Decision Analysis

for

Comparative Life Cycle Assessment

by

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ABSTRACT

Life Cycle Assessment (LCA) quantifies environmental impacts of products in raw material extraction, processing, manufacturing, distribution, use and final disposal. The findings of an LCA can be used to improve industry practices, to aid in product development, and guide public policy. Unfortunately, existing approaches to LCA are unreliable in the cases of emerging technologies, where data is unavailable and rapid technological advances outstrip environmental knowledge. Previous studies have demonstrated several shortcomings to existing practices, including the masking of environmental impacts, the difficulty of selecting appropriate weight sets for multi-stakeholder problems, and difficulties in exploration of variability and uncertainty. In particular, there is an acute need for decision-driven interpretation methods that can guide decision makers towards making balanced, environmentally sound decisions in instances of high uncertainty. We propose the first major methodological innovation in LCA since early establishment of LCA as the analytical perspective of choice in problems of environmental management. We propose to couple stochastic multi-criteria decision analytic tools with existing approaches to inventory building and characterization to create a robust approach to comparative technology assessment in the context of high uncertainty, rapid technological change, and evolving stakeholder values. Namely, this study introduces a novel method known as Stochastic Multi-attribute Analysis for Life Cycle Impact Assessment (SMAA-LCIA) that uses internal normalization by means of outranking and exploration of feasible weight spaces.

DEDICATION

To my grandparents, Olga Marmolejo and Hernán López

ACKNOWLEDGMENTS

I would like to thank the students and faculty of the Sustainable Energy and Environmental Decision Science (SEEDS) studio at Arizona State University.

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Chapter 1

INTRODUCTION TO BOOK CHAPTER

Existing interpretation practices for comparative LCAs rely in external normalization methods, do not provide sufficient decision support and can have misleading recommendations. The following chapter, which corresponds to the material previously published in the Handbook of Life Cycle Assessment in 2012, proposes alternative interpretation methods that rely in internal normalization methods. The following chapter addresses and explains the concerns surrounding internal normalization methods, and concludes that internal methods of normalization that derive from stochastic decisions analysis tools best fit comparative LCAs. The following chapter can be found under the citation:

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

Note: All co-authors have granted authorization to include publication as part of this MS thesis.

Chapter 2

MULTI-CRITERIA DECISION ANALYSIS FOR LCA

2.1 ABSTRACT

This chapter reveals how ISO normalization guidelines can have misleading recommendations, explains existing objections to descriptive approaches to normalization, and suggests a method that draws upon advances in stochastic multi-attribute analysis (SMAA) to resolve some of the most difficult challenges associated with LCA, such as eliciting criteria weights and understanding the uncertainty of those weights relative to other data. External normalization is unsuitable for comparative LCA because it derives from normative theories that use an absolute scale and assume transitivity. Impact assessment in comparative LCAs would benefit from the application of descriptive approaches extant in Multi Criteria Decision Analysis (MCDA) to help structure normalization and weighting stages. Specifically, outranking MCDA methods allow for the comparison of multiple competing alternatives by only allowing partial compensation. It is essential to provide robust methods for comparative LCAs that are sensitive to inherent uncertainties and capable of representing multiple viewpoints.

2.2 INTRODUCTION

Life Cycle Assessment is a powerful tool for comparing multiple products with respect to their overall environmental impact. However, the results from LCA are difficult to comprehend because of the vast amount of data, diversity of physical units, value judgments, and uncertainty in the parameters (Le Teno, 1999). LCA creates data, but is limited in its capacity to interpret information for decision makers (Canis et al., 2010, Boufateh et al., 2011). As a result, most comparative LCA studies do not perform any valuation and are left as a set of characterized data, leaving decision makers to confront multi-criteria, multi-stakeholder problems unaided (Rogers et al., 2008, Rowley and Peters, 2009). This can lead to confusion and bias among decision-makers and stakeholders since their cognitive ability to process large amounts of data is limited and subject to systematic flaws (Hertwich and Hammit, 2001). Additionally, the LCA studies that do complete impact assessment according to the current recommended practices typically result in a single overall environmental score that it is also subject to biases and fundamental flaws (Rowley and Peters, 2009).

Comparative LCA studies are multi-criteria decision type problems that involve decision makers (policy makers, public, and stakeholders), multiple criteria (e.g., global warming, eutrophication, human toxics, and acidification) and multiple competing alternatives (i.e., different products, policies or services). Therefore, comparative LCAs can benefit from borrowing tools from decision analysis methods such as Multi-criteria Decision Analysis (MCDA) to help structure the valuation phase (Rogers et al., 2008, Rogers and Seager, 2009, Jeswani et al., 2010, Hanandeh and El Zein, 2010, Le Teno and Mareschal , 1998, Basson and Petrie 2004, Seager et al., 2008, Benoit and Rousseaux, 2003, Elghali et al., 2008, Rowley and Shiels, 2011, Rowley and Peters, 2009, Dorini et al., 2011). MCDA refers to a variety of methods developed to help decision makers organize and synthesize information to select an alternative among competing options (Loken, 2007). The methods are not intended to make actual decisions, instead they are intended to guide the decision making process in a dynamic and iterative manner (Hersh, 1999, Seager et al., 2006). MCDA methods are capable of handling complex decision problems with multiple, conflicting criteria with incommensurate units (Hanandeh and El-Zein, 2010, Wang et al., 2009). Furthermore, MCDA methods are adequate to sustainability problems because they can integrate environmental, economic and social values (Jeswani et al., 2010).

There are two main types of MCDA methods that apply to comparative LCAs (Rowley and Peters, 2009, Boufateh et al., 2011). There are normative methods based on the Multi Attribute Utility Theory (MAUT), and descriptive methods such as outranking. MAUT methods are used the most, despite their highly compensatory nature, mathematical complexity, and resource intensity (Seager et al., 2006). Compensability is a fundamental characteristic of MCDA methods and it refers to the possibility of offsetting poor performance in one aspect of a problem with good performance in another (e.g., clean air makes up for contaminated water, or large profits make up for the loss of ecosystem habitat). Fully compensatory methods are undesirable for environmental problems because they represent an exclusively weak sustainability perspective where different forms of capital (financial, human, and ecological) are considered substitutable (Rowley and Peters, 2009). By contrast, outranking methods avoid full compensation and are easier for decision makers to understand (Loken, 2007, Benoit and Rousseaux, 2003).

Unfortunately, descriptive approaches to valuation in LCA have been for the most part rejected by the LCA community due to claims of theoretical issues (Basson and Petrie, 2004, Hertwich and Hammit, 2001, Giove and Brancia, 2009, Seppala et al., 2002). As a result, recommended normalization and weighting practices consist of fully compensatory external normalization, and single weights that yield a single score for each alternative. The following sections in this chapter go into further detail about the current practices, fundamental weaknesses in these, and ways to create a more robust framework for interpreting results from comparative LCAs.

