Stochastic Multi Attribute Analysis for Comparative Life Cycle Assessment

by

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ABSTRACT

Comparative life cycle assessment (LCA) evaluates the relative performance of multiple products, services, or technologies with the purpose of selecting the least impactful alternative. Nevertheless, characterized results are seldom conclusive. When one alternative performs best in some aspects, it may also performs worse in others. These tradeoffs among different impact categories make it difficult to identify environmentally preferable alternatives. To help reconcile this dilemma, LCA analysts have the option to apply normalization and weighting to generate comparisons based upon a single score. However, these approaches can be misleading because they suffer from problems of reference dataset incompletion, linear and fully compensatory aggregation, masking of salient tradeoffs, weight insensitivity and difficulties incorporating uncertainty in performance assessment and weights. Consequently, most LCA studies truncate impacts assessment at characterization, which leaves decision-makers to confront highly uncertain multi-criteria problems without the aid of analytic guideposts. This study introduces Stochastic Multi attribute Analysis (SMAA), a novel approach to normalization and weighting of characterized life-cycle inventory data for use in comparative Life Cycle Assessment (LCA). The proposed method avoids the bias introduced by external normalization references, and is capable of exploring high uncertainty in both the input parameters and weights.

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CHAPTER 1

INTRODUCTION

Comparative Life Cycle Assessments (LCAs) are useful in understanding the environmental implications of novel technologies, alternative processing techniques, potential business ventures and policy scenarios. Relative to previous applications, these new demands require LCA methods that address greater data uncertainties, elucidate environmental tradeoffs, and incorporate multiple stakeholder views (Canis, Linkov, & Seager, 2010; Prado-Lopez et al., 2014; Rogers & Seager, 2009). In particular, there is a growing need for LCA interpretation tools that can help decision makers navigate through complex comparative techno-environmental problems.

However, comparative LCA results are seldom conclusive. When one alternative is better in some areas but worse in others, the consensus-based ISO methods for conducting impact assessment are inadequate for identifying salient tradeoffs. These practices, currently codified in the ISO standards, can systematically hide the impacts that require the most attention. In addition, current approaches to weighing trade-offs rely on point estimates that ignore uncertainty in human values and provide an overly narrow view of complex environmental problems. Therefore, comparative LCAs are not equipped with interpretation tools that convert data to decision-relevant information in a concise and transparent manner.

These methodological limitations with respect to the interpretation stage of an LCA make comparison of alternatives difficult for analysts forced to confront multiple, often contradictory environmental indicators. In fact, it has recently become clear that the problem of environmental assessment in a comparative context raises different methodological issues than does the goal of existing process improvement. For example, interpretation of improvement assessment LCA focuses on the absolute magnitude of impacts for hotspot identification, while comparative LCA should focus on the relative differences between alternatives for trade off evaluation (Prado-lopez et al., 2015).

Specifically, comparative LCAs present analytic challenges because they:

- deal with environmental tradeoffs which decision-makers have relatively little analytical experience,
- are expressed with incommensurate physical units,
- typically engender relatively high uncertainty, and
- require subjective value judgments from decision makers and stakeholders that are often at odds (Boufateh, Perwuelz, Rabenasolo, & Jolly-Desodt, 2011; Téno, 1999).

Each of these challenges is characteristic of a set of problems in Multi Criteria Decision Analysis (MCDA), suggesting that comparative LCA can benefit from the incorporation of decision analytic tools in the interpretation stage (Benoit & Rousseaux, 2003; Dorini, Kapelan, & Azapagic, 2010; El Hanandeh & El-Zein, 2010; Jeswani, Azapagic, Schepelmann, & Ritthoff, 2010; Rogers & Seager, 2009; Rowley & Peters, 2009; Rowley & Shiels, 2011; Seager, Raffaelle, & Landi, 2008; Seppälä, Basson, & Norris, 2002).

This doctoral dissertation evaluates the appropriateness of stochastic multi attribute analysis (SMAA) as an interpretation method to guide the selection process in comparative LCAs. SMAA explores the significance of mutual differences at characterization in comparative problems via outranking normalization and performs a stochastic exploration of weights to include all possible perspectives. The goal is to implement interpretation methods that can work in the presence of tradeoffs, uncertainty and a diversity of stakeholders. This work is composed of four journal articles (the first two are available in the literature, the complete work of the last two are included in this dissertation document, Chapters 2 and 3 respectively):

1. Prado, V., Rogers, K., and Seager, T.P. 2012. "Integration of MCDA tools in valuation of comparative life cycle assessment" in Life Cycle Assessment: A Guide to Sustainable Products, Benefits of Life Cycle Thinking (Curran, M.A eds.). Wiley. ISBN: 9781118099728

This book chapter describes the state of practice in LCA interpretation, includes challenges and limitations of existing external normalization practices and takes a preliminary look into MCDA methods applicable to comparative LCAs. Two characteristics are key when selecting an MCDA method for an environmental comparative assessment: 1) a method should avoid full compensation by implementing a nonlinear aggregation function and 2) the assessment should be context dependent, meaning it should be relative, rather than absolute in nature. Implementing a partially compensatory method is important in an environmental context because it avoids trading one environmental impact for another. A relative assessment implies that the normalization stage utilizes data within the study (as opposed to external normalization) in order to identify the most significant mutual differences. Relative assessments support the deliberate process because they are easier to implement. In addition, this work re visits the issue of "congruency in normalization" by Norris, 2001 which calls for external normalization. This study shows alternative methods of internal normalization based in pair wise comparisons, not previously not accounted for in Norris, 2001. After evaluating the different types of MCDA methods, this chapter recommends the use of relative, partially compensatory methods such as outranking as a normalization approach in comparative LCAs. In specific, it calls for Stochastic Multi Attribute Analysis (SMAA) as a method for normalization and weighting in comparative LCAs because it is relative, partially compensatory, does not require value function elicitation, and it is inclusive of uncertainty in performances and weights.

2. Prado-Lopez, V., Seager, T.P., Chester, M., Laurin, L., Bernardo, M., Tylock, S. 2014. "Stochastic Multi-attribute Analysis (SMAA) as an interpretation method for comparative Life Cycle Assessment (LCA)" International Journal of Life Cycle Assessment. 19(2):405-416

This study goes a step further than the book chapter by applying SMAA to a comparative LCA of two laundry detergent formulations, powder and liquid, and contrasting SMAA with existing interpretation practices. While the final recommendation of both methods favored the same product, the impact categories that drove the assessment were different in each method. SMAA is driven by those impact categories most different among alternatives (in accordance with data uncertainty). In contrast, existing practice is driven by those aspects that are the largest according to the normalization reference. SMAA methods incorporate the range of possible performances via uncertainty analysis, while existing methods utilize average values all throughout the calculation process. Furthermore, weighting in SMAA includes all possible weights by doing a stochastic exploration, while existing methods are limited to applying an "equal weights" approach. SMAA represents a major advancement in LCA interpretation practice because it directly studies relevant differences as opposed to performances with respect to an external baseline.

3. Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted)

Current standards for interpretation are open, unstructured, and leave LCA practitioners to apply ad hoc heuristics provided by popular software packages, rather than by application of robust analytic methods. Most LCA practitioners leave comparative results as a bar chart or a radar plot. Bar charts may be useful for hotspot identification, but they fail to communicate important tradeoff information. Both, bar charts and radar plots portray mean values alone that do not quantify statistical significance. In addition, comparative and improvement assessment LCAs require distinct interpretation approaches because each formulates separate questions. Improvement assessment LCA is concerned with contribution analysis or magnitude of impacts for hotspot identification, while comparative LCA, is decision driven and it focuses on identifying the decision with the least environmental burden.

To aid in result interpretation at characterization, this study proposes examination of the area between probability distributions as a way to measure tradeoff significance. Standard LCA software packages allow for exploration of uncertainty through Monte Carlo simulation which results in a lognormal distribution for each impact category based on the Pedigree Matrix. When alternatives perform very similar in a given impact category (yielding a greater overlapping area), the tradeoff becomes less significant. However, when alternatives have distinct contributions to an impact category (smaller overlapping area), this tradeoff becomes more significant. Here, choosing one alternative over the other makes a difference for such impact category independently of weights. This approach can help reduce the list of indicators to the most meaningful to the decision at hand and render a more tractable problem, both cognitively and computationally.

Demonstration of this approach is done via a comparative LCA of five different photovoltaic (PV) technologies for a domestic installation. Findings show that tradeoff significance does not correlate with hotspot analysis since each measure distinct properties of the data.

Calculations in this study was done with a customized software tool, SMAA-LCA, currently under a provisional patent application.

4. Prado-Lopez V, Wender B, Seager TP, 2015. Systematic evaluation of normalization (to be submitted to Environmental Science and Technology)

Recommendations of a decision support tool in an LCA context are difficult to validate. Instead, a systematic evaluation of the methodology can evaluate whether biases exist and determine the method with the least bias. This study is the first in evaluating the systematic effects of external and outranking normalization (as in SMAA) over three different impact assessment methods (ReCiPe, CML and TRACI) and four different comparative LCA applications (PV, paper pulp production, electric grid mixes and lightweight concrete materials).

Effects of normalization approaches are evaluated in terms of individual contributions of impact categories, variability of normalized results and to a lesser extent, weight sensitivity. Findings show that external normalization approaches tend to highlight the same set of impact categories regardless of the application. The same pattern was further validated by the most recent published works in the International Journal of Life Cycle Assessment. For instance, external normalization in CML consistently highlights Marine Aquatic Ecotoxicity. Furthermore, variability of externally normalized results across all LCIA methods is much smaller than in outranking normalization, which indicates higher insensitivity to inventory and tradeoffs between alternatives. Weight sensitivity in this case is a function of the normalization approach. If the normalization step generates results that are dominated by a few or a single impact category, this leads to greater weight insensitivity as shown with an example using CML. In contrast, outranking normalization highlights different impact categories in each application and its larger variability indicates a higher sensitivity to inventory and technology applications. Therefore, given ReCiPe, CML or TRACI characterization, it is best to avoid external normalization as a way to guide the decision making process in a comparative LCA. Instead, comparative LCAs should apply interpretation methods that are sensitive to uncertainty and the tradeoffs present in each application.

Together, these four studies, build a new method for interpreting comparative LCAs. The new method, SMAA-LCA, is inclusive of uncertainty in parameters, weights and does not rely in external reference values – making LCA more applicable in decision driven contexts.

CHAPTER 2

TRADEOFF EVALUATION

2.1 Abstract

Current life cycle assessment (LCA) interpretation practices typically emphasize hotspot identification and improvement assessment. However, these interpretation practices fail in the context of a decision driven comparative LCA where the goal is to select the best option from a set of dissimilar alternatives. Interpretation of comparative LCA results requires understanding of the tradeoffs between alternatives – instances in which one alternative performs better or worse than another – to identify the environmental implications of a specific decision. In this case, analysis must elucidate relative trade-offs between decision alternatives, rather than absolute description of the alternatives individually. Here, typical practices fail. This paper introduces a probability distribution-based approach to assess the significance of performance differences among alternatives that allows LCA practitioners to focus analyses on those aspects most influential to the decision, identify the areas that would benefit the most from data refinement given the level of uncertainty, and complement existing hotspot analyses. In a case study of a comparative LCA of five photovoltaic (PV) technologies, findings show that thin film Cadmium Telluride (CdTe) and amorphous cells (a-Si) panels are most likely to perform better than other alternatives. Additionally, the impact categories highlighted by the new approach are different than those highlighted by typical external normalization practices, suggesting that a decision-driven approach to interpretation would redirect environmental research efforts.

2.2 Decision driven comparative LCAs

Comparative Life Cycle Assessments (LCAs) quantify the life cycle environmental impacts of equivalent products, technologies or processes throughout all the life phases, from raw material extraction to final disposal (Prado, Rogers, & Seager, 2012). A decision-driven comparative LCA, where the goal is to identify the most environmentally viable alternative(s) among a set of options, can guide material and processing selection in industry, identify a best policy scenario to inform environmental regulations, and lead researchers towards the most promising areas for reduction of environmental impacts in technology development. However the results are seldom conclusive and when one alternative performs best in some aspects, it often also performs worse in others - these tradeoffs among the different impact categories make it difficult to identify the most viable alternative.

Because ISO guidelines leave all steps after characterization as optional, the majority of comparative LCAs truncate analysis at characterization (ISO, 2006). Thus comparative LCA results are typically presented as bar charts or radar plots generated by popular software packages and informed by ad hoc heuristics as opposed to robust decision analytic methods. While existing data visualization techniques can identify tradeoffs, they are based solely on the difference of mean values and fail to evaluate the significance of tradeoffs (Dias & Domingues, 2014; Heijungs & Kleijn, 2001; Heijungs, Suh, & Kleijn, 2005).

Comparative LCAs that go beyond characterization and perform external normalization (at midpoint or endpoint) leave decision makers vulnerable to biases because they introduce uncertainty that is unquantifiable. Therefore, regardless of data completion, results remain subject to the characteristics of the external reference (Finnveden et al., 2009; Heal, 2000;

Heijungs, Guinée, Kleijn, & Rovers, 2007; Lautier et al., 2010; Prado et al., 2012; Reap, Roman, Duncan, & Bras, 2008; Rogers & Seager, 2009). Most importantly, external normalization evaluates magnitude for hotspot identification rather than the statistical significance of mutual differences for tradeoff evaluation. The size of the impacts relative to an external reference do not inform how distinguishable the differences between alternatives are. Therefore, hotspots and tradeoffs refer to different characteristics of the data and should implement distinct evaluation approaches. Tradeoff evaluation in comparative LCA can narrow down the assessment to those aspects that are most different among alternatives and more clearly describe the compromises of each choice. Proper tradeoff evaluation should take into account distributional characteristics to assess the impact categories most significant to the decision, and those which benefit the most from data refinement because their respective uncertainties remain too large to make a distinction between alternatives. To aid in result interpretation of comparative LCAs at characterization, we present a tradeoff identification approach that measures the overlap area between probability distributions as a way to evaluate tradeoff significance. Illustration of the overlap area approach, as compared to a bar chart or external normalization, is done with a case study of a comparative LCA of five photovoltaic (PV) technologies.

2.2.1 Case Study: Comparative LCA of PV technologies for a roof installation

Current practice in the PV industry is to select technologies either for maximum return on investment (as in utility scale installations) or maximum energy generation per square foot (as in some building integrated installations), without knowledge of the comparative environmental life-cycle tradeoffs. To demonstrate the advantages of full tradeoff evaluation, we present a comparative LCA to inform the selection of photovoltaic (PV) technologies for domestic installation. The case study compares the environmental impacts associated with production of one MJ electricity generated by five PV alternatives in a 3kWp slanted-roof installation. The different PV technologies for this type of installation are: single crystalline silicon cells (single-Si), multi crystalline silicon cells (multi-Si), thin film Cadmium Telluride (CdTe), amorphous cells (a-Si) and ribbon silicon (ribbon-Si) (Table 1).

Table 1. Photovoltaic technologies description (Chapter 12, Jungbluth, Stucki, Flury, & Frischknecht, 2012)

PV Technology alternative	Ecoinvent v3 inventory process	Cell efficiency (%)	comments
Single-Si	Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, laminated, integrated | Alloc Def, U	15.3	Made from a single crystal and has the highest efficiency, but requires more processing.
Multi-Si	Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, laminated, integrated | Alloc Def, U	14.9	Formed by multiple crystals in different orientation which results in lower efficiencies but cheaper manufacturing
CdTe	Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, CdTe, laminated, integrated | Alloc AU	13.7	Done by depositing thin layers of PV material on a glass, steel or plastic backing. Cost reductions because it uses less semiconductor materials
a-Si	Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, laminated, integrated | Alloc Def, U	6.5	Glass type mix made from silicon and hydrogen
Ribbon-Si	Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, laminated, integrated | Alloc Def, U	11.7	Made from multi crystalline wafers that are directly crystallized from silicon melt thus avoids sawing losses.

All life cycle inventories are based on Jungbluth et al (2012) and are modeled in Ecoinvent 3 (Muller et al., 2014). Ecoinvent uses data from PV systems in Switzerland, Germany, Spain and the US, assumes a 30 year life span, and models dismantling and disposal according to standard scenarios. For the silicon based PV technologies, life cycle inventory data includes impacts associated with quartz reduction, silicon purification, wafer and laminate production. For the thin film CdTe alternative, inventory data includes the raw material extraction of semiconductor, panel and auxiliary materials that go into production. In addition, modeling includes, transportation, infrastructure and the materials required for installation and operation such as the inverter, mounting equipment, cleaning and wiring. The results of this case study can be applied to at least two ways: 1) to identify those PV technologies that offer environmental advantages in market segments for which they are currently not selected, and 2) to steer the research and development agenda towards environmental improvement of those technologies that dominate certain market segments.

The comparative LCA will inform the selection of PV technologies to be installed in a building and evaluate the implications of increasing efficiency by implementing more intensive manufacturing or vice versa. To address parameter uncertainty in Ecoinvent data, this study performs uncertainty analysis with 1000 Monte Carlo runs based on the Pedigree Matrix parameters (Lewandowska, Foltynowicz, & Podlesny, 2004; Prado-Lopez et al., 2014). While there are other ways of generating uncertainty data (Lloyd & Ries, 2007) this study uses the Pedigree Matrix because of its accessibility through standard LCA software packages. The Pedigree Matrix generates a lognormal distribution for each characterized impact category based on uncertainty coefficients for six data quality indicators: reliability of source, completeness, sample size, temporal differences, geographical differences and further technological differences (Weidema & Wesnæs, 1996). The PV Ecoinvent processes used in this study include the data quality indicator scores that generate the corresponding standard deviations and mean values. We apply ReCiPe Europe Hierarchist as a midpoint impact assessment method and thus generate 18 different impact categories for each of the five PV technology alternatives (Table 2).

Table 2. Characterized results with ReCiPe Midpoint World Hierarchist impact assessment (Goedkoop et al., 2009).

