA. European working group multiple criteria decision aiding

Struhala K, Stránská Z, Jan P (2014) Environmental assessment of thermal insulation composite material. Int J Life Cycle Assess 19:1908–1918. doi:10.1007/s11367-014-0796-0

Suh S, Huppes G (2005) Methods for life cycle inventory of a product. J Clean Prod 13:687–697. doi:10.1016/j.jclepro.2003.04.001

Van Hoof G, Vieira M, Gausman M, Weisbrod A (2013) Indicator selection in life cycle assessment to enable decision making: issues and solutions. Int J Life Cycle Assess 18:1568–1580. doi:10.1007/s11367-013-0595-z

Van Zelm R, Huijbregts MAJ, Van De Meent D (2009) USES-LCA 2.0—a global nested multi-media fate, exposure, and effects model. Int J Life Cycle Assess 14:282–284. doi:10.1007/s11367-009-0066-8

Verbeeck G, Hens H (2010) Life cycle inventory of buildings: a calculation method. Build Environ 45:1037–1041. doi:10.1016/j.buildenv.2009.10.012

Wei W, Larrey-Lassalle P, Faure T, et al. (2016) Using the reliability theory for assessing the decision confidence probability for comparative life cycle assessments. Environ Sci Technol acs.est.5b03683. doi: 10.1021/acs.est.5b03683

Wender BA, Prado V, Fantke P, et al. (2016) Calculating stochastic characterization factors in USEtox enables sensitivity-based research prioritization: the importance of C60 partitioning to suspended solids

Wernet G, Bauer C, Steubing B et al (2016) The Ecoinvent database version 3 (part I): overview and methodology. Int J Life Cycle Assess 21:1218–1230. doi:10.1007/s11367-016-1087-8

White P, Carty M (2010) Reducing bias through process inventory dataset normalization. Int J Life Cycle Assess 15:994–1013. doi:10.1007/s11367-010-0215-0

Yuan ZW, Zhu YN, Shi JK et al (2013) Life-cycle assessment of continuous pad-dyeing technology for cotton fabrics. Int J Life Cycle Assess 18:659–672. doi:10.1007/s11367-012-0470-3