2.3 CURRENT PRACTICES IN LIFE CYCLE IMPACT ASSESSEMT

The valuation or interpretation stage in LCIA is composed of normalization and weighting, and it helps convey the results of an LCIA study to stakeholders and decision-makers. The results of an LCIA study prior to valuation show the different performances of the alternatives in several impact categories. For example, the performances of a set of products in categories like carbon emissions, water use, and energy requirements. It is difficult to judge the overall environmental performance of alternatives based on multiple criteria with incommensurate units (e.g., tons of CO_2, gallons of water, and kWh). In practice, when comparing the environmental impacts associated with alternatives, it is rare to find an alternative that outperforms the rest in all impact categories. In fact, most of the time products perform differently in all impact categories, which make normalization and weighting instrumental steps in comparative LCAs. The purpose of normalization is to convert the different units of the impact categories into one dimensionless unit for easier comparison (Bare, 2010, De Benedetto and Klemes, 2009, Bare, et al., 2006 and, Pennington, 2004). Normalization provides context and adds significance to the results. However, deciding on appropriate normalization methods is still an area of controversy (Bare, 2010).

After normalization, weighting reflects the relative importance of environmental impacts according to the stakeholders and the decision maker's preferences and values (Seppala et al., 2002). The weighting process helps to simplify tradeoffs when dealing with competing alternatives and opposing values within the panel of decision makers. For example, a stakeholder might value global warming over ozone depletion. Weighting allows for impacts to be aggregated into a single score for easier evaluation, according to appropriate preferences. However, weights are inherently subjective and can vary depending on culture, political views, gender, demographics, and professional opinion of stakeholders. Consequently, single-score results are criticized by some practitioners. While it is true that other aspects of LCA are also subjective, like the selection of impact categories, Schmidt and Sullivan (2002) make a distinction between choices based on values and choices based on technical assumptions. Therefore, weighting and normalization are categorized as optional steps by the ISO standards. Current research in LCIA deals primarily with impact categories and characterization factors, and pays little attention to normalization practices. Reap et al. (2008) perform a survey of major problems in LCA which highlights issues in impact categories and characterization factors, such as spatial variation, local uniqueness, environmental dynamics, and decision time horizon. Bare (2010) mentions termination points (inventory, midpoint, and endpoint) as one of the main research needs in LCIA, and mentions normalization only with respect to the need for more comprehensive external normalization reference databases that report the total amount of emissions in a specific reference system (e.g., total carbon emissions in the US, or total NO_x in the state of California – e.g., Finnveden et al., 2009).

2.4 PRINCIPLES OF EXTERNAL NORMALIZATION

External normalization relates the results of an LCIA study to an external database or normalization reference, thus the results are in terms of a fraction of a broader reference, like total regional or national emissions. External normalization relies on information outside the study and is intended to show the significance of a result relative to a chosen region or reference system (Norris, 2001). By contrast, internal normalization utilizes values within the study and shows the relative significance of an impact with regards to the other competing alternatives. For example, external normalization relates the carbon emissions of products to the region's total carbon emissions, and internal normalization provides the significance of the product's carbon emission relative to the amount of emissions of the other competing alternatives. Thus, external normalization uses an absolute scale, and internal normalization uses a relative scale (although it can be argued that the "absolute scale" is also relative because it comes from an ideal which is relative by nature -- Saaty, 2006).

External normalization is a normative concept based in utility theory which assumes transitivity (Seppala et al., 2002). Utility theory assigns a number value (or utility) to each alternative with the implicit goal of utility maximization (Fishburn, 1970). Thus, an alternative with the greater utility is preferred to lesser. Transitivity requires that when alternative A is preferred over B, and B is preferred over C, then A must be preferred over C (Edwards, 1954). Utility theory *rates* alternatives with respect to an *absolute* scale (Saaty, 2006). In the case of external normalization in LCIA, the absolute scale is the database of total regional, national or global impacts. Mathematically external normalization is done by dividing the characterized result of each impact category by the value of the normalization reference system (Equation 1):

$$N_i = S_i/A_i$$

Where N is the normalized value for impact category *i*, S is the characterized impact and A is the normalization reference value from an external database (Bare et al., 2006). The rating of each alternative is independent of each other and it is not subject to change if other alternatives are added or removed (Vargas, 1994, Saaty, 2006). Therefore, rating in external normalization is transitive. However, not all rational decisions follow a transitive pattern (Vargas, 1986). For example, consider the intransitive order of the rock-paper-scissors game: rock beats scissors, scissors beats paper, and paper beats rock. In this case, there is no dominant winning strategy. In fact

May (1954) mentions multiple examples that violate the principle of transitivity and shows how intransitivity arises when choosing alternatives with conflicting criteria.

2.5 ISSUES WITH EXTERNAL NORMALIZATION

External normalization gives context to the characterized results and places different criteria in common terms. However, there are severe disadvantages and fundamental issues that come with applying external normalization to comparative LCAs.

2.5.1 Inherent data gaps

Utilizing external normalization references introduces additional uncertainty to the study because of the lack of consensus in data (Bare et al., 2006). Any overestimation or underestimation in the external normalization references can have a significant impact in the results (Heijungs et al., 2007). For instance, a lack of emission data in the NR yields a normalized result that is too high. Such bias is especially problematic when comparing alternatives (White and Clark, 2010). Studies dedicated to the reduction of bias in normalization are often concerned with methods for filling data gaps (Bare, 2010, White and Carty, 2010, Finnveden, 2009, Heijungs et al., 2007). Addressing data gaps is resource intensive and time consuming (White and Carty, 2010), and such efforts can prove to be impractical for comparative LCIA studies. Even a comprehensive database can lead to biased results because of fundamental issues such as: risk of masking salient aspects, compensation, boundary issues and discrepancy between different databases.

2.5.2 Masking salient aspects

In external normalization, impact categories with large annual per capita values (e.g., eutrophication) yield small normalized results, as opposed to impact categories with relatively small annual per capita values (e.g., ozone depletion), which yield large normalized values. According to White and Carty (2010) this phenomenon is referred to as “inverse proportionality” and can lead to confusion and counterproductive actions. The bias introduced by external normalization can be so high as to completely exceed the effects of weighting (Rogers and Seager, 2009). For example, Figure 1 shows this bias by applying six different weight sets to a normalized data, but obtaining the same rank ordering of alternatives in each case. The overall environmental scores change in magnitude, but their ranking remains the same. This shows that the outcome of a comparative LCA study can be independent of stakeholder values’ and completely driven by normalization. In Figure 1, the weights for HHCR range from zero in long term users, to 61% in short term LCA experts. Similarly, other impact categories like GW the weights range from 9% to 92%, and FFD ranges from 2% to 28%.