Impact Category	Unit	a-Si		CdTe		Multi- Si		Ribbon-Si		Single-Si	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Agricultural land occupation	m2a	4.9E-4	1.9E-4	6.9E-4	2.0E-4	1.2E-3	3.6E-4	1.0E-3	3.0E-4	1.1E-3	3.5E-4
Climate change	kg CO2 eq	1.6E-2	4.1E-3	1.3E-2	2.5E-3	1.9E-2	4.0E-3	1.7E-2	3.6E-3	2.2E-2	4.8E-3
Fossil depletion	kg oil eq	4.1E-3	1.1E-3	3.3E-3	6.8E-4	5.0E-3	1.1E-3	4.4E-3	9.1E-4	5.8E-3	1.3E-3
Freshwater ecotoxicity	kg 1,4-DB eq	7.3E-6	2.4E-6	7.7E-6	2.3E-6	9.4E-6	2.8E-6	9.6E-6	2.7E-6	9.5E-6	2.7E-6
Freshwater eutrophication	kg P eq	1.7E-5	1.0E-5	2.0E-5	2.1E-5	1.8E-5	1.0E-5	1.7E-5	1.1E-5	1.9E-5	1.2E-5
Human toxicity	kg 1,4-DB eq	8.5E-3	3.6E-3	1.1E-2	4.8E-3	1.1E-2	4.1E-3	1.1E-2	4.0E-3	1.1E-2	4.6E-3
Ionising radiation	kBq U235 eq	2.1E-3	2.5E-3	2.2E-3	3.2E-3	2.8E-3	2.9E-3	2.6E-3	2.8E-3	3.6E-3	4.5E-3
Marine ecotoxicity	kg 1,4-DB eq	9.1E-5	4.0E-5	1.1E-4	5.8E-5	1.5E-4	7.5E-5	1.6E-4	7.3E-5	1.5E-4	6.9E-5
Marine eutrophication	kg N eq	5.6E-6	1.5E-6	6.2E-6	1.6E-6	8.8E-6	2.1E-6	8.8E-6	2.1E-6	9.8E-6	2.3E-6
Metal depletion	kg Fe eq	9.0E-3	2.5E-3	8.5E-3	2.1E-3	7.1E-3	1.9E-3	6.9E-3	1.9E-3	7.2E-3	2.0E-3
Natural land transformation	m2	2.4E-6	1.5E-6	1.9E-6	1.6E-6	2.8E-6	2.8E-6	2.5E-6	2.4E-6	3.0E-6	2.5E-6
Ozone depletion	kg CFC-11 eq	9.5E-10	3.2E-10	9.6E-10	2.9E-10	3.4E-9	9.28E-10	3.36E-9	8.85E-10	3.28E-9	8.40E-10
Particulate matter formation	kg PM10 eq	4.7E-5	1.2E-5	3.8E-5	7.9E-6	5.0E-5	1.0E-5	4.8E-5	9.8E-6	5.9E-5	1.3E-5
Photochemical oxidant formation	kg NMVOC	5.8E-5	1.5E-5	5.1E-5	1.1E-5	8.0E-5	1.7E-5	7.7E-5	1.6E-5	8.9E-5	2.0E-5
Terrestrial acidification	kg SO2 eq	1.2E-4	3.1E-5	1.1E-4	2.3E-5	1.4E-4	2.9E-5	1.3E-4	2.7E-5	1.6E-4	3.4E-5
Terrestrial ecotoxicity	kg 1,4-DB eq	2.4E-6	9.8E-7	3.0E-6	1.3E-6	3.5E-5	3.4E-5	3.9E-5	3.0E-5	3.4E-5	2.8E-5
Urban land occupation	m2a	1.9E-4	5.7E-5	1.8E-4	4.6E-5	2.1E-4	5.3E-5	1.9E-4	5.1E-5	2.3E-4	6.5E-5
Water depletion	m3	8.9E-2	2.6E-2	5.9E-2	1.4E-2	3.1E-1	8.8E-2	2.3E-1	5.7E-2	2.9E-1	7.7E-2

According to the LCA classification matrix by Herrmann, Hauschild, Sohn, & McKone, 2014, the selection of PV technologies for domestic installation corresponds to an LCA type with an inevitable large scope and uncertainty (type: TMi-PCY). Therefore, results and comparison of this study to other PV applications should be done among studies with the same classification.

The comparative LCA results in Table 2 are typically presented as a bar chart (Figure 1), to display the results in a more approachable format. Figure 1 identifies advantages and disadvantages of each alternative based on mean estimates, and calls attention to tradeoffs in nearly all categories.

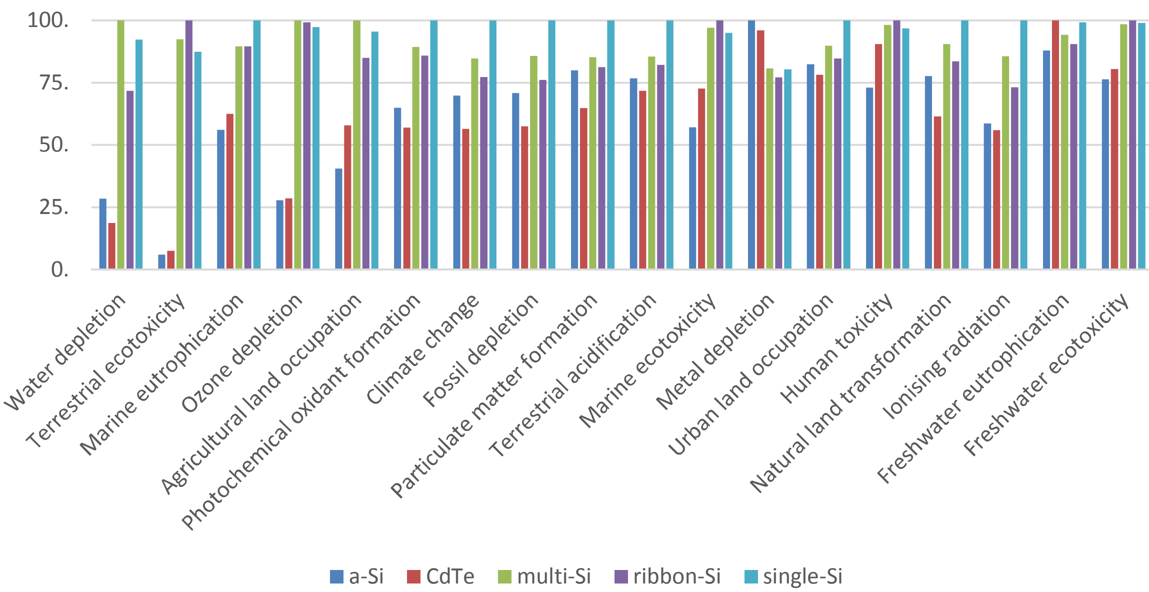

Figure 1. Bar chart representation of mean characterized results. Greatest differences between PV alternatives appear to be in Water Depletion, Terrestrial Ecotoxicity, Marine Eutrophication and Ozone Depletion. A-Si and CdTe perform best is most categories, although CdTe has the highest impact in Freshwater Eutrophication.

The bar chart shows that single-Si and multi-Si perform worse in a majority of impact categories, while CdTe and a-Si perform best in most categories. However, CdTe demonstrates the greatest environmental burden in Freshwater Eutrophication. In addition, the greatest differences between alternatives appear to be in Ozone Depletion, Terrestrial Ecotoxicity and Water Depletion.

Another common approach is to apply external normalization to these results (Figure 2). Externally normalized results highlight the impacts in Freshwater Eutrophication, Human Toxicity, Marine Ecotoxicity, Natural Land Transformation and Metal Depletion. The Water Depletion impact category is excluded because there is no normalization reference available for it.

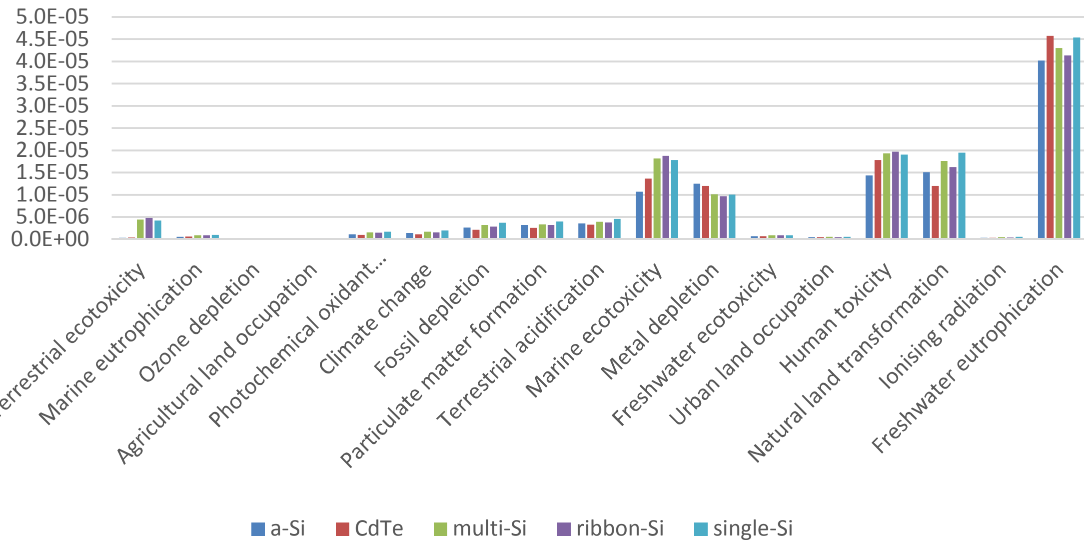

Figure 2. Normalized results with ReCiPe Europe. The Water Depletion category is excluded in this figure because there is no reference available for it. Externally normalized results highlight the impact categories Freshwater Eutrophication, Natural Land Transformation, Marine Ecotoxicity and Metal Depletion. The impact categories highlight here differ from those aspects that appear to have the greatest difference among alternatives in the bar chart (Figure 1).

Externally normalized results are often used in a comparative assessment to highlight those tradeoffs that are most significant. However, this practice assesses alternatives individually according to the area of reference for hotspot identification rather than measuring the significance of mutual differences relative to data uncertainty. Therefore, while external normalization continues to provide valuable information for hotspot identification and can guide improvement actions, the impacts highlighted in Figure 2 do not correspond to the most salient tradeoffs in the decision.

2.3 Overlapping area approach for tradeoff evaluation

An alternative approach to interpret comparative LCA results is to evaluate the significance of tradeoffs by utilizing the probability distributions of characterized results (Table 2). By calculating the overlapping area between each alternative's probability distribution in every impact category, the significance of each tradeoff is assessed relative to data uncertainty. Impact categories in which alternatives perform alike display greater overlap area between the distributions (Figure 3a), and the tradeoff is revealed as less significant than cases in which performance is substantially different (i.e., smaller overlap area, Figure 3b).

In this way, tradeoff significance informs the impact of the decision: when alternatives have very similar contributions to an impact category, the decision makes less of a difference than when alternatives have distinct performances. Therefore, the overlapping area between two probability distributions of characterized results can systematically sort impact categories according to the significance of the tradeoff independent of weight selection.

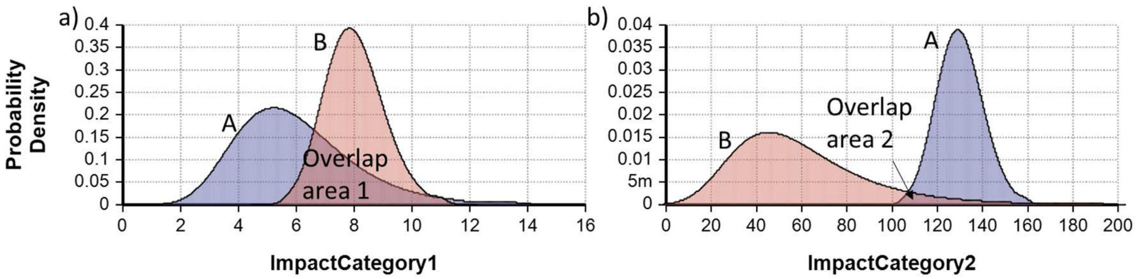

Figure 3. Example showing the characterized impact of two alternatives, A and B, over two impact categories. Given the size of the overlap areas, there is a greater tradeoff in impact category 2 (3b).

The shaded area in Figure 4 represents the overlapping area of two probabilistic distributions of a characterized impact. The overlapping area ranges between 0 and 1(for identical distributions). The goal is to identify the impact categories in which alternatives perform the most different from each other and yield a smaller overlapping area.

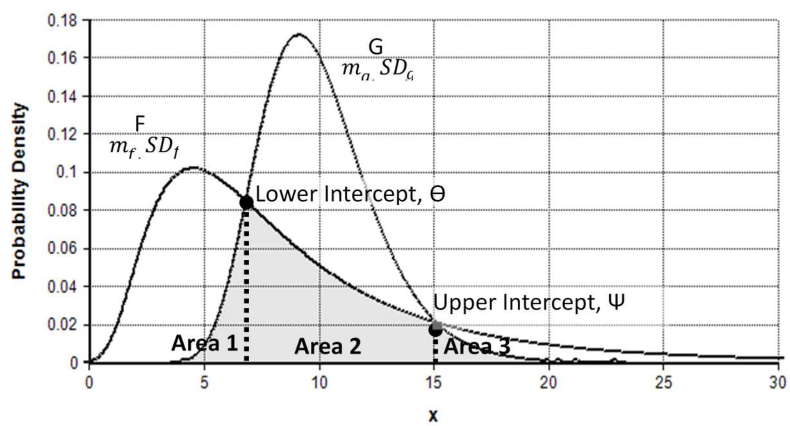

Figure 4 Shows two overlapping lognormal distributions (F and G) with arithmetic parameters of mean, m and standard deviation, SD. The two curves intersect at x values of Θ and Ψ. The x-axis represents the characterized performance of an impact category. F and G in this case represent the uncertain performance of two different alternatives on a single impact category.

The overlap area is a function of the mean and distribution of the characterized inventory after uncertainty analysis (Table 2). Calculation has three main parts: conversion of normal parameters, solution of intercepts, and summation of areas, described in detail below.

Conversion of normal parameters

Normal parameters of the mean, m, and standard deviation, SD, as generated by the uncertainty analysis via the Pedigree Matrix (Table 2), must be converted to lognormal parameters, μ and σ, respectively for each alternative on each impact category accordingly:

$$\sigma = \sqrt{\ln(1 + \frac{SD^2}{m^2})} \qquad \text{Eq. 2.1}$$

And $\mu = \ln(m) - \frac{1}{2}\sigma^2$ Eq. 2.2

Solution of intercepts

Two lognormal distributions have two intercepts that yield three areas (Area 1, Area 2 and Area 3) as shown in Figure 4. The two intercepts are solved by calculating the x-value, Θ and Ψ, at which both of the alternatives, F and G, have the same probability distribution function (PDF) value:

$$PDF_f = PDF_g \qquad \text{Eq. 2.3}$$

$$\frac{1}{x\sigma_f\sqrt{2\pi}} e^{-\frac{(lnx - \mu_f)^2}{2\sigma_f^2}} = \frac{1}{x\sigma_g\sqrt{2\pi}} e^{-\frac{(lnx - \mu_g)^2}{2\sigma_g^2}} \qquad \text{Eq. 2.4}$$

$$x = \exp\left[\frac{1}{2\left(\sigma_f^2-\sigma_g^2\right)}\left(\pm\sqrt{\begin{matrix}[\left(2\sigma_f^2\mu_g - 2\mu_f\sigma_g^2\right)^2 - 4(\sigma_g^2-\sigma_f^2)(\mu_f^2\sigma_g^2 - \sigma_f^2\mu_g^2 + \\ 2\sigma_f^2\sigma_g^2\log\left(\sigma_f\right) - 2\sigma_f^2\sigma_g^2\log\left(\sigma_g\right)]\end{matrix}} - 2\mu_f\sigma_g^2 + 2\sigma_f^2\mu_g\right)\right] \qquad \text{Eq. 2.5}$$

Solving for the intercepts, Θ and Ψ in Equation 5, provide the bounds for the three partial areas. Each of these areas can be measured by the value of the cumulative distribution function (CDF) of either F or G – depending which one yields a smaller value. The ranges for the CDFs are: x<Θ, Θ<x<Ψ, and x>Ψ. For the specific case of Figure 4 the overlap area, A, in grey, is calculated as follows:

A =if $(\sigma_f = \sigma_g\ and\ \mu_f = \mu_g\ then\ 1, else\ (Area_1 + Area_2 + Area_3))$ Eq. 2.6

Where:

$$Area_1 = CDF_g\ (x = \theta) \qquad \text{Eq. 2.7.1}$$

$$Area_2 = CDF_f(x = \Psi) - CDF_f(x = \theta) \qquad \text{Eq. 2.7.2}$$

$$Area_3 = 1 - CDF_g(x = \Psi) \qquad \text{Eq. 2.7.3}$$

After calculating the overlap areas across all impact categories, these can be sorted in ascendant order depending on their magnitude. That is, the most significant tradeoffs would be the ones where the overlap area is smaller.

The overlap area approach is similar to the discernibility analysis as proposed by Heijungs & Kleijn, 2001 because both evaluate tradeoff significance. However, the overlap area approach facilitates sorting the impact categories according to tradeoff significance in problems involving more than two alternatives. In addition, this approach could be expanded to fit all distributions other than lognormal (Muller et al., 2014). For comparisons with more than two alternatives, significance of tradeoffs in each impact category is measured in a pair wise basis. Therefore, given the number of alternatives greater than two, n, there are $f(n)$ number of possible pair wise area calculations for each impact category, i

$$f(n)_i = \binom{n}{2} = \frac{n(n-1)}{2} \qquad \text{Eq. 2.8}$$

Let $G = \{1,2,\ldots,n\}$ be the set of alternatives and C is the 2-subset of G ({{1, 2}, {1, 3}, …, {n-1, n}}) then the overlapping areas can be calculated for all A_α where $\alpha \in C$.

For example, in the PV case study with 5 alternatives, there are 10 distinct overlap areas for each of the 18 impact categories. Overall tradeoff significance of each impact category, i, can then be evaluated according to the average of the overlap areas resulting from all possible pairs (Eq. 2.9). The average values are then sorted in an ascending order so that impact categories are organized from most to least significant (See Appendix). This information can then help narrow the analysis to those indicators most influential to the decision.

$$\frac{2}{n(n-1)} \sum_{\alpha \in C} A_\alpha \qquad \text{Eq. 2.9}$$

2.4 Results

Results from the application of the overlap area approach to the case study of PV technologies indicate that the most significant tradeoffs among alternatives are in the categories of Water Depletion, Terrestrial Ecotoxicity and Ozone Depletion (Figure 5).

Tradeoff significance

	Impact Category	Average area Eq. 9	Top 2
1	Water depletion	0.26	CdTe A-Si
2	Terrestrial ecotoxicity	0.37	A-Si CdTe
3	Marine eutrophication	0.40	A-Si CdTe
4	Ozone depletion	0.48	A-Si CdTe
5	Agricultural land occupation	0.51	A-Si CdTe
6	Photochemical oxidant	0.54	CdTe A-Si
7	Climate change	0.56	CdTe A-Si
8	Fossil depletion	0.57	CdTe A-Si
9	Particulate matter formation	0.67	CdTe A-Si
10	Terrestrial acidification	0.73	CdTe A-Si
11	Marine ecotoxicity	0.75	A-Si CdTe
12	Metal depletion	0.78	Ribbon-Si Single-Si
13	Freshwater ecotoxicity	0.79	A-Si CdTe
14	Urban land occupation	0.83	CdTe A-Si
15	Human toxicity	0.84	A-Si CdTe
16	Natural land transformation	0.84	CdTe A-Si
17	Ionising radiation	0.85	CdTe A-Si
18	Freshwater eutrophication	0.88	A-Si Ribbon-Si

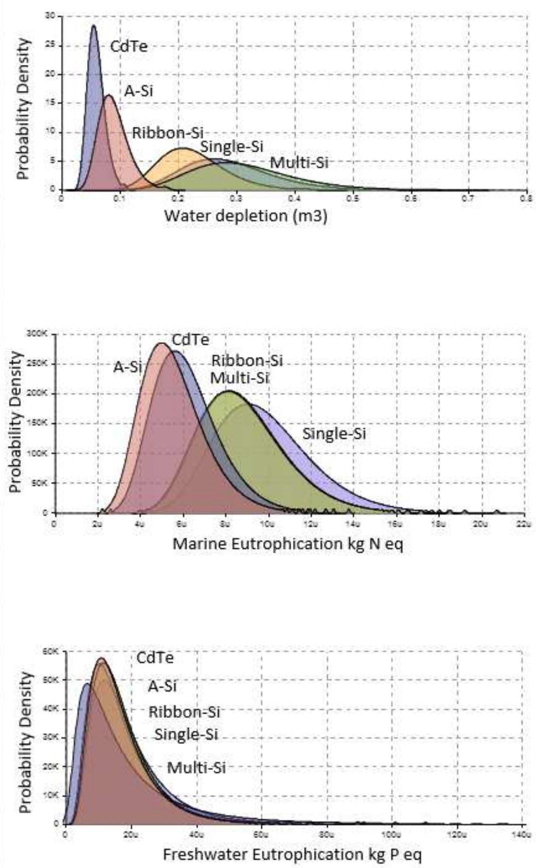

Figure 5. Relative tradeoff significance according to the overlap area approach. Each list sorts tradeoff significance according to Eq. 9 and shows the PV alternatives with best performances in each impact category. Impact categories in grey are those highlighted by external normalization in Fig. 2

CdTe and a-Si have the smallest impact in the top 5 impact categories, thus indicating greater environmental promise. The impact categories towards the bottom of the list (Freshwater Eutrophication, Ionizing Radiation, and Natural Land Transformation) have smaller influence in the decision because the PV alternatives perform very similar to each other. Given the large uncertainty, it is difficult to make a case for either PV alternative. Therefore, data refinement should focus in the processes contributing to the impact categories on the bottom of the list. According to the mean values in the bar chart (Figure 1), CdTe had the highest impacts in Freshwater Eutrophication, but such disadvantage has a low significance as seen by Figure 5. When plotting the probabilistic performance of the PV alternatives in Freshwater Eutrophication, it is seen that all PV alternatives have very similar performances so the difference in means becomes undistinguishable. The plots for the performances in Water Depletion, Marine Eutrophication, and Freshwater Eutrophication in Figure 5 support the results of the overlap area approach. As tradeoff significance increases the differences between alternatives become more apparent. The impact categories towards the bottom of the lists are those which will benefit from data refinement in order to better evaluate the impact of the decision.

The shaded impact categories in Figure 5 are those highlighted according to external normalization in Figure 2. In fact, the impact categories in Figure 2 are organized from left to right according to the results of the overlap area, but there is no correlation. These results do not coincide because they evaluate distinct characteristics of the data (hotspot vs tradeoff). External normalization can be useful to identify those issues that require the most attention within a product system, but do not evaluate the impact of the decision. In this case, all five PV technologies should focus improvement actions in the processes contributing to Marine

Ecotoxicity, Metal Depletion, Human Toxicity, Natural Land Transformation and Freshwater Eutrophication as highlighted by external normalization. However, the selection of either of these PV technologies will result in a relatively small difference for these environmental concerns. Basing a decision on the aspects with a large overlap area (closer to 1) can lead to decision making based on noise given the high uncertainty in these aspects.

The selection of a PV technology should focus on the aspects that are most distinguishable from one another given the data uncertainty: Water Depletion, Terrestrial Ecotoxicity, Marine Eutrophication, Ozone Depletion, and Agricultural Land Occupation. Since CdTe and a-Si perform the best in these impact categories, they are most likely to be environmentally preferred.

2.5 Discussion

When faced with a comparative LCA for understanding the relative environmental implications of each alternative to inform a selection, it is necessary to focus the analysis in the mutual differences in way that takes into account uncertainty. The bar chart does look at mutual differences but fails to incorporate statistical information. The external normalization approach does not focus on mutual differences, but rather it calculates the magnitude relative to an external measure. Consequently, the results on external normalization inform hotspots, not tradeoffs. As seen in the results in Figure 5, the hotspots as highlighted by external normalization, do not coincide with the impact categories with most significant tradeoffs. For example, Freshwater eutrophication is an area that can benefit from improvement actions, but it does not represent a significant impact in the decision.

The overlap area approach provides a way to interpret comparative LCA results at characterization. For the PV case study it showed more clearly that the largest tradeoffs between the five PV technologies were found in Water Depletion, Terrestrial Ecotoxicity and Ozone Depletion. These differences were also shown in the bar chart (Figure1), but without a consistent way to sort the impact categories. The discernibility analysis in LCA is also aimed at evaluating tradeoffs, but it does not provide a way to evaluate overall tradeoff significance when faced with more than two alternatives. Given the results in Figure 5, CdTe and a-Si are most likely the best alternatives overall given they perform best in those impact categories with small overlap area. One of the limitations of the overlap area approach is that it requires an understanding of data uncertainty. While analysis via the Pedigree Matrix and Monte Carlo is available in standard LCA software packages, results can change depending on the data quality of different LCA tools (i.e Simapro or GaBi) (Herrmann & Moltesen, 2015). In cases where Pedigree coefficients are not available for all data categories, uncertainty information may be assigned by expert judgment or prospective analytical tools and tested for decision relevance (O'Hagan et al., 2006; Refsgaard, van der Sluijs, Højberg, & Vanrolleghem, 2007; Wender, Foley, Hottle, et al., 2014; Wender, Foley, Prado-lopez, et al., 2014). Thus, further analytic efforts may be conserved for only those data categories that emerge as influential, rendering the decision problem more tractable, both cognitively and computationally.

2.6 Conclusion

Hotspot and tradeoff evaluation provide different types of information in LCA. External normalization evaluates the magnitude of results to help prioritize areas for improvement. Alternatively, tradeoffs require evaluation of mutual differences taking into account uncertainties that are masked by bar chart and radar plot visualizations that do not evaluate the significance of mutual differences. Instead, measurement of the relative significance of tradeoffs using data uncertainty can help the interpretation process by identifying the most significant impact categories among all the ones calculated. In an impact assessment that generates a dozen or more different indicators amongst a number of alternatives, identifying which indicator differences are most significant will help guide the analysis towards those issues that are most influential to the comparison. Proper tradeoff identification informs decision makers and LCA practitioners as to where the compromise lies when selecting one alternative over the other. This understanding is key in transparent environmental decision making.

CHAPTER 3

SYSTEMATIC EFFECTS OF NORMALIZATION

3.1 Abstract

The majority of research efforts in Life Cycle Assessment (LCA) focuses on inventory, mid-point characterization factors and damage modeling. While these advancements improve understanding of life cycle environmental impacts, these efforts may prove ineffective for decision making given systematic biases in the interpretation stage. This study evaluates the influence of normalization methods on interpretation of comparative LCA to facilitate use of LCA in decision driven applications and inform LCA practitioners of latent systematic biases. 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. Specifically, this study evaluates external normalization practices used in CML baseline, ReCiPe Midpoint H, and TRACI LCIA methods, as well as one internal normalization method based on outranking, through application of four comparative studies: photovoltaic technologies, regional grid mixes, concrete formulations, and paper pulp processing. For each representative application we call attention to 1) the contribution of impact categories in external normalization for improvement assessment 2) the significance of tradeoffs between alternatives in each impact category according to outranking normalization 3) the variability of external and outranking normalization results across different technologies, and 4) the weight sensitivity as a result of the normalization approach.

There is a systematic bias in hotspot identification via external normalization that emphasizes the same impact categories regardless of the comparative LCA application: marine aquatic

ecotoxicity for CML, all ecotoxicities for ReCiPe, and human toxicities for TRACI. Consequently, the results of comparative LCA studies employing external normalization may result in recommendations dominated entirely by the normalization reference, insensitive to data uncertainty and independent of stakeholder weights. Conversely, normalization via outranking in comparative LCA evaluates the impact of the decision by calling attention to the impact categories with the most significant differences between alternatives relative to data uncertainty. Outranking normalization results do not show a systematic bias across LCA applications and generates an assessment inclusive of uncertainty and stakeholder weights.

This study shows that the effects of external normalization may be so strong as to overpower differences in inventory, making it inappropriate for decision support in comparative LCA applications. Conversely, novel methods of internal normalization that evaluate tradeoffs directly, incorporate uncertainty and do not rely on external references show greater sensitivity to tradeoffs and weight preferences.

Decision support in comparative LCA requires normalization methods capable of evaluating significant differences between alternatives to help identify the decision resulting in the least overall environmental impact.

3.2 Introduction

Research efforts in life cycle assessment (LCA) methods focus predominantly on building life cycle inventory (LCI) databases (Dones et al., 2007; Frischknecht et al., 2004; Jungbluth et al., 2012; Miller & Theis, 2006; Suh & Huppes, 2005; Verbeeck & Hens, 2010), calculating new mid-point characterization factors (Gallego, Rodríguez, Hospido, Moreira, & Feijoo, 2010; Hauschild et al., 2013; Koellner & Scholz, 2007; Pfister, Koehler, & Hellweg, 2009; Saad, Margni, Koellner, Wittstock, & Deschênes, 2011; Van Zelm, Huijbregts, & Van De Meent, 2009), and improving end-point damage modeling (Boulay, Bulle, Deschênes, & Margni, 2011; Hayashi, Nakagawa, Itsubo, & Inaba, 2006; Motoshita et al., 2014). Less emphasis has been placed on normalization and weighting, which are optional practices in life cycle impact assessment (LCIA) following characterization. There are numerous impact assessment methods available to LCA analysts that apply to any life cycle inventory, each with different characterization factors, impact categories, and normalization references. Some of the most widely applied LCIA methods are: 1) the Tool for Reduction and Assessment of Chemical and Other Environmental Impacts (TRACI) developed by the US Environmental Protection Agency (Jane Bare, 2011), 2) the Institute for Environmental Sciences (CML) impact assessment tool developed at the University of Leiden in the Netherlands (Guinee, 2002), and 3) ReCiPe which is the latest impact assessment methodology developed in partnership between four leading institutions (Goedkoop et al., 2009). These tools provide alternative methods of characterizing and interpreting environmental impacts from the myriad and disparate chemical releases reported in a life cycle inventory.

Studies have found that the results of an LCA can vary depending on the choice of impact assessment method and to date there are no specific guidelines for choosing one method over another (Dreyer, Niemann, & Hauschild, 2003; Zhou, Chang, & Fane, 2011). Instead, ISO guidelines recommend application of multiple impact assessment methods to test the robustness of the results (ISO, 2006). Previous evaluations of LCIA methods compare results at characterization (Cavalett, Chagas, Seabra, & Bonomi, 2012; Dreyer et al., 2003; Martínez, Blanco, Jiménez, Saenz-Díez, & Sanz, 2015; Owsianiak, Laurent, Bjørn, & Hauschild, 2014;

Renou, Thomas, Aoustin, & Pons, 2008) while some single out specific impact categories relevant to a particular application (Pant et al., 2004; Pizzol, Christensen, Schmidt, & Thomsen, 2011; Van Caneghem, Block, & Vandecasteele, 2010). A majority of these studies conclude that the choice of LCIA method influences recommendations based on characterized results, yet these studies stop short of evaluating the effects of normalization and weighting useful for decision-driven LCAs.

Although normalization is an optional step in LCIA, it remains crucial in providing decision support when facing environmental tradeoffs in comparative assessments with inconclusive results – such as when one alternative performs best in some areas and worse in others. Therefore, in problems of comparative technology assessment, characterized results alone seldom result in a definitive environmental choice, leaving decision makers to confront complex environmental trade-offs largely unaided in examples critical to sustainability. 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. This paper reviews current practices including approaches adopted by commercial LCIA packages, in comparison to one novel internal normalization method identified in the literature (Prado-Lopez et al., 2014). Next we demonstrate use of external and internal normalization approaches in four comparative LCA studies to evaluate patterns in the results indicative of systematic biases in normalization. Findings can help inform LCA practitioners of the implications in the choice of normalization methods in comparative assessments.

3.2.1 External normalization

External normalization provides context to characterized results by dividing them by an estimate of the total or per capita equivalent emissions in that impact category associated with an entire geographical region, as shown below in Equation 3.1. 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).

$$NI_{a,i} = \frac{CI_{a,i}}{NR_i} \quad \text{Equation 3.1}$$

Where:

$NI_{a,i}$ is the dimensionless normalized impact of alternative *a* in impact category *i*,

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

NR_i is the normalization reference representing a specific geographical region for impact category *i* in the same physical units as the corresponding characterized impact $CI_{a,i}$.

External normalization is intended to facilitate decision making by calling attention to damages in those impact categories that are the largest as compared to reference conditions and in this manner identify the aspects most relevant to a decision (Bare & Gloria, 2006; Van Hoof, Vieira, Gausman, & Weisbrod, 2013). However, external normalization faces several practical challenges, including gaps in normalization reference databases, lack of uncertainty information in normalization references, and limited coverage of geographical areas (Heijungs et al., 2007; Lautier et al., 2010; Prado et al., 2012). Beyond such practical limitations, critics argue that external normalization is fundamentally misleading because impact categories with larger regional emissions generate a smaller normalized impact and are thereby identified as less relevant (Rogers & Seager, 2009; White & Carty, 2010). This inverse proportionality effect between normalization references and normalized impacts may systematically mask salient aspects. For example, when White and Carty (2010) evaluate externally normalized results of 800 processes taken from Ecoinvent using CML Global 1995 and TRACI US 2000 normalization references authors find a bias where each normalization approach repeatedly highlights the same set of impact categories regardless of the process inventory used. 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 and do not coincide with th BEES stakeholder-based weighting schemes (Lippiatt & Boyles, 2001). White and Carty (2010), propose reducing the bias by applying external normalization in combination with internal normalization by division within a data set. However, regardless of the reference value and data set, external normalization and internal normalization by division, by definition apply a linear aggregation function that is fully compensatory (Prado et al., 2012). This means that it is possible for a single good performance to drive the results entirely, hiding multiple poor performances in other areas of the environment and promoting burden shifting. Despite these limitations, external normalization has become the preferred way of normalization due to earlier criticisms of internal normalization methods. “The requirement for congruence in normalization”, perhaps one of the most influential works regarding normalization in LCA, by Norris (2001) identifies issues of magnitude insensitivity and rank reversal when internal normalization *by division* is followed by external weighting. The study calls for both, external normalization and weighting. These criticisms assume all internal normalization to be "by division" and takes a normative, rather than descriptive approach to decision making (Prado et al., 2012). There are alternative methods of internal normalization via pair wise comparisons, such as outranking, with non-linear aggregation functions that are partially compensatory.

3.2.2 Outranking Normalization

Comparative LCA results present decision makers with multi criteria decision analysis (MCDA) problems, and numerous studies recommend incorporating MCDA tools to offer improved decision support (Benoit & Rousseaux, 2003; El Hanandeh & El-Zein, 2010; Jeswani et al., 2010; Rowley & Peters, 2009; Rowley & Shiels, 2011; Seppälä et al., 2002). Most recently, Stochastic Multi Attribute Analysis for LCA (SMAA-LCA), an interpretation method consisting of internal normalization via stochastic outranking and stochastic weighting, has been applied as an approach to enhance decision support in LCA (Canis et al., 2010; Prado-Lopez et al., 2014; Prado-lopez et al., 2015; Rogers & Seager, 2009; Wender, Foley, Prado-lopez, et al., 2014). SMAA-LCA is applied after characterization and can be implemented with all LCIA methods for comparative assessments. The main innovations of outranking normalization in SMAA-LCA are: 1) internal normalization via pair wise comparisons relative to measures of parameter uncertainty 2) non-linear and partially compensatory aggregation functions, and 3) stochastic exploration of uncertainties. By contrast, existing normalization methods within the LCIA methods are external, linear and predicated on point estimates of reference data.

Normalization within SMAA-LCA is based on a stochastic outranking algorithm that evaluates the significance of pair wise differences in characterized results relative to data uncertainty

(Prado-Lopez et al., 2014). Outranking normalization is concerned with finding differences among alternatives. The premise being that when faced with a comparison, distinct aspects drive the selection. For example, given a comparative LCA where all alternatives have the same global warming potential, selection of any alternative results in the same impacts to global warming regardless of stakeholder weights. Alternatively, if alternatives have different contributions in eutrophication, then eutrophication plays a larger role in the decision. 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 can 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., 2015).

Results from outranking are represented by a probability distribution with values ranging from 0 to 1, where 0 represents a negligible different between alternatives, and 1 represents a complete preference for each pair wise comparison on a single criterion. The effects of outranking normalization are easier represented by the overlap area approach in Prado-Lopez et al (2015) because it uses a single indicator per impact category rather than a probability distribution. The overlap area applies to 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. Like outranking, the overlap area focuses on mutual differences and favors those aspects where alternatives are the most distinguishable from one another.

3.2.3 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 (Cortés-Borda, Guillén-Gosálbez, & Esteller, 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., 2015). Discreet weight values can be derived from a panel of experts in a professional field (Gloria, Lippiatt, & Cooper, 2007), through surveys (Schmidt, Sullivan, & Strasse, 2002), monetization or willingness-to-pay techniques (Finnveden, 1999), linear programming (Cortés-Borda et al., 2013) and distance-to-target approaches (Seppälä & 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 (Prado-Lopez et al., 2014; Rogers & Seager, 2009). However, regardless of the elicitation process, weighting can remain ineffective depending on the aggregation function of the 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 (Cortés-Borda et al., 2013; Myllyviita, Leskinen, & Seppälä, 2014; Rogers & Seager, 2009; White & Carty, 2010). For instance, Myllyviita et al (2014) evaluates different weight elicitation approaches and finds that most weights have little influence in the results given external normalization. Myllyviita et al (2014) then concludes that in such instances weighting could be avoided. However, weighting should not be avoided in a decision driven context as identification of the best compromise is also a function of the decision maker preferences and not the normalization algorithm alone. Alternatively, in high uncertainty cases, internal normalization along with uncertainty analysis can generate more reliable results. In fact, decision support in LCA should guide the decision making process, not replace human judgment in its entirety. A method that provides a recommendation irrespective of stakeholder input is inadequate for transparent decision making. Weight insensitivity represents a major issue for environmental decision making, because it can yield results that are unsatisfactory for problems involving multi stakeholder groups.

3.3 Methods

This study applies both external and outranking normalization methods to characterized impacts of four comparative LCA applications to evaluate the influence of each approach. Specifically, we apply external normalization from: 1) CML EU25 2006 and World 2000 (Sleeswijk, van Oers, Guinée, Struijs, & Huijbregts, 2008), 2) ReCiPe midpoint H version 1.10 European and World (Goedkoop et al., 2009), and 3) TRACI US 2008 (Jane Bare, 2011; Ryberg, Vieira, Zgola, Bare, & Rosenbaum, 2014) LCIA methods. In addition, we apply the overlap area approach (Prado-lopez et al., 2015) to CML baseline, ReCipe midpoint H and TRACI characterized results to capture the effects of outranking normalization within SMAA-LCA (Prado-Lopez et al., 2014).

3.3.1 Representative Applications

This study uses four comparative LCA applications as variables to evaluate *how* normalization approaches handle characterized data. These applications represent broad sectors such as centralized and distributed energy, construction materials and paper pulp production, as summarized in Table 1. Inventory data for each process included in these comparative LCA applications is taken from the Ecoinvent 3.01 database (Ecoinvent, 2013).