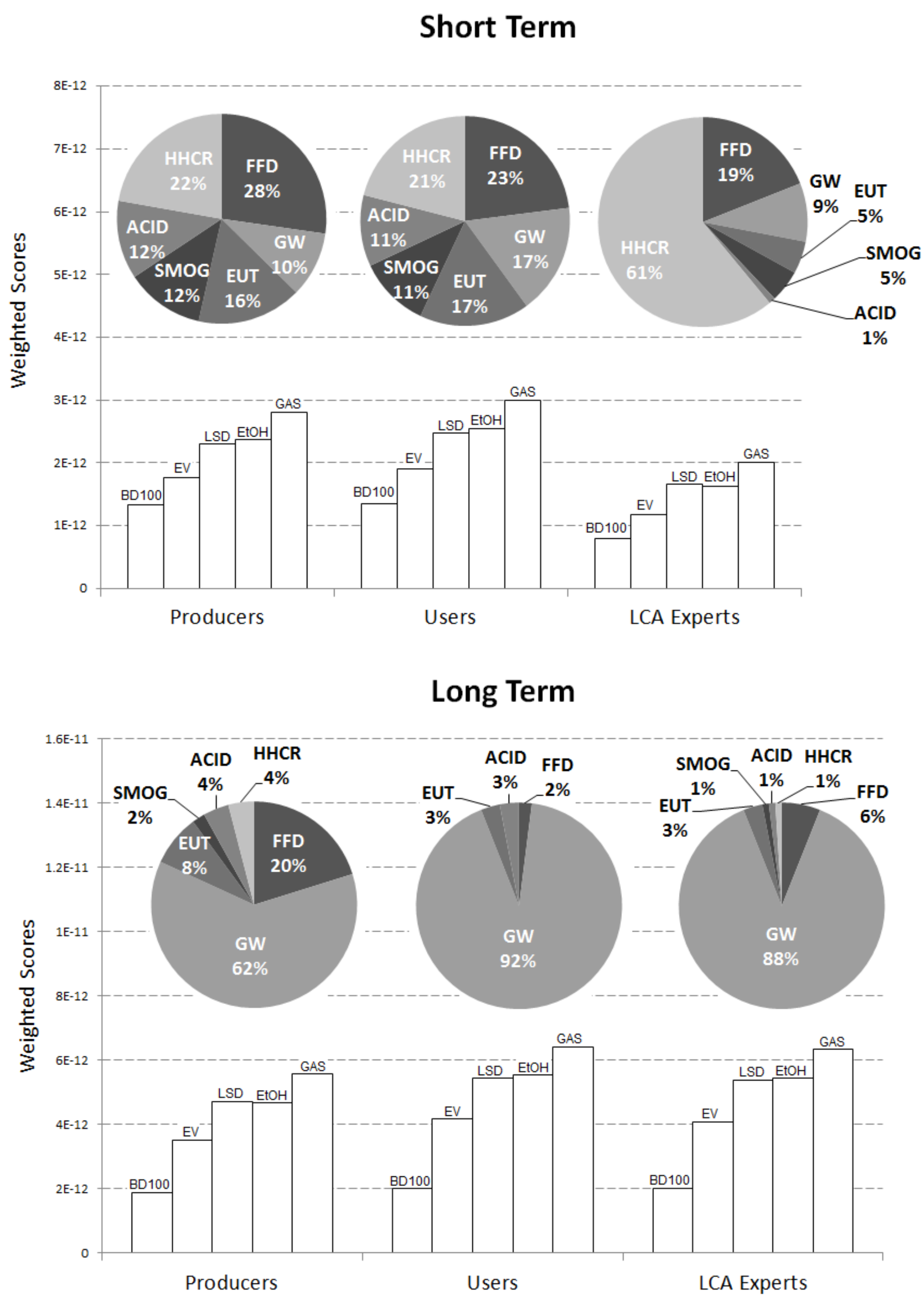

Figure 1. Weighted Scores for various transportation fuels: 100% Biodiesel (BD100), Electrical Vehicle (EV), Low Sulfur Diesel (LSD), Ethanol (EtOH), and Gasoline (GAS). The scores are according to a weight set given by Producers, Users and Experts for Short and Long Term impacts. The criteria evaluated were Fossil Fuel depletion (FF), Global Warming (GW), Smog (SMOG), Acidification (ACID), Eutrophication (EUT), and human health criteria air pollutants (HHCR). (Adapted from Rogers and Seager, 2009).

2.5.3 Compensation

External normalization uses utility functions to aggregate values into a single number (Seppala et al., 2002) and allows for a product's poor performance in one category to be compensated by a good performance in another category. Thus, external normalization is fully compensatory (Rogers, 2008). However, compensation is problematic when dealing with environmental decisions because it represents a weak sustainability perspective, to the exclusion of strong sustainability (Rowley and Peters, 2009). For example, given a product's outstanding performance in a single category, it is possible that it can offset its poor performance in several others. However, the strong sustainability view rejects such unlimited substitution for pragmatic as well as ideological reasons (Ayers et al., 1998)

2.5.4 Spatial boundaries and Time Frames

Because environmental data is often reported by federal agencies, normalization reference data is typically compiled on a national basis. However, not all environmental impacts have national effects (Bare and Gloria, 2006). For instance, smog has a more localized effect than global warming. Thus, it is possible that impacts outside the reference area will not be accounted for (Heijungs et al., 2007). Similar to the spatial boundary issues, different processes and products generate emissions over different time periods. Since most normalization references exist on an annual basis, external normalization becomes problematic when dealing with emissions outside this time frame (Finnveden et al., 2009). For example, landfilling continues to generate emissions even after decades of storage.

2.5.5 Divergence in data bases.

All of the issues combined lead to a great deal of discrepancy between normalization databases. This is clear when different data bases yield significantly different results.

White and Clark (2010) offer an example of biases in external normalization. Here, the authors select 800 random materials and processes in the Ecoinvent life cycle inventory and utilize two methods of characterization and normalization. The first one uses TRACI characterization factors normalized according to 2000 US per capita values. The second one uses CML baseline 2001 for characterization factors normalized with CML 1995 database. The results show that the first approach focuses exclusively on human toxicity, human cancer and ecotoxity categories, whereas, the second approach focuses on completely different categories like marine toxicity, freshwater toxicity and fossil fuel depletion.