Table 1. Comparative LCA applications*

Comparative LCA application	Description	Alternatives	Functional unit of the comparison
Photovoltaic Technologies (PV)	Electricity production of five PV technology alternatives in a 3kWp slanted-roof installation	Single crystalline silicon cells (single-Si), multi crystalline silicon cells (multi-Si), thin film Cadmium Telluride (CdTe), amorphous cells (a-Si) and ribbon silicon (ribbon-Si)	MJ
US electric grid mixes (eGrid)	High voltage electricity production from the ten regions in the US 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, and pumice	kg
Paper Pulp	Paper pulp production with five different processes	Chemi-thermomechanical pulp (CTM), stone groundwood pulp (SG), sulfate pulp, bleached sulfite pulp, thermo-mechanical pulp (TM)	kg

*Processes as they appear in Ecoinvent 3 in Supplementary Information.

Probability distributions at characterization used in the overlap area calculations, and consequently in SMAA-LCA, derive from an uncertainty analysis using the Pedigree Matrix coefficients available in Ecoinvent 3.01 (Lewandowska et al., 2004; Lloyd & Ries, 2007;

Weidema & Wesnæs, 1996). This procedure consisted of 1,000 Monte Carlo runs done separately for each alternative within each comparative LCA application using the three LCIA methods using Simapro. Here, characterized results consist of lognormal distributions per impact category (mean and standard deviation) rather than single value (Refer to supplementary information for complete set of results at characterization). Overlap area, outranking and stochastic weighting calculations are done via a standalone Java tool, SMAA-LCA, programmed as illustrated in Prado-Lopez et al (2014).

To evaluate the effects of external and outranking normalization in ReCiPe, CML baseline and TRACI, we isolate the normalization step by applying each LCIA method and corresponding normalization approaches to a set of four comparative LCA applications (Table 1). In this manner, the inventory and characterization factors remain constant while the normalization step changes. Here, the independent variable is the normalization approach and the results, broken down by impact category, represent the dependent variable (Figure 1). For each representative application we call attention to 1) The contribution impact categories in external normalization for improvement assessment 2) the significance of tradeoffs between alternatives in each impact category according to outranking normalization 3) the variability of external and outranking normalization results across different technologies, and 4) the weight sensitivity as a result of the normalization approach.

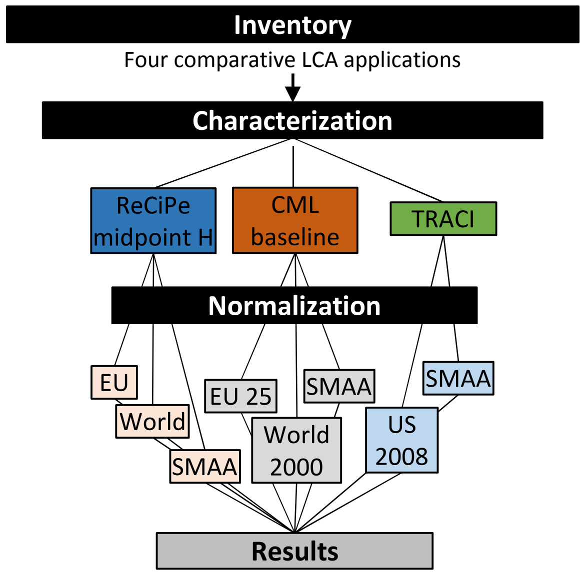

Figure 1. Schematic of the methodology evaluating the effects of normalization approaches in three LCIA methods.

3.3.2 Contribution impact categories in external normalization for improvement assessment

The contribution of each impact category, Θ_i describes the extent that each normalized impact category influences the results prior to weighting in each of the comparative LCA applications. 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. Contribution calculations are given by Equation 3.2 and 3.3. We evaluate these individual normalized contributions with respect to data uncertainty by arranging impact categories according to the coefficient of variation (more details in supplementary information).

$$\Theta_i = \frac{\sum_a \beta_{a,i}}{n} \quad \text{Equation 3.2}$$

$$\beta_{a,i} = \frac{NI_{a,i}}{\sum_i NI_{a,i}} \quad \text{Equation 3.3}$$

Where:

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),

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

$NI_{a,i}$ is the dimensionless normalized impact in impact category *i* of alternative a, given by Equation 3.1.

3.3.3 Significance of tradeoffs between alternatives in each impact category according to outranking normalization

In outranking normalization, the most influential impact categories in outranking normalization are those with the most significant tradeoffs between alternatives. A tradeoff significance, is defined as the mutual differences between the alternatives at characterization with relative to data uncertainty. These impact categories can be identified via the overlap area analysis as described by Prado-Lopez et al (2015). We evaluate the most influential impact categories across the set of comparative LCA applications and determine if a pattern exists.

Tradeoff significance, Ψ_i, of each impact category is a function of the pair wise overlap areas between alternatives, and is calculated according to Equation 3.4. The smaller the overlap area between two alternatives in an impact category, the more influential that impact category becomes in the assessment..

$$\Psi_i = 1 - (\frac{2}{n(n-1)} \sum_{\alpha \in C} A_\alpha) \quad \text{Equation 3.4}$$

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.

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

A_α is the overlap area of all pairs where G={1,2,…,n} represents the set of alternatives and C is the 2-subset of G ({{1, 2}, {1, 3}, …, {n-1, n}}). Individual overlap areas are a function of the mean and standard deviations of characterized results. Further calculation details are available in Prado-Lopez et al (2015).

3.3.4 Variability of external and outranking normalization results across different technologies

Variability of normalized results measures the similarity of outputs across applications to further examine biases. For instance, in the extreme case of a fully biased normalization approach, the results across various applications would be identical to one another. In this extreme case, calculation of the standard deviation of results yields 0 because outputs are identical. Similarly, we calculate, the standard deviation of all outputs by external normalization (Equation 3.5) and outranking normalization (Equation 3.6). Results are aggregated according to LCIA method: ReCiPe, CML and TRACI.

$$\sigma_{Ext,i} = \sqrt{\frac{1}{n}\sum_{n}(\beta - \mu_{ext})^2} \text{ and } \mu_{ext} = \frac{1}{n}\sum_{n}\beta \qquad \text{Equation 3.5}$$

$$\sigma_{out,i} = \sqrt{\frac{1}{n_p}\sum_{n_p}(A_\alpha - \mu_{out})^2} \text{ and } \mu_{out} = \frac{1}{n_p}\sum_{n_p}A_\alpha \qquad \text{Equation 3.6}$$

Where:

$\sigma_{Ext,i}$ is defined as the standard deviation of externally normalized results per impact category, i, according to a specific reference (i.e World 2000 in CML or US 2008 in TRACI) and includes outputs of all comparative LCA applications.

n is the number of outputs, which corresponds to the total number of alternatives in all comparative LCA applications. For external normalization, n = 25 in each impact category, i.

β is the value of each normalized contribution described in Equation 3.3

μ_{ext} is the average of all normalized contributions per impact category, i

$\sigma_{out,i}$ is defined as the standard deviation of outputs per impact category according to outranking normalization.

n_p is total number of outputs in all comparative LCA applications according outranking. For a comparison with 5 alternatives (as in PV, concrete and paper) there are 10 pairs. In a comparison with 10 alternatives (like in eGrid), there are 25 pairs. For all comparative LCA applications combined, $n_p = 75$

A_α refers to the magnitude of individual overlap areas which ranges from 0 to 1 and it is a function of the mean and standard deviation of characterized results. Calculation details in Prado-Lopez et al (2015).

3.3.5 Weight sensitivity

To explore the weight sensitivity of normalization approaches we extend the application of stochastic weights in SMAA (Prado-Lopez et al., 2014; Rogers & Seager, 2009; Tylock, Seager, Snell, Bennett, & Sweet, 2012) to all external normalization methods described above. Stochastic weights explore the entire weight space given the number of impact categories where weights are equally distributed and their sum equals one. For example, in the case of four impact categories, weights can equal 0.25 each or they can equal 0.7, 0.1, 0.1 and 0.1. This corresponds to two of the many possible weight sets. Stochastic weights capture all possible weight sets. Specific weight spaces change according to the number of impact categories. For example, ReCiPe characterizes inventory to 18 impact categories while TRACI characterizes the same inventory to 10 impact categories (weight distributions for all LCIA in supplementary information). We take the product of the normalized result and the weight function to aggregate results into a probabilistic ranking known as a rank acceptability index (Lahdelma & Salminen, 2001; Tervonen & Lahdelma, 2007).

The rank acceptability indices represents the portion of weights that position an alternative in a specific rank. For example, given all possible weights, alternative A ranks first 80% of the times. Comparing the rank acceptability index associated with each normalization method identifies those approaches that are more and least sensitive to different weight ranges. Rank orderings with larger rank acceptability indices are more weight insensitive because results remain the same given most weight values. Weight sensitivity is a key characteristic of any decision analytic method because it represents the receptiveness of the method to stakeholder or decision-maker values. Since weight sensitivity is a direct effect of the normalization method, we limit Illustration to one application in a single LCIA.

3.4 Results

Results show the systematic effects of external and outranking normalization approaches in ReCiPe, CML and TRACI by evaluating the contributions of externally normalized impact categories, tradeoff significance inherent in each application according to outranking normalization, variability of normalized results and weight sensitivity.

3.4.1 Contribution impact categories in external normalization for improvement assessment

Figure 2 shows the contribution of each impact category after applying external normalization in each of the four comparative LCA applications for ReCipe H midpoint, CML baseline and TRACI. The x-axis represents the impact category within each LCIA method organized according to the coefficient of variation (See Appendix for Chapter 3) so that the impact categories to the right have the largest uncertainty. The y-axis shows the contribution according to Equation 3.3.

Individual contributions of normalized impact categories in ReCiPe H Midpoint show that EU and World normalization methods both highlight toxicity and eutrophication related impact categories with the exception of natural land transformation, which is larger when using the EU reference. Impact categories with the largest contributions in EU and World references seem to replicate across the four LCA applications indicating the possibility of a systematic bias in the normalization approach. With the exception of Kasah (2014), this pattern was further validated by recent studies showing externally normalized results in ReCiPe (Corona, San Miguel, & Cerrajero, 2014; Ibbotson & Kara, 2013; Kapur et al., 2012; Mirabella, Castellani, & Sala, 2013; Prado-Lopez et al., 2014; Prasara-A & Grant, 2011; Van Hoof et al., 2013).

In CML baseline, contribution of normalized impact categories of EU25 and World2000 references across the four comparative LCA applications reveal that a single impact category, marine aquatic ecotoxicity, as the most and only dominant impact category (Figure 2). Here, the selection of alternatives in each example (PV, eGrid, concrete and paper pulp) is guided by a single impact category irrespective of data uncertainty. 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 (Barjoveanu, Comandaru, Rodriguez-Garcia, Hospido, & Teodosiu, 2014; Mirabella et al., 2013; Monteiro & Freire, 2012; Navajas, Bernarte, Arzamendi, & Gandía, 2014; Struhala, Stránská, & Jan, 2014; White & Carty, 2010), with some exceptions (Busset, Sangely, Montrejaud-Vignoles, Thannberger, & Sablayrolles, 2012; Yuan, Zhu, Shi, Liu, & Huang, 2013). 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. Normalized impact categories in TRACI with US2008 reference show high contributions of impact categories with relatively high uncertainty. In particular, carcinogenics, non carcinogenics and ecotoxicity have the largest contributions, as shown in Figure 2. These externally normalized results are also replicated by Rostkowski et al (2012) in a bioplastic example and by White and Carty (2010) in 800 different processes.

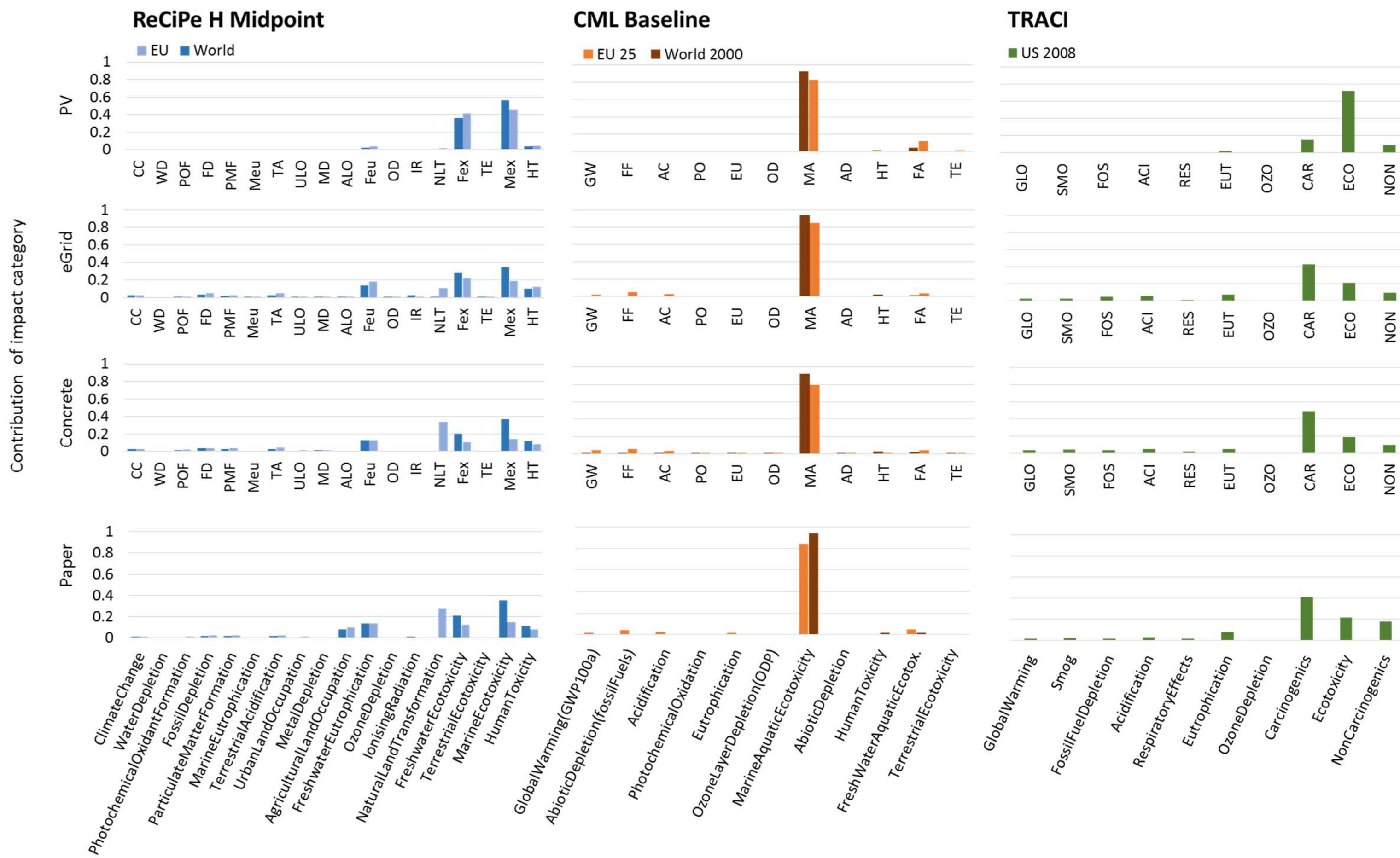

Figure 2. Shows the contribution per impact category according to normalization references across the four comparative LCA applications (top to bottom: PV, eGrid, Concrete and Paper Pulp) using ReCiPe midpoint H, C ML Baseline and TRACI LCIA methods (left to right). The impact categories in the x-axis correspond to each LCIA method and are arranged according to the average coefficient of variation.

3.4.2 Significance of tradeoffs between alternatives in each impact category according to outranking normalization

Figure 3 shows the tradeoff significance in each impact category for each application and LCIA method as evaluated by outranking in Equation 3.4. 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. For example, in the PV comparative LCA application (individual graph in the top left corner of Figure 2), 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, outranking calls attention to the most significant differences, the tradeoffs, to guide the selection process. Unlike in external normalization, outranking normalization 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.

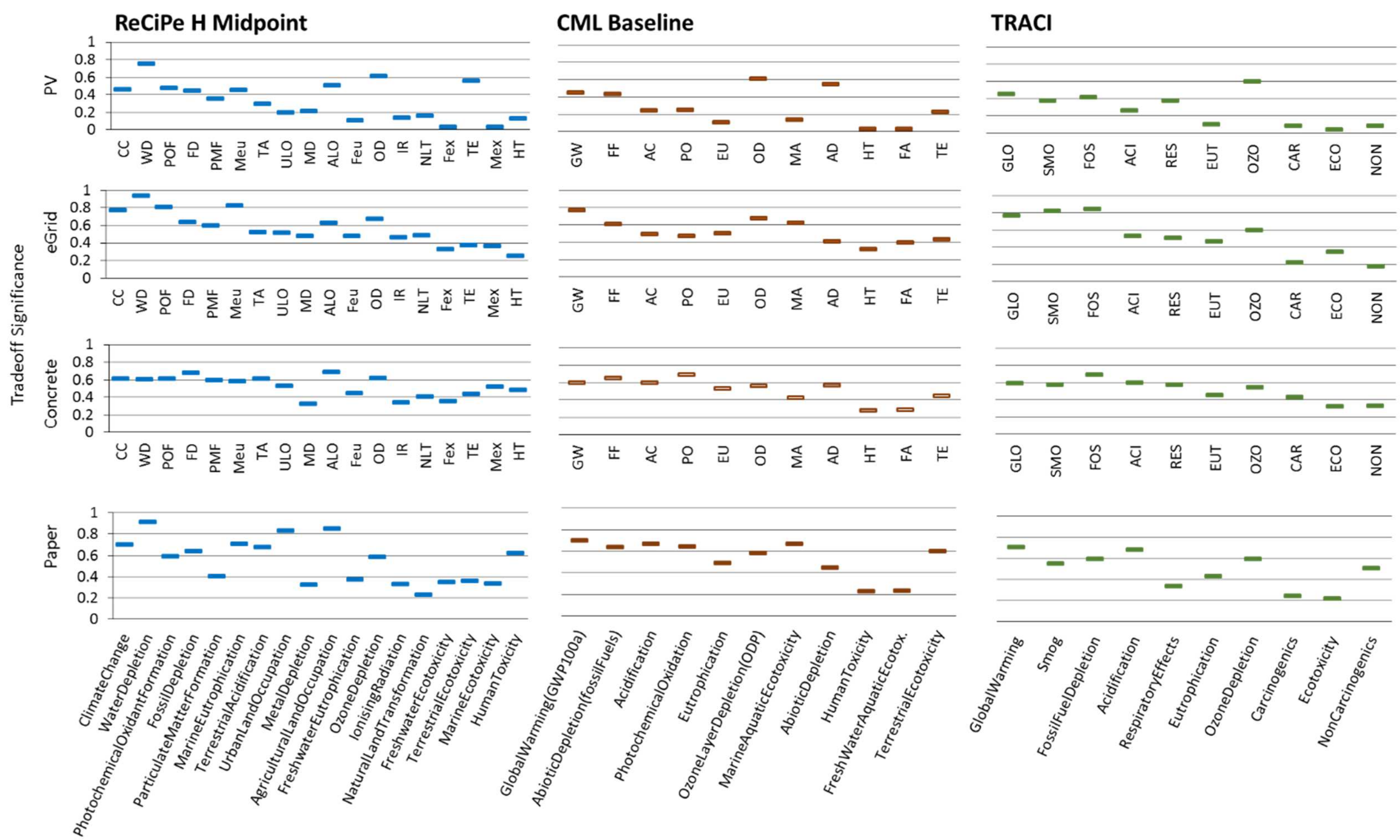

Figure 3. Shows tradeoff significance per impact category in each application (PV, eGrid, Concrete and Paper) and LCIA method (ReCiPe, CML and TRACI) according to outranking normalization3.4.3 Variability of external and outranking normalization results across different technologies.