2.6 PRINCIPLES OF INTERNAL NORMALIZATION

Normalization can also be performed internally in a variety of ways, either by division (division by maximum, division by minimum, division by baseline, division by sum), by applying methods from MCDA like the Analytic Hierarchy Process (AHP -- Saaty, 1980), or outranking (Behzadian et al., 2010, Figueira et al., 2005). Internal normalization is descriptive rather than normative approach, and gives a *ranking* to alternatives that is dependent on other alternatives, rather than a rating. The ranking is based on a relative scale, and it can change when the number of alternatives changes. Relative scales can result in rank reversal (Saaty, 2004), but only when relevant alternatives are introduced or removed from the analysis (Harker and Vargas, 1990). Rank reversal occurs when the addition or removal of one alternative causes the rank of other alternatives to change. For example, consider that alternative A is ranked higher than Alternative B, but once alternative C is introduced, B becomes the highest ranked alternative followed by A, then C. As opposed to normative approaches, descriptive approaches allow and accept intransitive preferences, thus rank is not always preserved. In fact, the notion of rank preservation or rank invariance principle (Vargas, 1994), is a normative concept stating that the ranking of alternatives should remain the same regardless of the number of alternatives introduced or deleted. According to this theory, rank is to be preserved even if there is new information added to the problem. The fact that rank reversal is a real life occurrence is not addressed by the ideal of rank preservation. Rank reversal remains a highly controversial subject within the normative and descriptive communities (Harker and Vargas, 1987, Harker and Vargas, 1990, Vargas, 1994, Erdogmus et al., 2006, Dyer, 1990, Schenkerman, 1994), also referred to as classical and naturalistic approaches respectively (Hersh, 1999). In LCIA, rank reversal from internal normalization is not well analyzed and understood. Instead, it has been automatically discarded as inappropriate without any further consideration. Initially, LCIA studies applied internal normalization but because of criticisms due to the rank reversal phenomenon, and to ensure congruency in the valuation stage, external normalization became the common practice (Bare, 2010, Wang and Elhag, 2006, Norris, 2001). Nevertheless, deciding on appropriate normalization guidelines is still an area of controversy (Bare, 2010).

2.6.1 Compensatory methods:

Internal normalization by maximum is a method in which the values of all alternatives in each category are divided by the maximum value in that category prior to weighting. For example, if three alternatives having lead emissions of 2, 4, and 10 mg each were to be normalized, the values will be normalized with respect to the alternative with the highest lead emissions (10 mg of Pb). Thus, it yields dimensionless normalized results of 0.2, 0.4, and 1 respectively. Likewise, internal normalization by minimum would yield 1, 2 and 5. Internal normalization by a baseline, divides the values in the category by the selected baseline alternative. An issue with this method is that it may lead to a division by zero for nonexistent flows (Norris, 2001). Division by sum normalization divides the attributes in each category by the sum of the category (Norris and Marshal, 1995). A drawback from this method is that it can yield biased results when most values are closer to the top or bottom of the range (Norris, 2001). Although these methods do not have the some of the issues of external normalization, internal normalization by means of division still allows for full compensation between categories. This feature leads to an unsatisfactory framework for environmental type decisions where tradeoffs between criteria (e.g., water quality and air quality) are undesirable.

The AHP method was developed by Saaty (1980) with the realization that humans are more capable of making relative judgments over absolute judgments (Linkov et al., 2007). The AHP uses pair wise comparisons between attributes of two alternatives at a time, and asks questions such as “How much more important is one attribute over the other?” For example, “How much more important is water quality over air quality?” Decision makers are then asked to assign a value from a 0 to 9 scale, where 0 means equally important and 9 means extremely more important. The verbal mediation in the 0-9 scale helps decision makers translate fuzzy judgment into number values (Norris and Marshall, 1995). After the pair wise comparisons, an eigenvector analysis yields weights. Once the decision makers assign a value to their preferences and their respective weights calculated, the alternative with the highest overall ranking is said to be the preferred alternative. Although AHP is also a complete method of aggregation that allows for full compensation, it is an intuitive and flexible tool that can deal with tangible and intangible criteria (Ramanathan, 2001, Erdogmus et al., 2006). Nevertheless, AHP is limited in some respects (Macharis et al., 2004).

2.6.2 Partially compensatory methods.

Alternate methods of internal normalization performing outranking such as PROMETHEE (Preference Ranking Organization Method of Enrichment Evaluation) and ELECTRE (ELimination and Et Choice Translating REality), specifically ELECTRE III and PROMETHEE I, II, are advantageous for environmental problems. These methods are partially compensatory, allow for easier value elicitation, and can work with partially quantitative data (Geldermann and Schobel, 2011). Outranking judges alternatives with regard to each other on each criterion, provided there is enough evidence to judge one alternative to outrank another (Loken, 2007).

There are two main steps to these methods: one involves the normalization process by means of pair wise comparisons, and the second is the process of producing the ranking of alternatives. Both, ELECTRE III and PROMETHEE I and II require a preference function (Figure 2) with preference (p) and indifference (q) thresholds. The preference threshold (p) is the smallest deviation between two alternatives considered significant, or enough to be preferred, and the indifference threshold (q) is the largest deviation considered negligible (Brans and Mareschal, 2005). Thresholds can be selected arbitrarily (Linkov et al., 2007) or based on the uncertainty of a given criteria (Rogers and Bruen, 1998). Preference values are real numbers between 0 and 1, where 1 is strict preference and 0 is indifference. A weak preference of one alternative over another alternative results in an interpolated preference value between 0 and 1.

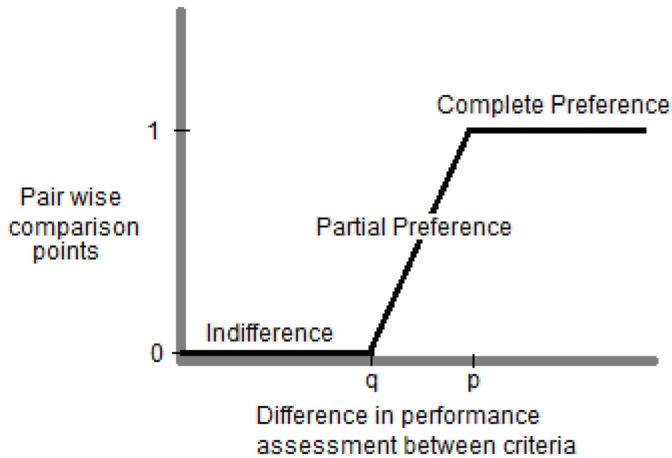

Figure 2. Linear preference function

After gathering the preference indices for each pair wise comparison, the preference indices for each alternative are aggregated along with the weights. The weights are specific of each impact category, and they reflect the importance of the category as assigned by decision makers. Finally, alternatives are ranked depending on their overall score. The decision making process is an iterative process, and it is not meant to provide an absolute single answer. Instead, it is intended to help decision makers better understand the problem and organize their judgment (Seager et al., 2006).