Figure 4 shows the variability of external and outranking normalization results per impact category in ReCiPe H midpoint, CML and TRACI (top to bottom). The x-axis represents the impact categories of each LCIA arranged according to the coefficient of variation the same way as Figures 1 and 2. The y-axis is the standard deviation of each set of normalized results following Equation 3.5 for external normalization approaches and Equation 3.6 for outranking normalization. Outranking normalization results show larger variations in outputs than external normalization, with the exception of carcinogenics in TRACI US 2008. Variations from CML World 2000 and EU25 stand out by showing a result orders of magnitude smaller (middle graph in Figure 4). Furthermore, within externally normalized results, the variability tends to be much greater in those impact categories with larger contributions as shown in Figure 1. For instance, marine aquatic ecotoxicity has the largest variability in World 200 and EU 25 as compared to the other impact categories. This is because the magnitude of contributions for marine aquatic ecotoxicity, as seen by Figure 1, is much larger than the rest. Conversely, variations in outranking results across impact categories are much closer to one another.

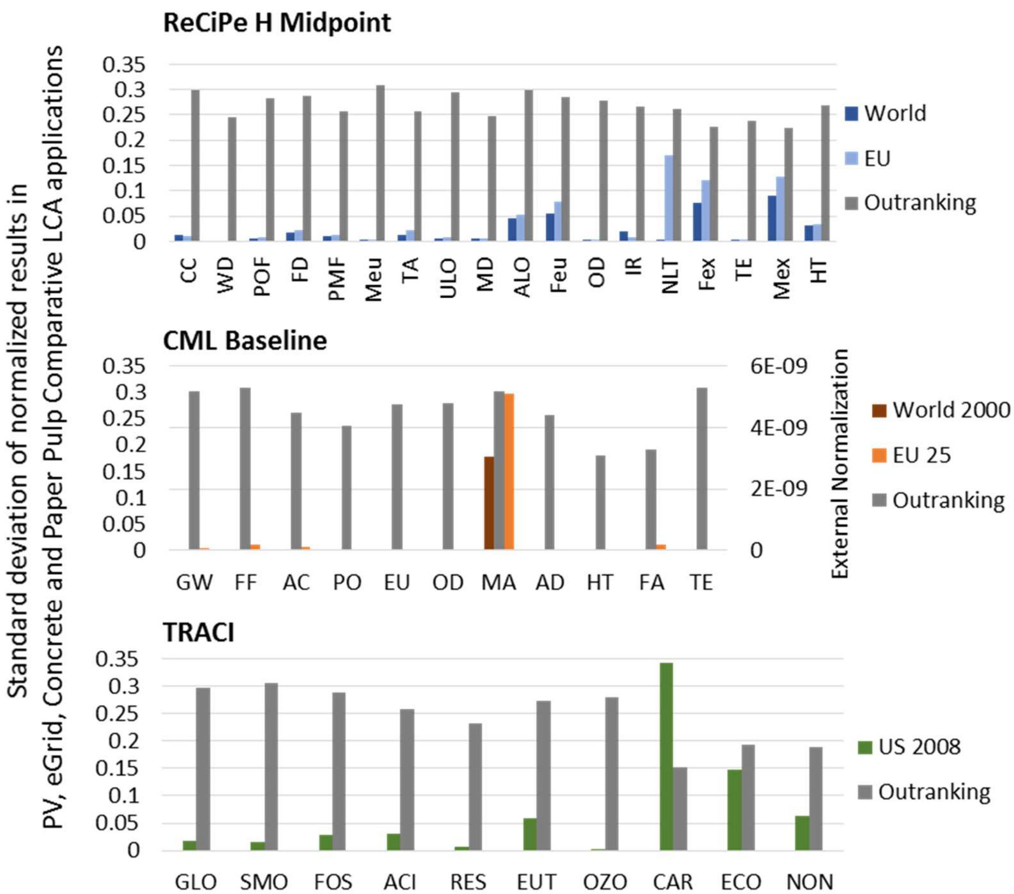

Figure 4. Shows the variability in normalized results across the four LCA applications per impact category in ReCiPe, CML and TRACI (Top to bottom). The impact categories of each LCIA in the x-axis are arranged according to the average coefficient of variation so that the ones with largest uncertainties are further to the right. Nomenclature of impact categories follows that of Figures 1 and 2.

3.4. 4 Weight sensitivity

Weight sensitivity as evaluated here, is a function of the normalization step and it measures the sensitivity of final results to diverse weight values. We limit illustration of weight sensitivity of external and outranking normalization to one comparative LCA application. We depict the weight sensitivity effects in CML baseline where external normalization biases are most prominent as compared to ReCiPe and TRACI (Figure 2). The goal is to show how the relative scales of normalized contributions can affect weighting rather than a thorough measure of weight sensitivity in each application. Figure 5 shows the rank acceptability indices for the PV comparative LCA using CML baseline characterization and three normalization approaches: World 2000, EU 25 and outranking. Rank compositions in World 2000 are the most weight insensitive because each alternative has a high probability of remaining in one single rank. For example, rank orderings in World 2000 show alternatives A-Si, CdTe, Single-Si, Multi-Si, and Ribbon-Si to have a 98%, 77%, 77%, 92% and 94% probability of ranking first to fifth respectively. This means that for most weight sets, the rank ordering of alternatives remains the same. Rank orderings in EU 25 show alternatives A-Si, CdTe, Ribbon-Si, Multi-Si, and Single-Si to have a 97%, 85%, 58%, 64% and 49% probability of occupying the first to fifth ranks respectively. Rank orderings generated with outranking normalization show alternatives CdTe, A-Si, Ribbon-Si, Multi-Si, and Single-Si with a 64%, 43%, 34%, 33% and 55% of ranking first to fifth respectively. Overall, the rank acceptability indices in outranking are smaller than in World 2000 and EU 25, indicating that the rank ordering of alternatives generated by outranking normalization is more sensitive to changes in weighting than any of the external normalization method.

Beyond changes in rank acceptability indices, the order of alternatives differs between the applied normalization approaches. Both, World 2000 and EU 25 place A-Si as the least environmentally burdensome alternative nearly 100 percent of the time, whereas CdTe is most likely to remain second. Alternatively, outranking places CdTe in first place followed closely by A-Si. In SMAA, CdTe and A-Si are both competitive alternatives.

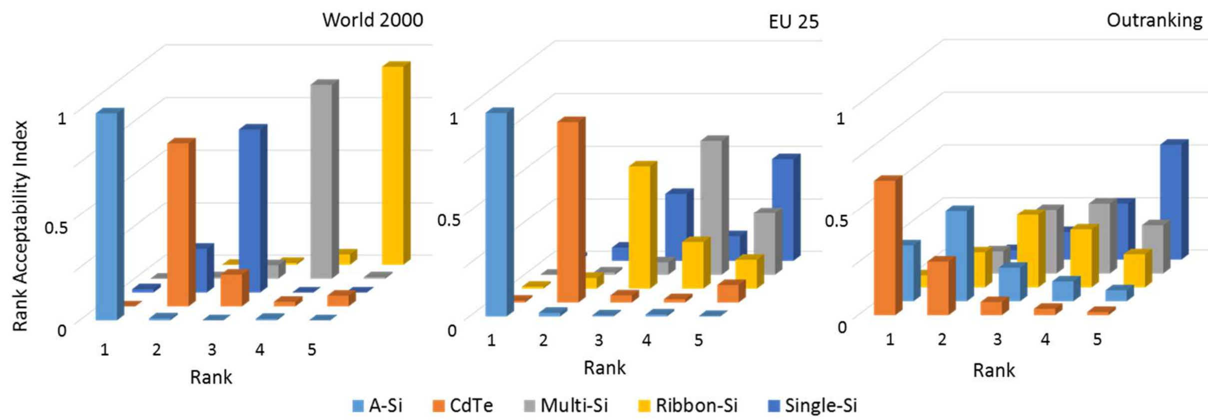

Figure 5. Rank acceptability indices of the Comparative LCA of PV using three normalization approaches in CML baseline. From left to right: World 2000 external normalization, EU 25 external normalization and outranking. The x-axis represents the rank ordering, the y-axis represents the rank acceptability index and the z-axis represents each individual alternatives also denoted by color.

Overall, we expect more weight insensitivity when normalized contributions are dominated by a few or even a single impact category (as the case with CML in Figure 2). Alternatively, when normalized contributions of impact categories are closer to one another as shown by outranking (Figure 3), it generates a rank ordering that is most variable with respect to weight values (See supplementary information).

3.5 Discussion

ReCiPe H Midpoint, CML baseline and TRACI external normalization methods highlight the same set of impact categories across LCA applications (Figure 2). With both, the EU and World normalization references within ReCiPe H midpoint, the highest normalized contributions come from freshwater ecotoxicity, marine Ecotoxicity and human toxicity (Figure 2). In fact, the three most influential impact categories are the same in ReCiPe EU and World except in natural land transformation, which is more salient in the EU normalization reference. 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 (Figure 2). Finally, TRACI US 2008 normalization reference identifies carcinogenics, ecotoxicity, and non carcinogenics the most influential impact categories in all four comparative LCA applications. (Figure 2). Application of external normalization for hotspot identification should be used carefully as there is a risk of systematic biases that highlights the same set of impacts regardless of the inventory, characterization factors, and completeness or geographical coverage (regional or global) of the normalization reference. Outputs from external normalization are not a representation of reality, but an artifact of the normalization step. Contributions are driven entirely by the normalization reference and do not represent the impacts significant to a decision.

Outranking results in Figure 3 do not appear to suffer from systematic biases as the outputs vary for each application. Outranking highlights impact categories where alternatives are the most distinguishable from one another within each application (Figure 3). These significant differences in characterized results between alternatives inform the decision. Otherwise we can end up choosing between two nearly identical options. Unlike external normalization, outputs of outranking normalization as applied in SMAA-LCA, adapt to changes in inventory and characterization factors that may increase or decrease the uncertainty of characterized results. Therefore, outranking guides 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., 2015).

Variability profiles per impact category according to external and outranking normalization approaches further support the existence of systematic biases (Figure 4). Variation of externally normalized results is greater in those aspects that tend to systematically dominate results. Furthermore, the relative scales of normalized impact categories affect how weights influence a final rank ordering of alternatives. In external normalization the scales refer to contribution (Figure 2) and in outranking describes tradeoff significance (Figure 3). When the scales of normalized results overemphasize a single or a few impact categories, it takes extreme weight choices to alter the rank ordering. In the case of CML where external normalization references have the strongest effect, both World 2000 and EU 25, show more weight insensitivity than outranking (Figure 5). In World 2000 and EU 25, A-Si ranks first given 98% and 97% of the possible weight spaces respectively, whereas in outranking, the first alternative, CdTe, ranks first for 64% of the times. Outranking shows the most weight sensitivity because normalized contributions are more evenly spread out between impact categories and no single impact category dominates results Figure 3. Furthermore, each normalization approach generates a different rank ordering which is a consequence of the normalization step. World 2000 and EU25 utilize average performances at characterization and normalization, meaning that evaluation between alternatives remains static. However, outranking normalization takes into account the full range of performances. Therefore, rank orderings in World 2000 and EU25 show A-Si to have a very high probability of ranking first, while in outranking, CdTe and A-Si are two equally competitive alternatives when we take into account the best and worst case scenarios. Unlike in external normalization, outranking (as applied in SMAA) takes into account uncertainty, focuses in mutual differences and generates normalized scales that are closer to one another because it is partially compensatory. This enables and assessment that is better at elucidating tradeoffs while maintaining weight sensitivity. These effects are due to the fundamentals of external normalization independent of the reference values. Biases as identified in this paper are not a function of completeness of characterization factors nor modelling assumptions in an LCIA up to characterization.

3.6 Conclusion

This study shows that the effects of external normalization may overwhelm differences in inventory, technology application, and weights. In ReCiPe, CML and TRACI, external normalization highlights the same set of impact categories across four diverse representative applications. The same results were found in multiple other studies. These biases result in recommendations based entirely in the normalization approach, thus they should be applied carefully when identifying hotspots.

These findings challenge existing practices of normalization based on external references as an approach for guiding the selection process in comparative LCAs. For ReCiPe and CML, systematic biases in external normalization exist in European and Global references, thus deeming this practice unsatisfactory regardless of the area of coverage and data completion. Alternatively, decision support in a comparative LCA should focus on evaluating the impact of the decision (tradeoffs) rather than the impact of individual alternatives (hotspot). Tradeoff evaluation helps narrow the decision to the aspects where we have the most evidence and direct research efforts where we have the least knowledge. Therefore stochastic approaches of outranking normalization is most appropriate in comparative applications as it highlights context specific aspects, takes into account uncertainty, avoids full compensation and generates an assessment that is more receptive of weights.

CHAPTER 4

CONCLUSION

This work advances decision support in comparative LCAs by integrating decision analysis in the interpretation stages of normalization and weighting. Specifically it calls for SMAA-LCA consisting of outranking normalization and stochastic weighting.

Current practice of external normalization was found problematic because it generates results that are insensitive to weights and subject to systematic biases – regardless of improvements to data completion in normalization references. Along with discrete approaches to weighting, the dominant practice in interpretation that culminates in a single score, is incapable of providing robust decision support for high uncertainty, complex environmental decisions. Perhaps the main contribution of this work is the distinction between hotspots and tradeoffs and its relationship to normalization. External normalization is concerned with evaluating the magnitude of impact of individual alternatives, rather than the impact of the decision. Magnitude of impact relates to hotspot identification which can guide improvement actions. However, making a selection in a comparative LCA, requires a different normalization approach that can evaluate the impact of the decision. What happens when we select A over B? By focusing on the tradeoffs, we can guide the decision towards those aspects that change the most given a particular selection (A or B). Similar aspects between alternatives have little impact to the decision regardless of their magnitude. Whereas, significant differences represent aspects most influential to the decision. Here, the normalization should elucidate tradeoffs that can be resolved with weighting for a final recommendation. This deals with identifying the relevance of facts (performances at characterization) to values for improved decision making - It is the goal of a decision support tool to combine science and preference values and not replace the decision maker entirely (Hertwich, Hammitt, & Pease, 2000).

The normalization step in SMAA-LCA consists of outranking which utilizes uncertainty information to highlight those aspects most impactful to the decision and applies a non-linear aggregation function with normalized scales that are more sensitive over larger weight ranges. With value functions that derive directly from uncertainty parameters, outranking facilitates the deliberative process. As compared to axiomatic methods of decision analysis that can potentially apply to comparative LCAs, where the construction of value functions demands large cognitive efforts from the decision makers and the analyst (Tsoukiàs, 2008).

There were no systematic biases found in outranking normalization that overpower differences in inventory and weight schemes. Thus, SMAA-LCA provides a final recommendation as a function of both, normalization and weighting. SMAA-LCA can help guide the selection process given current (and improved) inventories, uncertainty and characterization factors. It can also be used for data refinement in those aspects where uncertainties make alternatives undistinguishable from one another. As illustrated here, uncertainty estimations are based in data quality indicators for input parameters, and while uncertainty can be propagated to include uncertainty of characterized factors, SMAA-LCA explores parameter uncertainty, as opposed to model or scenario type uncertainties (Hertwich, McKone, & Pease, 2000; Huijbregts, Gilijamse, Ragas, & Reijnders, 2003).

This dissertation offers a methodological innovation in interpretation of comparative LCAs. The new approach, SMAA-LCA, elucidates tradeoffs pertinent to the decision and utilizes uncertainty information to guide the decision making process.

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APPENDIX A

CHAPTER 2

Table S1. Individual overlap area results

Impact category	All pairs										Average area (Eq.9)
	A-Si:CdTe	A-Si:Multi-Si	A-Si:Ribbon-Si	A-Si:Single-Si	CdTe:Multi-Si	CdTe-Ribbon-Si	CdTe:Single-Si	Multi-Si:Ribbon-Si	Multi-Si:Single-Si	Ribbon-Si:Single-Si	
Water depletion	0.43	0.02	0.08	0.03	0.00	0.01	0.00	0.54	0.88	0.64	0.26
Terrestrial ecotoxicity	0.80	0.04	0.01	0.03	0.07	0.03	0.05	0.86	0.94	0.89	0.37
Marine eutrophication	0.83	0.35	0.34	0.25	0.46	0.45	0.34	0.99	0.00	0.00	0.40
Ozone depletion	0.93	0.03	0.03	0.03	0.86	0.02	0.02	0.98	0.95	0.96	0.48
Agricultural land occupation	0.57	0.18	0.26	0.21	0.35	0.51	0.42	0.78	0.92	0.87	0.51
Photochemical oxidant formation	0.79	0.48	0.53	0.35	0.29	0.33	0.19	0.93	0.80	0.73	0.54
Climate change	0.65	0.66	0.78	0.44	0.32	0.43	0.17	0.83	0.71	0.56	0.56
Fossil depletion	0.67	0.66	0.82	0.46	0.34	0.49	0.20	0.78	0.74	0.53	0.57
Particulate matter formation	0.64	0.86	0.90	0.63	0.51	0.58	0.30	0.91	0.71	0.62	0.67
Terrestrial acidification	0.87	0.79	0.85	0.57	0.67	0.75	0.45	0.91	0.74	0.66	0.73
Marine ecotoxicity	0.81	0.58	0.52	0.56	0.77	0.71	0.75	0.94	0.97	0.95	0.75
Metal depletion	0.91	0.66	0.62	0.68	0.72	0.67	0.73	0.94	0.98	0.93	0.78
Freshwater ecotoxicity	0.92	0.68	0.63	0.64	0.74	0.70	0.70	0.95	0.96	0.99	0.79
Urban land occupation	0.91	0.85	0.91	0.72	0.81	0.89	0.66	0.91	0.84	0.76	0.83
Human toxicity	0.79	0.69	0.67	0.73	0.88	0.86	0.93	0.98	0.94	0.92	0.84
Natural land transformation	0.76	0.81	0.81	0.86	0.82	0.87	0.75	0.95	0.92	0.88	0.84
Ionising radiation	0.92	0.82	0.89	0.80	0.77	0.83	0.76	0.94	0.92	0.89	0.85
Freshwater eutrophication	0.77	0.96	0.97	0.92	0.75	0.80	0.78	0.94	0.94	0.92	0.88

APPENDIX B

CHAPTER 3

S1. Comparative LCA applications

The following represent the processes used in each of the comparative LCA applications (Table 1) as referred to in Ecoinvent 3:

Photovoltaic Technologies (PV)

- Single-Si: Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, single-Si, laminated, integrated | Alloc Def, U
- Multi-Si: Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, multi-Si, laminated, integrated | Alloc Def, U
- CdTe: Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, CdTe, laminated, integrated | Alloc AU
- a-Si: Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, a-Si, laminated, integrated | Alloc Def, U
- Ribbon-Si: Electricity, low voltage {RoW}| electricity production, photovoltaic, 3kWp slanted-roof installation, ribbon-Si, laminated, integrated | Alloc Def, U

US electric grid mixes (eGrid)

- WECC: Electricity, high voltage {WECC, US only}| production mix | Alloc Def, U
- ASCC: Electricity, high voltage {ASCC}| production mix | Alloc Def, U
- HICC: Electricity, high voltage {HICC}| production mix | Alloc Def, U
- MRO: Electricity, high voltage {MRO, US only}| production mix | Alloc Def, U
- SPP: Electricity, high voltage {SPP}| production mix | Alloc Def, U
- TRE: Electricity, high voltage {TRE}| production mix | Alloc Def, U
- RFC: Electricity, high voltage {RFC}| production mix | Alloc Def, U

- SERC: Electricity, high voltage {SERC}| production mix | Alloc Def, U
- FRCC: Electricity, high voltage {FRCC}| production mix | Alloc Def, U
- NPCC: Electricity, high voltage {NPCC, US only}| production mix | Alloc Def, U

Paper Pulp

- CTM: Chemi-thermomechanical pulp {GLO}| market for | Alloc Def, U
- SG: Stone groundwood pulp {GLO}| market for | Alloc Def, U
- Sulfate: Sulfate pulp {GLO}| market for | Alloc Def, U
- Sulfite: Sulfite pulp, bleached {GLO}| market for | Alloc Def, U
- TM: Thermo-mechanical pulp {GLO}| market for | Alloc Def, U

Concrete

- Clay: Lightweight concrete block, expanded clay {RoW}| production | Alloc Def, U
- Perlite: Lightweight concrete block, expanded perlite {RoW}| production | Alloc Def, U
- Vermiculite: Lightweight concrete block, expanded vermiculite {RoW}| production | Alloc Def, U
- Polystyrene: Lightweight concrete block, polystyrene {RoW}| production | Alloc Def, U
- Pumice: Lightweight concrete block, pumice {RoW}| production | Alloc Def, U

S2. Comparative LCA Uncertainty Analysis results of 1000 Monte Carlo Runs (TS1-TS12)

Table S1. Uncertainty analysis results of PV comparative LCA with ReCiPe H Midpoint

Impact category	Unit	Single-Si		Multi-Si		CdTe		a-Si		Ribbon-Si	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Agricultural land occupation	m2a	1.1E-03	3.4E-04	1.2E-03	3.7E-04	7.0E-04	2.2E-04	4.8E-04	1.9E-04	1.0E-03	3.1E-04
Climate change	kg CO2 eq	2.2E-02	4.8E-03	1.9E-02	4.0E-03	1.3E-02	2.5E-03	1.6E-02	4.1E-03	1.7E-02	3.6E-03
Fossil depletion	kg oil eq	5.8E-03	1.3E-03	5.0E-03	1.1E-03	3.3E-03	6.9E-04	4.1E-03	1.1E-03	4.4E-03	9.4E-04
Freshwater ecotoxicity	kg 1,4-DB eq	4.8E-03	3.2E-03	5.0E-03	3.4E-03	4.8E-03	3.2E-03	4.7E-03	3.1E-03	4.9E-03	3.1E-03
Freshwater eutrophication	kg P eq	1.9E-05	1.2E-05	1.8E-05	1.1E-05	1.8E-05	9.6E-06	1.6E-05	7.3E-06	1.7E-05	1.2E-05
Human toxicity	kg 1,4-DB eq	3.2E-02	4.6E-01	4.3E-02	4.4E-01	3.5E-02	4.5E-01	3.6E-02	4.9E-01	6.0E-02	4.2E-01
Ionising radiation	kBq U235 eq	3.6E-03	4.6E-03	3.0E-03	3.3E-03	2.0E-03	2.4E-03	2.2E-03	3.0E-03	2.7E-03	3.2E-03
Marine ecotoxicity	kg 1,4-DB eq	4.3E-03	2.7E-03	4.4E-03	2.9E-03	4.3E-03	2.7E-03	4.2E-03	2.6E-03	4.3E-03	2.6E-03
Marine eutrophication	kg N eq	9.7E-06	2.2E-06	8.9E-06	2.2E-06	6.1E-06	1.6E-06	5.5E-06	1.5E-06	8.8E-06	2.0E-06
Metal depletion	kg Fe eq	7.2E-03	1.9E-03	7.4E-03	2.1E-03	8.5E-03	2.2E-03	9.0E-03	2.5E-03	6.9E-03	1.9E-03
Natural land transformation	m2	3.1E-06	2.6E-06	2.9E-06	2.7E-06	1.9E-06	1.6E-06	2.4E-06	1.4E-06	2.6E-06	2.2E-06
Ozone depletion	kg CFC-11 eq	3.3E-09	8.4E-10	3.4E-09	9.0E-10	9.6E-10	2.8E-10	9.4E-10	3.2E-10	3.4E-09	8.7E-10
Particulate matter formation	kg PM10 eq	5.9E-05	1.2E-05	5.1E-05	1.0E-05	3.8E-05	8.2E-06	4.7E-05	1.2E-05	4.8E-05	9.8E-06
Photochemical oxidant formation	kg NMVOC	9.0E-05	1.9E-05	8.2E-05	1.7E-05	5.1E-05	1.1E-05	5.8E-05	1.5E-05	7.7E-05	1.6E-05
Terrestrial acidification	kg SO2 eq	1.6E-04	3.3E-05	1.4E-04	2.9E-05	1.1E-04	2.4E-05	1.2E-04	3.0E-05	1.3E-04	2.7E-05
Terrestrial ecotoxicity	kg 1,4-DB eq	3.5E-05	3.4E-05	3.9E-05	3.6E-05	3.2E-06	1.2E-05	2.7E-06	1.3E-05	3.9E-05	3.4E-05
Urban land occupation	m2a	2.3E-04	6.0E-05	2.1E-04	5.2E-05	1.8E-04	4.4E-05	1.9E-04	5.9E-05	2.0E-04	5.2E-05
Water depletion	m3	2.9E-01	7.9E-02	3.2E-01	8.6E-02	5.7E-02	1.4E-02	8.8E-02	2.5E-02	2.2E-01	5.6E-02

Table S2. Uncertainty analysis results of PV comparative LCA with CML baseline

Impact category	Unit	Single-Si		Multi-Si		CdTe		a-Si		Ribbon-Si	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Abiotic depletion	kg Sb eq	9.1E-07	2.1E-07	9.4E-07	2.3E-07	5.1E-07	1.1E-07	4.9E-07	1.1E-07	9.9E-07	2.3E-07
Abiotic depletion (fossil fuels)	MJ	3.0E-01	7.0E-02	2.6E-01	5.5E-02	1.7E-01	3.6E-02	2.2E-01	6.1E-02	2.3E-01	4.8E-02
Acidification	kg SO2 eq	1.9E-04	4.1E-05	1.6E-04	3.4E-05	1.5E-04	3.1E-05	1.5E-04	3.9E-05	1.6E-04	3.4E-05
Eutrophication	kg PO4--- eq	7.1E-05	3.6E-05	6.3E-05	3.2E-05	6.8E-05	4.5E-05	5.9E-05	2.8E-05	6.2E-05	3.1E-05
Fresh water aquatic ecotox.	kg 1,4-DB eq	5.7E-02	4.3E-02	5.7E-02	4.1E-02	5.7E-02	4.3E-02	5.9E-02	4.5E-02	5.8E-02	4.0E-02
Global warming (GWP100a)	kg CO2 eq	2.2E-02	4.9E-03	1.9E-02	4.0E-03	1.3E-02	2.6E-03	1.6E-02	4.4E-03	1.7E-02	3.5E-03
Human toxicity	kg 1,4-DB eq	2.2E-02	2.9E-02	2.3E-02	2.9E-02	2.3E-02	2.9E-02	2.4E-02	3.1E-02	2.1E-02	2.4E-02
Marine aquatic ecotoxicity	kg 1,4-DB eq	8.5E+01	2.5E+01	8.5E+01	2.7E+01	8.9E+01	3.0E+01	1.1E+02	3.8E+01	8.5E+01	2.7E+01
Ozone layer depletion (ODP)	kg CFC-11 eq	3.2E-09	8.6E-10	3.3E-09	9.1E-10	8.6E-10	2.6E-10	8.7E-10	3.0E-10	3.3E-09	8.7E-10
Photochemical oxidation	kg C2H4 eq	8.5E-06	1.8E-06	7.5E-06	1.6E-06	6.3E-06	1.4E-06	7.1E-06	1.9E-06	7.1E-06	1.5E-06
Terrestrial ecotoxicity	kg 1,4-DB eq	1.5E-04	1.8E-02	4.1E-04	1.8E-02	8.5E-04	1.7E-02	6.3E-04	1.9E-02	5.4E-04	1.5E-02

Table S3. Uncertainty analysis results of PV comparative LCA with TRACI

Impact category	Unit	Single-Si		Multi-Si		CdTe		a-Si		Ribbon-Si	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Acidification	kg SO2 eq	1.8E-04	3.8E-05	1.6E-04	3.3E-05	1.3E-04	2.7E-05	1.4E-04	3.5E-05	1.5E-04	3.1E-05
Carcinogenics	CTUh	2.4E-09	3.2E-09	2.2E-09	2.9E-09	2.5E-09	4.1E-09	2.9E-09	3.6E-09	2.2E-09	2.7E-09
Ecotoxicity	CTUe	2.5E+00	1.4E+00	2.6E+00	1.5E+00	2.7E+00	1.4E+00	2.5E+00	1.4E+00	2.6E+00	1.4E+00
Eutrophication	kg N eq	1.5E-04	8.8E-05	1.4E-04	8.6E-05	1.5E-04	1.1E-04	1.3E-04	6.5E-05	1.4E-04	6.9E-05
Fossil fuel depletion	MJ surplus	2.0E-02	4.4E-03	1.8E-02	4.0E-03	1.2E-02	2.7E-03	1.4E-02	3.5E-03	1.5E-02	3.1E-03
Global warming	kg CO2 eq	2.2E-02	4.8E-03	1.9E-02	4.1E-03	1.3E-02	2.5E-03	1.6E-02	4.0E-03	1.7E-02	3.5E-03
Non carcinogenics	CTUh	2.4E-08	2.7E-07	2.8E-08	2.6E-07	3.5E-08	2.6E-07	3.4E-08	3.0E-07	3.3E-08	2.4E-07
Ozone depletion	kg CFC-11 eq	3.4E-09	9.0E-10	3.5E-09	9.2E-10	9.9E-10	3.0E-10	1.0E-09	3.6E-10	3.4E-09	8.9E-10
Respiratory effects	kg PM2.5 eq	2.6E-05	5.7E-06	2.2E-05	4.6E-06	1.5E-05	3.6E-06	2.1E-05	5.4E-06	2.1E-05	4.7E-06
Smog	kg O3 eq	1.4E-03	3.1E-04	1.2E-03	2.6E-04	8.6E-04	1.9E-04	9.8E-04	2.6E-04	1.1E-03	2.4E-04

Table S4. Uncertainty analysis results of eGrid comparative LCA with ReCiPe H Midpoint

Impact category	Unit	WECC		ASCC		HICC		MRO		SPP		TRE		RFC		SERC		FRCC		NPCC	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Agricultural land occupation	m2a	9.6E+00	2.8E+00	1.6E+00	6.4E-01	1.5E+01	3.8E+00	1.5E+01	6.2E+00	9.2E+00	3.5E+00	3.4E+00	1.9E+00	8.2E+00	2.9E+00	1.3E+01	3.8E+00	1.1E+01	2.9E+00	2.0E+01	5.5E+00
Climate change	kg CO2 eq	6.1E+02	3.6E+01	7.4E+02	5.4E+01	9.3E+02	1.3E+02	1.1E+03	7.9E+01	1.1E+03	6.4E+01	7.4E+02	4.3E+01	7.6E+02	5.1E+01	7.1E+02	4.3E+01	8.0E+02	5.2E+01	4.2E+02	2.7E+01
Fossil depletion	kg oil eq	1.9E+02	2.3E+01	2.5E+02	3.5E+01	2.9E+02	8.1E+01	3.1E+02	4.6E+01	2.7E+02	3.6E+01	2.3E+02	2.8E+01	1.7E+02	2.4E+01	1.9E+02	2.4E+01	2.5E+02	3.5E+01	1.3E+02	1.9E+01
Freshwater ecotoxicity	kg 1,4-DB eq	6.9E+00	4.4E+00	6.8E+00	5.4E+00	2.0E+00	5.6E+00	1.1E+01	8.7E+00	9.6E+00	5.9E+00	8.5E+00	5.4E+00	6.0E+00	4.6E+00	6.3E+00	4.4E+00	8.0E+00	5.3E+00	4.3E+00	3.6E+00
Freshwater eutrophication	kg P eq	2.3E-01	1.8E-01	7.9E-02	6.1E-02	1.0E-01	7.8E-02	6.3E-01	4.4E-01	4.4E-01	3.3E-01	2.5E-01	2.6E-01	3.1E-01	2.3E-01	3.1E-01	2.3E-01	1.2E-01	8.3E-02	6.5E-02	4.4E-02
Human toxicity	kg 1,4-DB eq	2.2E+02	8.6E+02	1.5E+02	5.4E+02	5.0E+01	1.5E+03	4.5E+02	1.9E+03	3.0E+02	1.2E+03	2.2E+02	8.1E+02	2.6E+02	1.0E+03	2.2E+02	9.7E+02	1.4E+02	4.8E+02	7.2E+01	6.8E+02
Ionising radiation	kBq U235 eq	1.2E+02	1.3E+02	1.3E+01	8.3E+00	4.1E+01	2.2E+01	1.8E+02	2.3E+02	5.6E+01	5.8E+01	1.5E+02	1.9E+02	3.4E+02	4.5E+02	3.4E+02	4.7E+02	1.7E+02	1.8E+02	3.8E+02	4.8E+02
Marine ecotoxicity	kg 1,4-DB eq	4.8E+00	3.4E+00	3.2E+00	2.0E+00	3.1E+00	4.7E+00	1.0E+01	7.6E+00	7.7E+00	4.8E+00	5.5E+00	3.4E+00	5.4E+00	4.0E+00	5.2E+00	3.7E+00	3.7E+00	2.0E+00	2.2E+00	2.2E+00
Marine eutrophication	kg N eq	9.6E-02	1.1E-02	1.1E-01	2.5E-02	2.0E-01	2.6E-02	2.5E-01	2.9E-02	1.9E-01	2.1E-02	9.1E-02	1.2E-02	1.3E-01	1.5E-02	1.2E-01	1.4E-02	8.4E-02	1.1E-02	3.9E-02	5.1E-03
Metal depletion	kg Fe eq	5.3E+00	1.9E+00	3.0E+00	7.6E-01	5.7E+00	1.6E+00	1.3E+01	5.7E+00	8.8E+00	4.2E+00	4.9E+00	1.4E+00	6.1E+00	2.4E+00	5.7E+00	1.8E+00	3.5E+00	1.0E+00	4.5E+00	1.3E+00
Natural land transformation	m2	2.3E-02	3.0E-02	5.6E-02	2.5E-02	2.2E-01	1.2E-01	5.5E-02	5.3E-02	4.0E-02	3.5E-02	2.5E-02	1.6E-02	3.1E-02	3.0E-02	3.0E-02	3.7E-02	2.6E-02	3.2E-02	1.5E-02	5.7E-02
Ozone depletion	kg CFC-11 eq	1.4E-05	3.1E-06	1.2E-05	7.6E-06	5.1E-05	3.4E-05	2.1E-05	4.7E-06	9.2E-06	2.0E-06	1.6E-05	3.6E-06	3.4E-05	8.7E-06	3.1E-05	7.9E-06	1.9E-05	4.4E-06	3.5E-05	9.0E-06
Particulate matter formation	kg PM10 eq	7.7E-01	2.1E-01	1.4E+00	4.2E-01	1.7E+00	2.1E-01	1.4E+00	1.3E-01	1.3E+00	1.9E-01	9.3E-01	3.3E-01	1.4E+00	1.6E-01	1.1E+00	1.4E-01	1.3E+00	4.9E-01	7.2E-01	2.3E-01
Photochemical oxidant formation	kg NMVOC	1.4E+00	1.7E-01	2.6E+00	6.5E-01	3.8E+00	6.2E-01	3.1E+00	3.9E-01	2.6E+00	3.0E-01	1.2E+00	1.9E-01	2.0E+00	2.3E-01	1.7E+00	1.9E-01	1.9E+00	3.2E-01	8.2E-01	1.2E-01
Terrestrial acidification	kg SO2 eq	3.1E+00	1.1E+00	5.7E+00	2.0E+00	6.2E+00	8.6E-01	4.9E+00	5.4E-01	5.1E+00	8.9E-01	4.1E+00	1.6E+00	5.7E+00	7.8E-01	4.6E+00	6.7E-01	5.9E+00	2.4E+00	3.2E+00	1.2E+00
Terrestrial ecotoxicity	kg 1,4-DB eq	4.6E-02	4.0E-02	9.9E-02	9.0E-02	8.8E-02	1.1E-01	1.8E-02	4.8E-02	4.0E-02	4.2E-02	6.2E-02	6.8E-02	2.0E-02	2.7E-02	2.8E-02	3.1E-02	9.6E-02	8.4E-02	4.9E-02	4.6E-02
Urban land occupation	m2a	4.4E+00	2.6E+00	1.7E+00	9.3E-01	2.6E+00	1.1E+00	1.2E+01	7.3E+00	8.7E+00	5.5E+00	4.9E+00	3.2E+00	5.9E+00	3.5E+00	6.1E+00	4.2E+00	2.3E+00	1.3E+00	1.6E+00	7.1E-01
Water depletion	m3	7.9E+03	7.9E+02	6.8E+03	7.0E+02	5.6E+02	6.6E+01	1.6E+03	1.4E+02	1.5E+03	1.3E+02	1.6E+02	1.2E+01	3.8E+02	3.1E+01	1.4E+03	1.3E+02	1.6E+02	9.9E+00	4.8E+03	4.6E+02

Table S5. Uncertainty analysis results of eGrid comparative LCA with CML Baseline