Compared to ELECTRE, the calculation procedure in PROMETHEE is more transparent and easier for decision makers to understand (Seager et al., 2006). It is important for decision makers to understand the methodology so they feel comfortable and trust the recommendations otherwise the decision analysis is meaningless. For example, sometimes the ELECTRE method seems as a “black box” and it is unsatisfactory for decision makers (Loken, 2007). PROMETHEE avoids full compensation between criteria, deals with partial quantitative data, and it is easily understood by decision makers. However, PROMETHEE still relies upon point estimates for inputs with no uncertainty. In environmental decisions, uncertainty must be considered because the precise information is not always available within analytic time frames (Hersh, 1999). Specifically, there is a need for methods that can investigate the effects of changing input parameters and weights (Hersh, 1999). Recently, there have been modified versions of PROMETHEE that allow for uncertainty in the inputs and weights (Rogers, 2008, Canis et al., 2010, Tylock et al., 2011). These methods utilize Monte Carlo analysis to explore a range of inputs, and allow uncertainty in the input parameters (Lahdelma et al., 1998). Thus, it is possible to perform an analysis with basic information at an early stage of alternative development or where quantitative performance is difficult to obtain (Seager et al., 2006).

2.7 WEIGHTING

Weights can be obtained a number of ways (Wang et al., 2009), but typically are represented as a single vector for easier evaluation. Single-score results are problematic because they lead to an extreme simplification of problem, and lose important information (Brans and Mareschal, 2005). Appropriate methods should include sensitivity to weighting analysis (Brans and Mareschal, 2005, Hersh, 1999, Rogers and Bruen, 1998). In fact, there are studies that explore the entire weight set by means of Monte Carlo simulations, resulting in a probabilistic instead of absolute ranking of alternatives (Lahdelma and Salminen, 2001, Rogers et al., 2008).

Norris (2001) exemplifies the dominant views of normalization in LCA, which prefer external normalization and weighting. To prove the point, Norris (2001) presents a multi-alternative, multicriteria problem normalized internally by division-by-maximum and weighted with single weights. There are two instances in which, according to the paper, the results are debatable. The first example shows that the results are insensitive to changes in magnitude, and the second example shows a case of rank reversal. While

Norris (2001) rejects these results as “absurd” without any further analysis, the following sections discuss both examples from a descriptive, rather than normative perspective. Figure 3 presents the example from Norris (2001) in which two alternatives, A and B, are evaluated in three weighted categories: Global Warming, Acidification, and Human Toxics. Alternative B has a higher performance assessment in Acidification and Human Toxics, and Alternative A performs better in the most significant category, Global Warming. After division-by-maximum normalization and external weighting in Figure 4, Alternative A has a lower overall score which means A is preferred to B. (In this case, the score is associated with environmental impact, thus a lower score is better). Figure 4 shows the contribution of each category in the overall score. Alternative A has an overall score of 8.5 and Alternative B has a score of 13.1. Although A has a higher score in Human Toxics and Acidification, its score in Global Warming is significantly lower.

2.8 CASE STUDY 1: MAGNITUDE SENSITIVITY

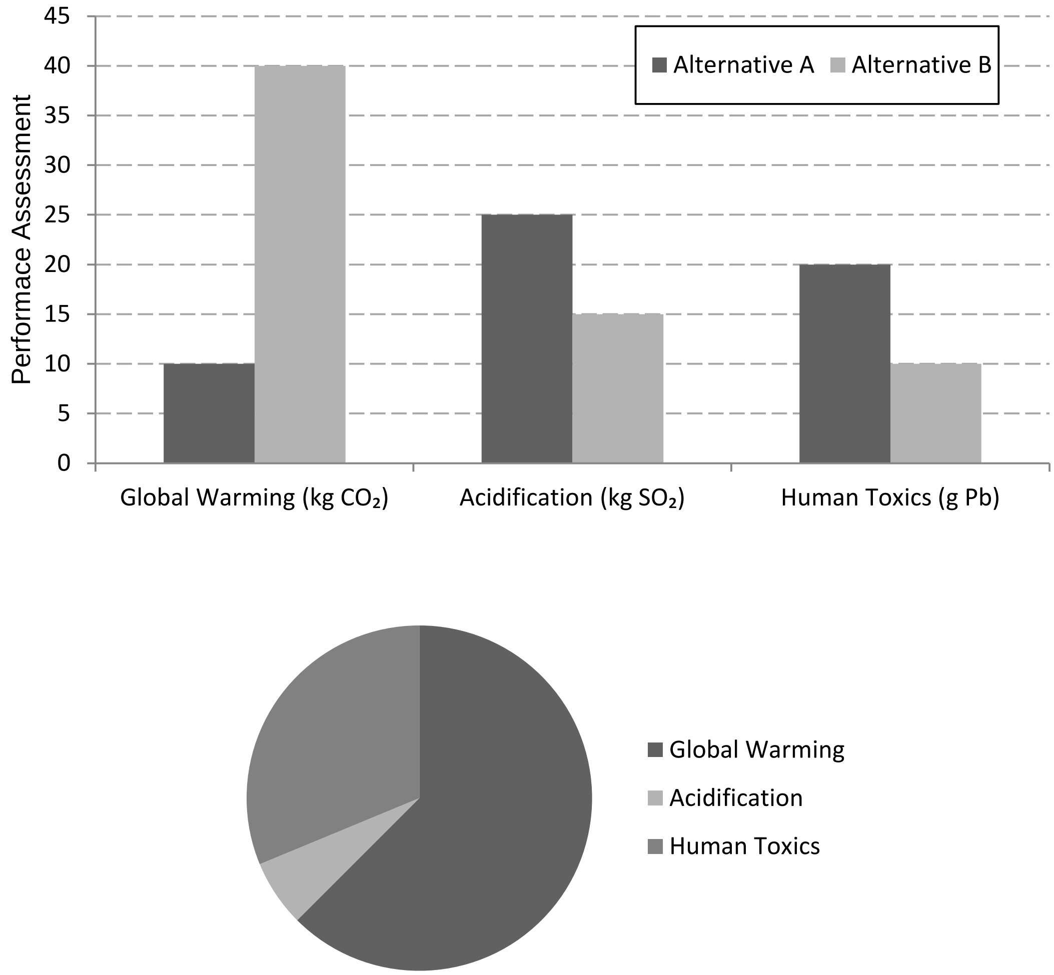

Figure 3 (Above): Performance Assessment of Alternatives A and B in three categories, note that each category is measured in different units. (Below): Assigned criteria weights. (Adapted from Norris, 2001).

To illustrate the effect of changes in magnitudes, now suppose alternative A emits 10 *micro*grams instead of 10 kilograms of CO_2, and alternative B emits 40 *micro*grams instead of 40 kilograms of CO_2. Furthermore, alternative A now releases 20 *tons* of Pb and alternative B releases 10 *tons* of Pb- instead of kg. Clearly, the minuscule difference between alternative A and B with respect to Global Warming is inconsequential. However, alternative A *still* results in a lower score despite the fact that the advantages of A over B are now comparatively inconsequential. In fact, by using the internal division-by-maximum approach, the overall scores remain the same for both alternatives despite the obvious differences in the character of the environmental inventories. Norris (2001) argues that:

> *"If the results are blind to information about significance, are unchanged by dramatic shifts in magnitude, and thus can clearly lead to absurd results on simple examples where we are able to 'know better', what meaning or reliability can they have on any problem?"*

While the fact that relative rank of A and B stay the same despite the change in magnitude between them *is* absurd, the fault doesn't lay in the normalization approach, but in the lack of judgment. When the performance assessments in Global Warming for both alternatives are practically identical (with only 30 *micro*grams of difference), then such criteria should be excluded from the analysis.

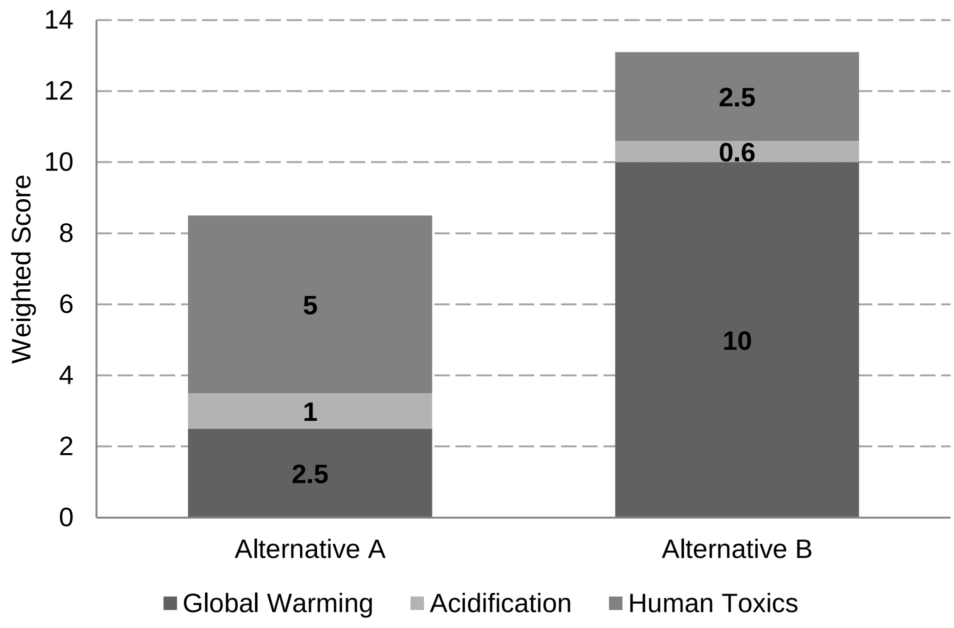

Figure 4. Overall weighted score after internal normalization of division by maximum and external single-value weighting for Alternatives A and B. (Adapted from Norris, 2001).

3

It is crucial to apply judgment in the valuation stage to make the distinction between *significant* and *negligible* values, and Norris' example fails to do so. By contrast, in outranking, preference and indifference thresholds set the difference at which a magnitude becomes significant or remains insignificant. Applying outranking normalization with preference thresholds as shown in Figure 5, results in B as the preferred alternative under conditions when the difference between B and A in global warming is insignificant. Results in Figure 5 are obtained by performing pair wise comparisons between alternatives A and B for all criteria. First, alternatives A and B are compared on each criterion and whichever is preferred beyond the preference threshold, earns one point. Then the points from each category are multiplied by the corresponding weights. Lastly, the weighted scores for all alternatives are added to form a total score. In this case the score is associated with environmental preference, thus the greater the score, the better. Figure 5 shows the outranking matrix for alternatives A and B, and unlike internal division-by-maximum, the rankings are sensitive to changes in magnitude.

There are several methods of internal normalization, each with different capabilities and applications. In the case of comparative LCAs, it is necessary to be able to input preference and indifference thresholds in order to avoid making selections based on negligible values. The fact that the rankings stayed the same after the change in magnitude shows that division-by-maximum may not be an appropriate method to use. Furthermore, the Norris example does not admit uncertainty in any parameters. Without uncertainty, what is the meaning of 15kg over 25kg? Because there is inherent uncertainty in every LCA stage, it must be considered in the interpretation stage. Weights are also uncertain. Single values for weights are not representative of the decision maker's preferences or values.

Global Warming Category (p= 1kg, q=1g)					
Performance Assessment	A	B	Pair-wise Comparison Score	Weights	Weighted Score
A (10µm)		0	0	10	0
B (40µm)	0		0	10	0

Acidification Category (p=1kg, q=1g)					
Performance Assessment	A	B	Pair-wise Comparison Score	Weights	Weighted Score
A (25kg)		0	0	1	0
B (15kg)	1		1	1	1

Human Toxics Category (p=1kg, q=1g)					
Performance Assessment	A	B	Pair-wise Comparison Score	Weights	Weighted Score
A (20 ton)		0	0	5	0
B (10 ton)	1		1	5	5

	Total Score
A	**0**
B	**6**

Figure 5. Outranking matrix with preference and indifference thresholds. Both alternatives have nearly the same performance in the most significant category, Global Warming, thus they both get a score of 0. However, in Human Toxics and Acidification categories, Alternative B outperforms Alternative A, yielding a higher rank for B.

2.9 CASE 2: RANK REVERSAL

The second example in Norris (2001) deals with ranking reversal. Ranking reversal occurs when a third alternative, C, is introduced to the previous comparison of A and B as shown in Figure 6. Alternative C performs the worst in the most important impact category (Global Warming), but it is competent in Human Toxics and Acidification. Prior to the introduction of alternative C, alternative A ranks higher than B. However, once alternative C is added, the new ranking becomes B, A then C (Figure 7). Note that the ranking of A and B is reversed. Before, alternative A had a considerably larger advantage over B in the Global Warming impact category, but compared to the high CO_2 emissions of alternative C, the difference between A and B becomes relatively insignificant. Rank reversal is an indication that the problem has changed. Comparing A and B, is very different than comparing A, B and C. Each alternative provides some information to the decision problem, and when one alternative is included or removed, the way the problem is perceived also changes.