Impact category	Unit	WECC		ASCC		HICC		MRO		SPP		TRE		RFC		SERC		FRCC		NPCC	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Abiotic depletion	kg Sb eq	8.9E-05	3.7E-05	4.8E-05	2.2E-05	1.2E-04	6.4E-05	2.2E-04	1.1E-04	1.5E-04	7.3E-05	9.2E-05	3.6E-05	1.0E-04	4.6E-05	9.8E-05	4.5E-05	5.8E-05	2.3E-05	7.8E-05	3.0E-05
Abiotic depletion (fossil fuels)	MJ	1.0E+04	1.3E+03	1.1E+04	1.5E+03	1.3E+04	3.2E+03	1.9E+04	3.0E+03	1.6E+04	2.2E+03	1.2E+04	1.5E+03	1.0E+04	1.5E+03	1.1E+04	1.5E+03	1.2E+04	1.5E+03	6.1E+03	8.1E+02
Acidification	kg SO2 eq	3.5E+00	1.3E+00	6.7E+00	2.5E+00	6.9E+00	9.7E-01	5.3E+00	6.5E-01	5.7E+00	1.1E+00	4.7E+00	2.0E+00	6.5E+00	9.4E-01	5.3E+00	9.0E-01	6.8E+00	2.9E+00	3.7E+00	1.5E+00
Eutrophication	kg PO4--- eq	8.6E-01	5.1E-01	5.0E-01	1.9E-01	7.6E-01	2.3E-01	2.4E+00	1.4E+00	1.7E+00	1.1E+00	8.8E-01	5.9E-01	1.2E+00	7.2E-01	1.1E+00	7.0E-01	5.3E-01	2.5E-01	2.8E-01	1.4E-01
Fresh water aquatic ecotox.	kg 1,4-DB eq	1.5E+02	8 3E+01	8.6E+01	5.6E+01	7.3E+01	1.0E+02	3.9E+02	9.1E+02	2.7E+02	1.5E+02	1.8E+02	1.3E+02	1.9E+02	1.7E+02	1.9E+02	1.2E+02	1.1E+02	7.0E+01	7.0E+01	5.6E+01
Global warming (GWP100a)	kg CO2 eq	6.1E+02	3.3E+01	7.4E+02	5.2E+01	9.3E+02	1.4E+02	1.1E+03	7.7E+01	1.1E+03	6.5E+01	7.4E+02	4.3E+01	7.6E+02	5.0E+01	7.1E+02	4.5E+01	8.0E+02	5.5E+01	4.2E+02	2.8E+01
Human toxicity	kg 1,4-DB eq	2.1E+02	1.0E+02	2.0E+02	1.2E+02	1.1E+02	9.6E+01	3.9E+02	3.8E+02	3.3E+02	1.4E+02	2.5E+02	1.1E+02	2.5E+02	1.2E+02	2.5E+02	1.4E+02	2.6E+02	1.6E+02	1.5E+02	7.9E+01
Marine aquatic ecotoxicity	kg 1,4-DB eq	8.0E+05	2.5E+05	4.1E+05	1.7E+05	3.7E+05	1.1E+05	2.1E+06	1.2E+06	1.7E+06	5.4E+05	9.2E+05	3.2E+05	1.3E+06	4.8E+05	1.1E+06	4.2E+05	6.3E+05	2.5E+05	3.4E+05	1.2E+05
Ozone layer depletion (ODP)	kg CFC-11 eq	1.3E-05	3.1E-06	1.2E-05	8.0E-06	4.9E-05	2.9E-05	2.1E-05	4.5E-06	9.0E-06	1.9E-06	1.6E-05	3.8E-06	3.3E-05	8.5E-06	3.1E-05	7.6E-06	1.9E-05	4.7E-06	3.5E-05	9.5E-06
Photochemical oxidation	kg C2H4 eq	1.5E-01	5.4E-02	2.9E-01	1.0E-01	2.6E-01	3.9E-02	1.8E-01	2.5E-02	2.2E-01	4.6E-02	2.1E-01	8.0E-02	2.5E-01	3.8E-02	2.1E-01	3.7E-02	3.1E-01	1.2E-01	1.7E-01	5.9E-02
Terrestrial ecotoxicity	kg 1,4-DB eq	1.1E+00	3.0E+01	1.9E-02	1.8E+01	3.2E+00	5.4E+01	1.2E+00	6.5E+01	3.2E+00	4.4E+01	1.0E+00	3.0E+01	4.6E-01	3.6E+01	9.2E-01	3.3E+01	9.9E-03	1.8E+01	1.3E+00	2.4E+01

Table S6. Uncertainty analysis results of eGrid comparative LCA with TRACI

Impact category	Unit	WECC		ASCC		HICC		MRO		SPP		TRE		RFC		SERC		FRCC		NPCC	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Acidification	kg SO2 eq	3.4E+00	1.2E+00	6.2E+00	2.1E+00	6.7E+00	8.7E-01	5.5E+00	5.7E-01	5.6E+00	9.8E-01	4.3E+00	1.4E+00	6.0E+00	7.7E-01	4.9E+00	7.0E-01	6.1E+00	2.4E+00	3.4E+00	1.3E+00
Carcinogenics	CTUh	2.4E-05	5.1E-05	1.1E-05	2.6E-05	1.2E-05	2.0E-05	6.7E-05	1.8E-04	4.5E-05	1.0E-04	3.0E-05	1.5E-04	2.9E-05	6.9E-05	2.9E-05	8.5E-05	1.4E-05	3.6E-05	9.1E-06	1.6E-05
Ecotoxicity	CTUe	2.5E+03	2.1E+03	1.4E+03	7.9E+02	1.6E+03	1.7E+03	6.0E+03	7.3E+03	4.2E+03	4.0E+03	2.9E+03	2.7E+03	2.8E+03	2.8E+03	2.9E+03	3.1E+03	1.7E+03	1.0E+03	1.4E+03	6.5E+03
Eutrophication	kg N eq	1.7E+00	1.2E+00	7.0E-01	3.9E-01	9.9E-01	5.0E-01	4.7E+00	3.3E+00	3.4E+00	2.7E+00	2.0E+00	1.4E+00	2.4E+00	1.6E+00	2.3E+00	1.9E+00	9.4E-01	5.9E-01	5.4E-01	3.7E-01
Fossil fuel depletion	MJ surplus	5.7E+02	9.0E+01	1.4E+03	2.2E+02	1.5E+03	4.7E+02	2.6E+02	3.5E+01	5.2E+02	7.4E+01	8.0E+02	1.4E+02	2.4E+02	3.0E+01	3.6E+02	5.0E+01	1.3E+03	2.2E+02	6.5E+02	1.1E+02
Global warming	kg CO2 eq	6.0E+02	3.5E+01	7.4E+02	5.5E+01	9.3E+02	1.5E+02	1.1E+03	7.8E+01	1.1E+03	6.4E+01	7.4E+02	4.5E+01	7.6E+02	4.8E+01	7.1E+02	4.5E+01	8.0E+02	5.4E+01	4.2E+02	2.7E+01
Non carcinogenics	CTUh	1.1E-04	4.7E-04	4.6E-05	3.0E-04	8.2E-05	9.4E-04	2.3E-04	1.1E-03	1.5E-04	6.7E-04	1.1E-04	4.9E-04	1.4E-04	5.4E-04	1.4E-04	5.5E-04	8.5E-05	3.3E-04	7.1E-05	3.6E-04
Ozone depletion	kg CFC-11 eq	2.1E-05	4.4E-06	1.8E-05	1.0E-05	7.0E-05	4.8E-05	4.1E-05	8.9E-06	2.6E-05	6.9E-06	2.5E-05	5.2E-06	4.8E-05	1.0E-05	4.4E-05	9.8E-06	2.6E-05	5.6E-06	4.0E-05	9.6E-06
Respiratory effects	kg PM2.5 eq	2.0E-01	7.1E-02	3.5E-01	1.3E-01	4.3E-01	6.7E-02	3.0E-01	3.7E-02	3.2E-01	6.0E-02	2.6E-01	8.6E-02	3.5E-01	4.8E-02	3.0E-01	4.4E-02	3.6E-01	1.5E-01	2.2E-01	8.0E-02
Smog	kg O3 eq	2.5E+01	3.4E+00	4.5E+01	1.4E+01	7.2E+01	1.2E+01	6.5E+01	9.2E+00	5.1E+01	7.2E+00	1.8E+01	2.8E+00	3.7E+01	5.2E+00	3.2E+01	4.4E+00	2.9E+01	5.3E+00	1.1E+01	1.3E+00

Table S7. Uncertainty analysis results of Concrete comparative LCA with ReCiPe H Midpoint

Impact category	Unit	Clay		Perlite		Vermiculite		Polystyrene		Pumice	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Agricultural land occupation	m2a	0.0487	0.0221	0.133	0.117	0.0418	0.0186	0.0156	0.00997	0.00848	0.00768
Climate change	kg CO2 eq	5.2E-01	1.7E-01	1.3E+00	1.0E+00	6.2E-01	2.1E-01	1.5E+00	8.0E-01	3.0E-01	8.7E-02
Fossil depletion	kg oil eq	1.0E-01	3.7E-02	3.1E-01	2.2E-01	1.4E-01	5.9E-02	2.9E-01	1.5E-01	3.8E-02	1.0E-02
Freshwater ecotoxicity	kg 1,4-DB eq	2.6E-03	2.4E-01	5.1E-02	1.5E+00	2.8E-03	3.5E-01	5.5E-03	7.6E-02	9.3E-04	4.8E-03
Freshwater eutrophication	kg P eq	1.3E-04	9.3E-05	3.4E-04	3.8E-04	1.2E-04	8.3E-05	1.4E-04	9.7E-05	3.4E-05	1.9E-05
Human toxicity	kg 1,4-DB eq	1.2E-01	6.6E+01	1.2E+01	4.1E+02	1.2E-01	9.3E+01	6.8E-01	2.1E+01	1.6E-02	1.3E+00
Ionising radiation	kBq U235 eq	2.1E-02	2.2E-02	6.2E-02	7.6E-02	3.7E-02	3.2E-02	5.1E-02	6.9E-02	1.2E-02	1.1E-02
Marine ecotoxicity	kg 1,4-DB eq	1.6E-04	2.0E-01	4.3E-02	1.2E+00	3.3E-03	2.8E-01	5.2E-03	6.2E-02	1.0E-03	3.9E-03
Marine eutrophication	kg N eq	8.1E-05	3.1E-05	2.3E-04	1.9E-04	1.6E-04	7.8E-05	1.7E-04	9.5E-05	4.0E-05	1.1E-05
Metal depletion	kg Fe eq	2.2E-02	1.5E-02	4.0E-02	2.2E-02	2.8E-02	2.0E-02	2.6E-02	1.5E-02	1.5E-02	1.1E-02
Natural land transformation	m2	5.6E-05	1.2E-04	3.5E-04	4.5E-04	1.2E-04	1.2E-04	9.5E-05	7.7E-05	1.6E-04	1.3E-04
Ozone depletion	kg CFC-11 eq	1.2E-08	2.4E-08	1.5E-07	1.7E-07	2.0E-08	4.0E-08	2.8E-08	2.0E-08	6.0E-09	2.8E-09
Particulate matter formation	kg PM10 eq	9.5E-04	3.5E-04	2.7E-03	1.9E-03	1.9E-03	8.3E-04	1.7E-03	9.8E-04	4.6E-04	1.2E-04
Photochemical oxidant formation	kg NMVOC	1.6E-03	5.2E-04	4.3E-03	2.9E-03	4.0E-03	2.0E-03	4.9E-03	2.7E-03	9.3E-04	2.6E-04
Terrestrial acidification	kg SO2 eq	2.8E-03	1.1E-03	7.8E-03	6.2E-03	5.5E-03	2.5E-03	4.5E-03	2.6E-03	1.0E-03	2.9E-04
Terrestrial ecotoxicity	kg 1,4-DB eq	6.5E-06	1.7E-03	3.8E-04	1.1E-02	3.1E-05	2.4E-03	4.4E-05	5.3E-04	8.3E-06	3.6E-05
Urban land occupation	m2a	5.1E-03	2.0E-03	1.6E-02	9.7E-03	1.1E-02	5.5E-03	6.9E-03	4.0E-03	2.0E-02	8.5E-03
Water depletion	m3	4.3E-01	1.1E-01	1.1E+00	4.9E-01	6.2E-01	2.0E-01	1.5E+00	9.1E-01	4.0E-01	1.1E-01

Table S8. Uncertainty analysis results of Concrete comparative LCA with CML baseline

Impact category	Unit	Clay		Perlite		Vermiculite		Polystyrene		Pumice	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Abiotic depletion	kg Sb eq	6.4E-07	2.3E-06	3.8E-07	1.6E-05	2.4E-06	3.6E-06	7.2E-07	7.9E-07	4.0E-07	2.8E-07
Abiotic depletion (fossil fuels)	MJ	5.6E+00	2.1E+00	1.6E+01	1.2E+01	7.1E+00	2.7E+00	1.3E+01	7.3E+00	1.9E+00	4.8E-01
Acidification	kg SO2 eq	3.2E-03	1.4E-03	8.6E-03	6.9E-03	6.1E-03	2.7E-03	4.8E-03	2.8E-03	1.1E-03	2.9E-04
Eutrophication	kg PO4--- eq	5.7E-04	3.2E-04	1.5E-03	1.3E-03	8.5E-04	3.8E-04	8.7E-04	5.1E-04	2.2E-04	8.4E-05
Fresh water aquatic ecotox.	kg 1,4-DB eq	2.2E-01	4.4E+00	2.1E-01	2.6E+01	6.0E-02	6.3E+00	6.3E-02	1.3E+00	2.6E-02	8.9E-02
Global warming (GWP100a)	kg CO2 eq	5.3E-01	1.8E-01	1.3E+00	9.9E-01	6.1E-01	2.0E-01	1.5E+00	8.6E-01	3.1E-01	8.7E-02
Human toxicity	kg 1,4-DB eq	2.4E-01	3.7E+00	3.1E-01	2.1E+01	1.2E-01	5.3E+00	1.1E-01	1.1E+00	4.4E-02	7.6E-02
Marine aquatic ecotoxicity	kg 1,4-DB eq	3.8E+02	5.8E+02	9.8E+02	3.3E+03	3.8E+02	8.0E+02	3.6E+02	2.5E+02	1.0E+02	3.8E+01
Ozone layer depletion (ODP)	kg CFC-11 eq	1.1E-08	2.5E-08	1.0E-07	1.8E-07	2.1E-08	3.9E-08	2.6E-08	1.7E-08	5.9E-09	3.1E-09
Photochemical oxidation	kg C2H4 eq	1.5E-04	6.4E-05	3.9E-04	3.2E-04	2.3E-04	9.7E-05	6.2E-04	4.6E-04	4.2E-05	1.1E-05
Terrestrial ecotoxicity	kg 1,4-DB eq	7.7E-02	2.4E+00	5.4E-04	1.4E+01	2.4E-04	3.4E+00	3.0E-04	7.3E-01	7.9E-05	4.8E-02

Table S9. Uncertainty analysis results of Concrete comparative LCA with TRACI

Impact category	Unit	Clay		Perlite		Vermiculite		Polystyrene		Pumice	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Acidification	kg SO2 eq	3.1E-03	1.3E-03	8.7E-03	7.8E-03	6.2E-03	3.0E-03	5.0E-03	2.7E-03	1.2E-03	3.1E-04
Carcinogenics	CTUh	1.9E-08	3.2E-07	6.2E-08	2.2E-06	8.3E-09	4.6E-07	2.8E-08	1.1E-07	9.2E-09	9.8E-09
Ecotoxicity	CTUe	1.5E+00	5.8E+01	7.1E+00	4.0E+02	1.8E+00	8.6E+01	2.5E+00	2.0E+01	7.6E-01	1.2E+00
Eutrophication	kg N eq	9.9E-04	7.0E-04	2.7E-03	2.8E-03	1.2E-03	7.1E-04	1.2E-03	7.8E-04	3.2E-04	1.5E-04
Fossil fuel depletion	MJ surplus	2.7E-01	9.4E-02	9.3E-01	5.8E-01	5.7E-01	3.1E-01	1.4E+00	8.8E-01	1.6E-01	4.9E-02
Global warming	kg CO2 eq	5.2E-01	1.9E-01	1.3E+00	1.1E+00	6.3E-01	2.2E-01	1.4E+00	8.0E-01	3.1E-01	8.9E-02
Non carcinogenics	CTUh	8.2E-08	3.7E-05	2.1E-06	2.6E-04	8.7E-08	5.5E-05	2.2E-08	1.3E-05	2.1E-08	7.1E-07
Ozone depletion	kg CFC-11 eq	1.4E-08	2.8E-08	1.2E-07	1.9E-07	2.6E-08	4.1E-08	3.2E-08	2.2E-08	7.7E-09	3.7E-09
Respiratory effects	kg PM2.5 eq	3.3E-04	1.3E-04	9.2E-04	7.6E-04	5.4E-04	2.4E-04	4.9E-04	2.7E-04	1.5E-04	3.8E-05
Smog	kg O3 eq	3.0E-02	1.0E-02	8.0E-02	5.7E-02	8.3E-02	4.2E-02	7.9E-02	4.5E-02	1.9E-02	5.4E-03

Table S10. Uncertainty analysis results of Paper Pulp comparative LCA with ReCipe H Midpoint

Impact category	Unit	CTM		SG		Sulfate		Sulfite		TM	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Agricultural land occupation	m2a	9.6E-01	3.2E-01	4.7E+00	1.4E+00	1.0E+01	2.2E+00	1.5E+01	3.5E+00	9.5E-01	3.3E-01
Climate change	kg CO2 eq	1.9E+00	1.2E-01	1.7E+00	1.2E-01	7.5E-01	5.0E-02	1.9E+00	4.7E-01	1.8E+00	1.1E-01
Fossil depletion	kg oil eq	4.7E-01	3.5E-02	4.4E-01	3.7E-02	2.1E-01	2.1E-02	4.6E-01	1.6E-01	4.7E-01	3.6E-02
Freshwater ecotoxicity	kg 1,4-DB eq	1.3E-02	4.4E-01	6.3E-02	7.5E-01	7.0E-03	4.5E-02	1.6E-02	7.2E+00	1.5E-02	1.8E-01
Freshwater eutrophication	kg P eq	7.9E-04	3.9E-04	7.2E-04	3.7E-04	2.7E-04	1.0E-04	8.3E-04	3.7E-04	8.2E-04	4.0E-04
Human toxicity	kg 1,4-DB eq	6.8E-01	1.2E+02	1.3E+01	2.0E+02	3.4E-03	1.2E+01	8.9E-01	1.9E+03	1.8E-02	4.8E+01
Ionising radiation	kBq U235 eq	4.6E-01	5.7E-01	3.9E-01	4.6E-01	1.0E-01	1.0E-01	1.5E-01	1.7E-01	4.7E-01	5.6E-01
Marine ecotoxicity	kg 1,4-DB eq	1.3E-02	3.6E-01	5.3E-02	6.0E-01	7.0E-03	3.6E-02	1.6E-02	5.8E+00	1.5E-02	1.4E-01
Marine eutrophication	kg N eq	8.4E-04	9.7E-05	4.9E-04	6.1E-05	5.2E-04	4.3E-05	1.2E-03	4.8E-04	5.1E-04	3.6E-05
Metal depletion	kg Fe eq	5.3E-02	1.2E-02	4.9E-02	1.1E-02	4.4E-02	9.3E-03	8.3E-02	4.8E-02	5.0E-02	1.0E-02
Natural land transformation	m2	2.1E-04	2.6E-03	4.3E-04	1.4E-02	3.0E-04	2.4E-02	1.2E-03	3.4E-02	3.8E-04	2.6E-03
Ozone depletion	kg CFC-11 eq	1.1E-07	4.9E-08	9.1E-08	7.8E-08	5.9E-08	1.5E-08	1.4E-07	7.3E-07	1.1E-07	2.4E-08
Particulate matter formation	kg PM10 eq	4.2E-03	3.4E-04	4.1E-03	3.5E-04	4.2E-03	5.5E-04	5.5E-03	1.3E-03	4.4E-03	3.6E-04
Photochemical oxidant formation	kg NMVOC	6.3E-03	5.8E-04	6.7E-03	6.6E-04	6.8E-03	6.7E-04	1.1E-02	2.1E-03	7.5E-03	6.6E-04
Terrestrial acidification	kg SO2 eq	1.1E-02	1.2E-03	1.1E-02	1.1E-03	6.3E-03	4.7E-04	1.6E-02	4.1E-03	1.2E-02	1.2E-03
Terrestrial ecotoxicity	kg 1,4-DB eq	9.1E-05	3.1E-03	4.8E-04	5.2E-03	8.5E-05	3.9E-04	1.4E-04	5.0E-02	1.4E-04	1.2E-03
Urban land occupation	m2a	2.4E-02	5.3E-03	4.1E-02	8.2E-03	1.0E-01	1.8E-02	1.4E-01	2.5E-02	2.3E-02	5.3E-03
Water depletion	m3	7.8E+00	4.1E-01	6.8E+00	3.7E-01	1.9E+00	1.3E-01	2.0E+00	1.1E+00	8.5E+00	4.5E-01