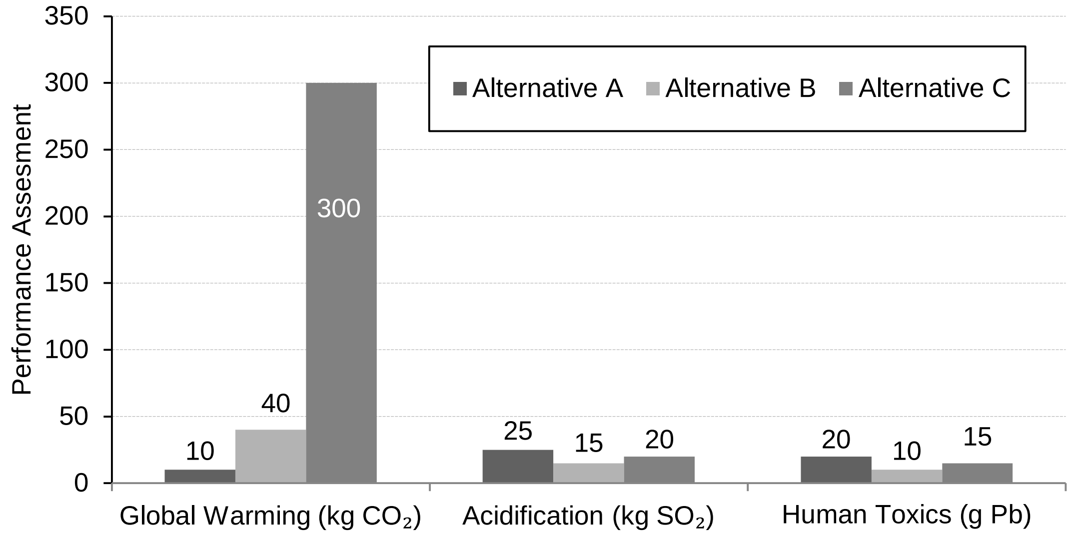

Figure 6. Performance Assessment of Alternatives A, B and C in Global Warming (GW), Acidification (A), and Human Toxics (HT) categories.

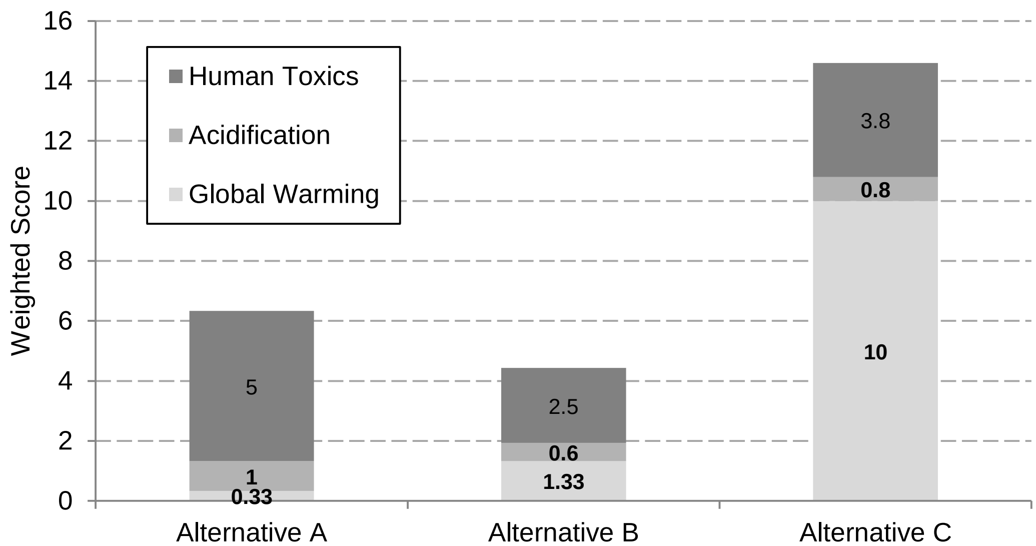

Figure 7. Weighted score for Alternatives A, B and C through internal division-by-maximum approach. According to the results, alternative B is ranked first followed by A and C.

When the number of alternatives changes in a choice set it can cause a *context effect*, which happens when adding alternatives changes the preferred choice even when the new alternative seems inferior (Johnson et al., 2007). Nonetheless, depending on the context, an alternative can become more or less desirable (Busemeyer et al., 2007). Context effects are often used as selling techniques in order to make a product seem better. For example, Shafir et al. (1993) provide an example of context effect when a baking equipment store in San Francisco started selling more ovens once it included a much more expensive option. The relatively higher price of the new oven made the other ones seem more reasonable purchases. Context effects can also be witnessed in wine purchasing in restaurants. For example, restaurant diners tend to buy the second cheapest wine in a list, to avoid being perceived as frugal. This behavior is often known to as the "second-cheapest syndrome" (*Telegraph UK*, 2007, *Harvard Law Record*, 2002). Consider a wine list that offers three wines with prices of $30, $45, $55. The $45 wine might seem like the best compromise, not too expensive, not too cheap. Now consider a wine list that offers a $45, $55 and an $80. The new addition ($80 wine) might motivate the costumer to purchase the $55 wine instead of the $45 wine. The new option reframes the problem, and consequently forms a different decision problem (with a different preferred resolution).

Performing the example in Norris (2001) with outranking also results in the rank reversal of A and B when C is introduced. However, our view is that rank reversal is not "absurd", but a fact of life (Vargas, 1994). Each alternative in a choice set provides information and whenever these change so does the way the problem is perceived. In the example provided in Norris (2001), introduction of alternative C, which is clearly worse than A and B in the most heavily weighted category, it change the way A and B are perceived. Previously A's "advantage" over B seemed strong. However, C makes this difference seem less significant and because B was superior than A in the other two categories, it outranked A.

Both examples of changes in magnitude and rank reversal suffer from the use of deterministic values in the performance assessment and weights, and consequently result in absolute rankings. However, in LCA there is uncertainty in every stage. Using point estimates can be useful for a basic understanding, but it can also result in an oversimplification of the problem with a narrow perspective. Comparative LCA deals with irreducible criteria that need more robust methods of analysis that allow for uncertainty in the performance assessment and weights. There are environmental decision problems that utilize an outranking approach with *probabilistic* ranking in areas such as transportation fuels (Rogers and Seager, 2009), emerging nanotechnologies (Canis et al., 2010), and energy technologies in buildings (Tylock et al., 2011).