Table S11. Uncertainty analysis results of Paper Pulp comparative LCA with CML Baseline

Impact category	Unit	CTM		SG		Sulfate		Sulfite		TM	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Abiotic depletion	kg Sb eq	2.7E-06	4.3E-06	2.5E-06	7.0E-06	2.8E-06	1.2E-06	4.2E-06	6.7E-05	2.5E-06	2.1E-06
Abiotic depletion (fossil fuels)	MJ	2.5E+01	1.9E+00	2.4E+01	2.1E+00	1.0E+01	9.1E-01	2.5E+01	8.0E+00	2.6E+01	2.1E+00
Acidification	kg SO2 eq	1.3E-02	1.3E-03	1.2E-02	1.3E-03	6.7E-03	5.2E-04	1.8E-02	4.9E-03	1.3E-02	1.4E-03
Eutrophication	kg PO4--- eq	3.7E-03	1.1E-03	3.6E-03	1.1E-03	2.1E-03	3.2E-04	5.2E-03	1.4E-03	3.6E-03	1.3E-03
Fresh water aquatic ecotox.	kg 1,4-DB eq	8.9E-01	8.1E+00	4.2E-01	1.3E+01	2.1E-01	8.0E-01	4.8E+00	1.4E+02	5.1E-01	3.2E+00
Global warming (GWP100a)	kg CO2 eq	1.9E+00	1.1E-01	1.7E+00	1.3E-01	7.4E-01	5.1E-02	1.9E+00	4.9E-01	1.8E+00	1.2E-01
Human toxicity	kg 1,4-DB eq	8.1E-01	6.7E+00	4.7E-01	1.1E+01	2.6E-01	6.7E-01	4.2E+00	1.1E+02	5.1E-01	2.7E+00
Marine aquatic ecotoxicity	kg 1,4-DB eq	2.4E+03	1.1E+03	2.1E+03	1.7E+03	7.3E+02	1.6E+02	2.1E+03	1.7E+04	2.4E+03	6.5E+02
Ozone layer depletion (ODP)	kg CFC-11 eq	1.1E-07	4.7E-08	9.1E-08	7.6E-08	5.9E-08	1.4E-08	1.4E-07	7.1E-07	1.1E-07	2.4E-08
Photochemical oxidation	kg C2H4 eq	5.3E-04	5.4E-05	5.7E-04	6.6E-05	4.3E-04	5.8E-05	1.0E-03	2.8E-04	4.9E-04	5.6E-05
Terrestrial ecotoxicity	kg 1,4-DB eq	1.5E-01	4.4E+00	3.6E-03	7.0E+00	1.3E-02	4.3E-01	2.4E+00	7.3E+01	3.6E-03	1.7E+00

Table S12. Uncertainty analysis results of Paper Pulp comparative LCA with TRACI

Impact category	Unit	CTM		SG		Sulfate		Sulfite		TM	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Acidification	kg SO2 eq	1.2E-02	1.2E-03	1.2E-02	1.2E-03	7.3E-03	5.5E-04	1.8E-02	4.8E-03	1.3E-02	1.3E-03
Carcinogenics	CTUh	1.1E-07	6.0E-07	1.1E-07	9.0E-07	5.7E-08	6.3E-08	5.8E-07	9.5E-06	8.5E-08	2.9E-07
Ecotoxicity	CTUe	1.4E+01	1.0E+02	1.5E+01	1.7E+02	6.3E+00	1.1E+01	9.8E+01	1.7E+03	8.9E+00	4.5E+01
Eutrophication	kg N eq	7.7E-03	2.8E-03	7.4E-03	2.5E-03	3.5E-03	6.9E-04	8.8E-03	3.4E-03	6.8E-03	3.2E-03
Fossil fuel depletion	MJ surplus	1.4E+00	1.3E-01	1.3E+00	1.4E-01	9.5E-01	1.2E-01	1.4E+00	7.2E-01	1.4E+00	1.2E-01
Global warming	kg CO2 eq	1.9E+00	1.2E-01	1.7E+00	1.2E-01	7.4E-01	5.3E-02	1.9E+00	5.1E-01	1.8E+00	1.1E-01
Non carcinogenics	CTUh	1.5E-06	6.4E-05	4.9E-06	1.1E-04	8.6E-07	6.9E-06	5.8E-05	1.1E-03	1.2E-07	2.8E-05
Ozone depletion	kg CFC-11 eq	1.3E-07	5.0E-08	1.0E-07	7.7E-08	6.8E-08	1.8E-08	1.5E-07	7.6E-07	1.2E-07	2.6E-08
Respiratory effects	kg PM2.5 eq	1.7E-03	1.8E-04	1.7E-03	1.8E-04	2.2E-03	3.7E-04	2.0E-03	5.0E-04	1.8E-03	2.0E-04
Smog	kg O3 eq	1.2E-01	1.3E-02	1.2E-01	1.3E-02	1.2E-01	1.3E-02	1.9E-01	4.2E-02	1.5E-01	1.5E-02

S3. Coefficient of variation

The coefficient of variation (CV) describes the dispersion of a probability distribution defined by the ratio of the standard deviation to the mean. Each impact category in ReCiPe (TS13), CML Baseline (TS14) and TRACI (TS15) has an average CV given by the alternatives in the comparative LCA applications (CV values shown in table are multiplied by 100). Data for calculations comes from the mean and standard deviations generated from the uncertainty analysis (Tables S1-S12). Figures 2-4 organize impact categories according to the overall average CV.

TS13. Average CV in ReCipE H Midpoint

Impact Category	Average CV per LCA application				Overall Average CV
	PV	eGrid	Concrete	Paper Pulp	
Agricultural land occupation	32.3	35.1	66.5	28.5	40.6
Climate change	21.9	7.3	45.4	10.2	21.2
Fossil depletion	22.4	15.0	46.0	13.6	24.3
Freshwater ecotoxicity	65.7	92.5	5345.5	10192.4	3924.0
Freshwater eutrophication	58.0	76.5	75.8	46.4	64.2
Human toxicity	1167.3	715.5	28904.6	170864.5	50413.0
Ionising radiation	121.2	108.3	107.9	114.2	112.9
Marine ecotoxicity	63.0	78.1	27709.8	8328.2	9044.8
Marine eutrophication	24.6	13.2	50.6	15.6	26.0
Metal depletion	27.1	33.7	65.8	28.5	38.8
Natural land transformation	81.8	118.8	122.1	3174.9	874.4
Ozone depletion	28.3	32.0	128.5	140.4	82.3
Particulate matter formation	21.6	22.2	47.6	12.2	25.9
Photochemical oxidant formation	22.0	14.8	46.6	11.3	23.7
Terrestrial acidification	21.9	25.8	50.4	13.0	27.8
Terrestrial ecotoxicity	222.5	120.6	7629.8	8196.0	4042.2
Urban land occupation	26.7	57.6	50.0	20.0	38.6
Water depletion	26.5	9.1	37.5	15.7	22.2

TS14. Average CV in CML Baseline

Impact Category	Average CV per LCA application				Overall Average CV
	PV	eGrid	Concrete	Paper Pulp	
Abiotic depletion	22.9	44.7	955.8	429.8	363.3
Abiotic depletion (fossil fuels)	22.9	14.8	46.8	13.3	24.5
Acidification	22.1	27.5	51.0	13.4	28.5
Eutrophication	52.9	53.5	56.9	27.9	47.8
Fresh water aquatic ecotox.	73.4	91.8	5468.9	1567.0	1800.3
Global warming (GWP100a)	22.4	7.3	46.1	10.5	21.6
Human toxicity	126.3	59.8	2809.9	1309.9	1076.5
Marine aquatic ecotoxicity	32.5	37.6	161.8	192.0	106.0
Ozone layer depletion (ODP)	29.2	31.9	140.8	138.6	85.1
Photochemical oxidation	22.2	26.3	54.0	14.9	29.4
Terrestrial ecotoxicity	4810.1	30187.6	849424.5	50377.6	233700.0

TS15. Average CV in TRACI

Impact Category	Average CV per LCA application				Overall Average CV
	PV	eGrid	Concrete	Paper Pulp	
Acidification	21.7	24.8	52.7	13.1	21.7
Carcinogenics	135.3	255.3	2260.6	689.3	135.3
Ecotoxicity	55.0	128.4	3033.3	840.2	55.0
Eutrophication	58.6	67.5	70.3	35.1	58.6
Fossil fuel depletion	22.5	16.9	48.6	18.6	22.5
Global warming	21.8	7.4	47.8	10.7	21.8
Non carcinogenics	878.8	528.5	36548.1	6630.4	878.8
Ozone depletion	29.1	30.4	127.5	132.4	29.1
Respiratory effects	23.2	25.7	49.6	14.9	23.2
Photochemical oxidation	23.0	16.3	48.2	12.7	23.0

S4. Stochastic weighting

Stochastic weight calculations for ReCiPe (Fig. S1), CML (Fig. S2) and TRACI (Fig. S3) were done in the SMAA-LCA software with 1000 Monte Carlo runs. Refer to Tylock et al 2012 for calculation procedure.

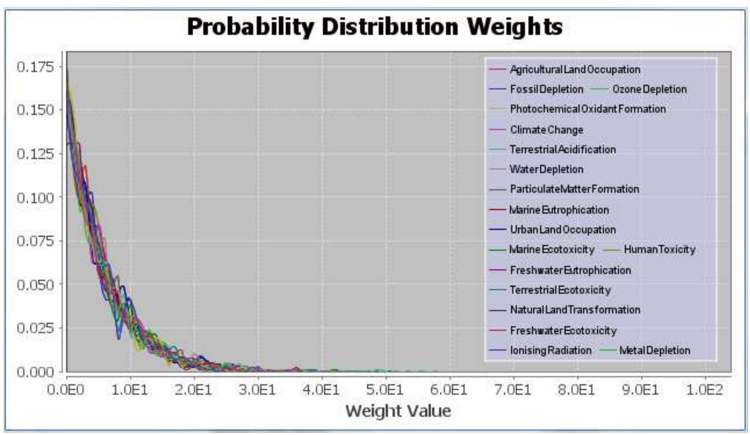

Figure S1. Weight distributions for the 18 impact categories in ReCiPe

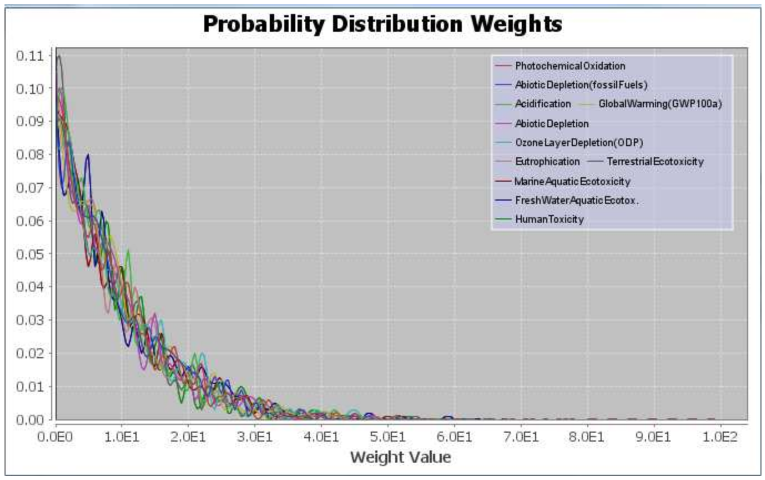

Figure S2. Weight distributions for the 11 impact categories in CML Baseline

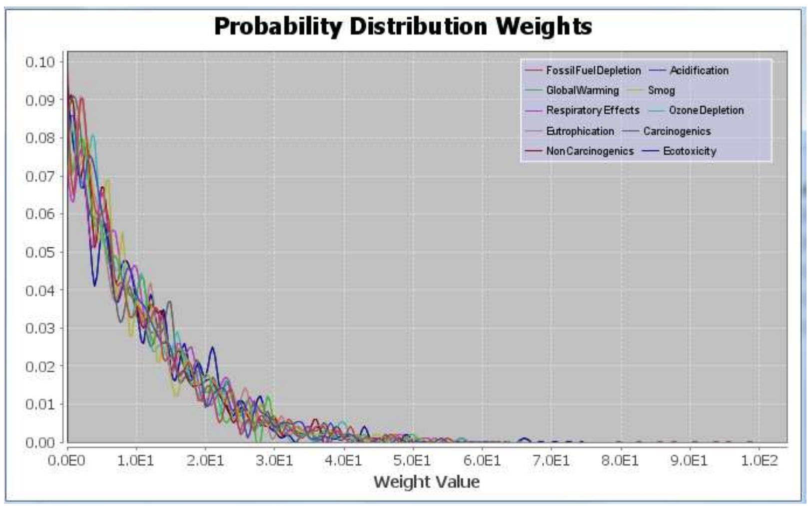

Figure S3. Weight distributions for the 10 impact categories in TRACI

S5. Weight sensitivity results

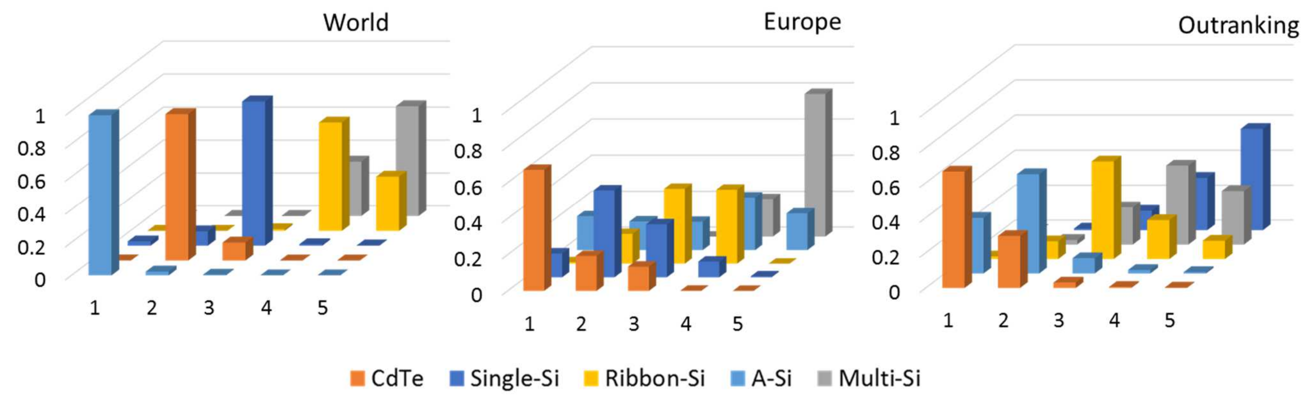

Figure S4. Rank acceptability indices of the Comparative LCA of PV using three normalization approaches in ReCiPe H midpoint. From left to right: World external normalization, Europe external normalization and outranking. The x-axis represents the rank ordering, the y-axis represents the rank acceptability index and the z-axis represents each individual alternatives also denoted by color.

Figure S4 shows the rank acceptability indices for the PV comparative LCA using ReCiPe H midpoint characterization and three normalization approaches. Rank compositions in World are the most weight insensitive because rank compositions tend to be larger than in Europe and Outranking. Rank orderings in World show alternatives A-Si, CdTe, Single-Si, Ribbon-Si and Multi-Si to have a 97%, 89%, 88%, 66%, 67% probability of ranking first to fifth respectively. Weight sensitivity of European reference and outranking is similar with a slight difference in the last rank composition. Rank orderings with an European normalization reference show CdTe, Single-Si, Ribbon-SI, A-SI, and Multi-Si to have a 67%, 48%, 42%, 29%, and 79% of ranking first to fifth respectively. Rank orderings in outranking show CdTe, A-SI, Ribbon-Si, Multi-Si, and Single –Si to have a 66%, 57%, 56%, 45% and 56% of ranking first to fifth respectively.

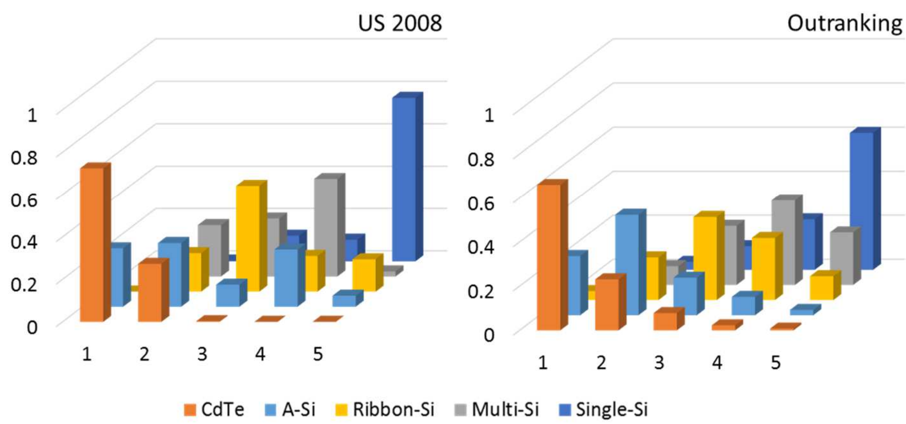

Figure S5. Rank acceptability indices of the Comparative LCA of PV using two normalization approaches in TRACI: US 2008 reference (left) and outranking (right) The x-axis represents the rank ordering, the y-axis represents the rank acceptability index and the z-axis represents each individual alternatives also denoted by color.

Figure S5 shows the rank acceptability indices for the PV comparative LCA using TRACI characterization and two normalization approaches. Both rank compositions are similar and both facor the same order of alternatives. Outranking generates slightly more weight sensitive results. Rank orderings in US 2008 show alternatives CdTe, A-Si, Ribbon-SI, Multi-Si and Single-Si to have a 72%, 30%, 50%, 46% and 77% probability of ranking first to fifth respectively. Rank orderings in outranking show CdTe, A-Si, Ribbon-Si, Multi-Si and Single-Si to have a 66%, 45%, 38%, 38%, 62% of ranking first to fifth respectively.

APPENDIX C
CO-AUTHOR AUTHORIZATIONS

February 24, 2015

I, Lise Laurin, give permission to **Valentina Prado Lopez** to submit the following manuscript:

Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted). As part of her PhD thesis at Arizona State University.

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Kittery ME

February 25, 2015

I, Mikhail Chester PhD, give permission to **Valentina Prado Lopez** to submit the following manuscript: Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted). As part of her PhD thesis at Arizona State University.

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I, Thomas P. Seager PhD, give permission to **Valentina Prado Lopez** to submit the following manuscript: Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted). As part of her PhD thesis at Arizona State University.

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I, Ben A. Wender, give permission to **Valentina Prado Lopez** to submit the following manuscript: Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted). As part of her PhD thesis at Arizona State University.

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I, Erdem Arslan PhD, give permission to **Valentina Prado Lopez** to submit the following manuscript: Prado-Lopez V, Wender B, Laurin L, Seager TP, Chester M, Arslan E. 2015. Tradeoff evaluation improves comparative life cycle assessment: A photovoltaic case study. Journal of Industrial Ecology (accepted). As part of her PhD thesis at Arizona State University.

3/15/2015

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