2.10 CONCLUSIONS

External normalization can be beneficial for improvement assessment in LCA, but is inadequate for comparative LCA because it can mask important criteria and introduce severe bias and uncertainty into the results. For comparative LCAs, it is best to normalize using outranking algorithms that avoid full compensation, work effectively with non-quantitative data and allow for judgment in terms of indifference and preference thresholds. Furthermore, given the inherent uncertainty in both weights and inventories, it is unrealistic to consider discrete values. Instead, by exploring a range of possible weights through Monte Carlo analysis and creating probabilistic, rather than discrete rankings, stakeholders can gain a greater understanding of the life-cycle environmental decision problem.

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Chapter 3

INTRODUCTION TO MANUSCRIPT

The following manuscript in Chapter 4 introduces a novel approach to normalization and weighting of characterized life-cycle inventory data for use in comparative LCAs. This novel approach applies a version of Stochastic Multi-attribute Analysis (SMAA), which consists of internal normalization by means of outranking and application of relative probabilistic weights. 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. To demonstrate the nature of both valuation methods, this study utilizes the characterized inventory of a comparative LCA of laundry detergents.

Prado-Lopez , V., Seager, TP., Chester, M., Laurin, L., Bernardo, M., Tylock, S., 2013. “Stochastic Multi-attribute Analysis (SMAA) as an Interpretation Method for Comparative Life Cycle Assessment (LCA)”. *International Journal of Life Cycle Assessment* (accepted)

Note: All co-authors have granted authorization to include publication as part of this MS thesis.

Chapter 4

SMAA AS AN LCA INTERPRETATION METHOD

4.1 ABSTRACT

Purpose: Comparative Life Cycle Assessments (LCAs) today lack robust methods of interpretation that help decision makers understand and identify tradeoffs in the selection process. Truncating the analysis at characterization is misleading and existing practices for normalization and weighting may unwittingly oversimplify important aspects of a comparison. This paper introduces a novel approach based on a multi-criteria decision analytic method known as Stochastic Multiattribute Analysis for Life Cycle Impact Assessment (SMAA-LCIA) that uses internal normalization by means of outranking and exploration of feasible weight spaces.

Methods: To contrast different valuation methods, this study performs a comparative LCA of liquid and powder laundry detergents using three approaches to normalization and weighting: (1) characterization with internal normalization and equal weighting, (2) Typical valuation consisting of external normalization and weights, and (3) SMAA-LCIA using outranking normalization and stochastic weighting. Characterized results are often represented by LCA software with respect to their relative impacts normalized to 100%. Typical valuation approaches rely on normalization references, single value weights and utilizes discrete numbers throughout the calculation process to generate single scores. Alternatively, SMAA-LCIA is capable of exploring high uncertainty in the input parameters, normalizes internally by pair-wise comparisons (outranking) and allows for the stochastic exploration of weights. SMAA-LCIA yields probabilistic, rather than discrete comparisons that reflect uncertainty in the relative performance of alternatives.

Results and Discussion: All methods favored liquid over powder detergent. However, each method results in different conclusions regarding the environmental tradeoffs. Graphical outputs at characterization of comparative assessments portray results in a way that is insensitive to magnitude and thus can be easily misinterpreted. Typical valuation generates results that are oversimplified and unintentionally biased towards a few impact categories due to the use of normalization references. Alternatively, SMAA-LCIA avoids the bias introduced by external normalization references, includes uncertainty in the performance of alternatives and weights, and focuses the analysis on identifying the mutual differences most important to the eventual rank ordering.

Conclusions and recommendations: SMAA is particularly appropriate for comparative LCAs because it evaluates mutual differences and weights stochastically. This allows for tradeoff identification and the ability to sample multiple perspectives simultaneously. SMAA-LCIA is a robust tool that can improve understanding of comparative LCA by decision- or policy-makers.

Key words Outranking Valuation Normalization Comparative life cycle assessment Decision analysis

4.2 INTRODUCTION

Methodological challenges in normalization and weighting have received comparatively less research attention than those of inventory building and characterization in Life Cycle Assessment (LCA). According to the International Standardization Organization (ISO), normalization and weighting are optional steps that require justification from LCA practitioners (ISO 14044, 2006). Although the ISO guidelines mention normalization by means of a reference (external normalization) or by a baseline (internal normalization), in practice, the LCA community applies external normalization. Therefore typical valuation as defined by this study is representative of methods such as ReCiPe, IMPACT 2002+, TRACI, and Ecoindicator- all which normalize externally (Lautier et al. 2010).

However, it is now recognized that problems in existing external normalization approaches include reference data gaps (Heijungs et al. 2007), a lack of consensus in data compilation (Bare et al. 2006), lack of uncertainty information (Lautier et al. 2010) and spatial and temporal variability (Finnveden et al. 2009; Bare and Gloria 2006). In addition, normalization references can be outdated, partly because compilation is a resource-intensive process. For example, the latest USA normalization reference, TRACI (Tool for the Reduction and Assessment of Chemical and other Environmental Impacts), released in 2006 has a reference year of 1999 (Bare et al. 2006).

In response to these shortcomings, current research efforts in normalization focus on repairing and building normalization references and in creating approaches to document spatial and temporal discrepancies (Lautier et al. 2010; White and Carty 2010). Nonetheless, even if current issues with normalization reference datasets are resolved, typical valuation approaches with regards to normalization and weighting remain mathematically incompatible for comparative LCAs, where the goal is to identify an environmental preferable product, process, or pathway from a set of comparable alternatives with the same functional unit (Prado et al. 2012). In fact, the use of external normalization references in a comparative LCA can mask important aspects of a decision problem because the normalized impact depends on the size of the normalization reference (White and Carty 2010). This effect is evident when the normalization step completely overcomes the weights elicited from stakeholders or decision-makers (Rogers and Seager 2009). For example, when using a normalization reference that includes a large inventory of emissions in a specific category, external normalization relative to that reference will systematically diminish differences between alternatives that might nevertheless be important to decision makers. To some, masking the environmental consequences of their choices by dividing them by emissions attributable to others may be the moral equivalent of justifying bad behavior by saying, “But everybody is doing it!”

Subjectivity concerns in the normalization and weighting stages of impact assessment often lead LCA practitioners to truncate impact assessment at characterization. While this may be effective for LCA motivated by improvement assessment, in a comparative LCA the characterized data present decision makers with too much information to interpret (Le Teno 1999; Boufateh et al. 2011). As a result, decision makers are forced to confront uncertain multi-criteria environmental problems without the aid of analytic guideposts, and may be subject to systematic biases, vulnerable to first impressions or prior stigmatization (Hertwich and Hammit 2001). To work around these difficulties, LCA practitioners may use the comparative impact representations built into several popular LCA software applications. These show the relative performance of a characterized inventory for each alternative, normalized so that 100% in any impact category represents the worst performer among all the alternatives. In contrast to the ISO recommendations, this *internal normalization* approach avoids the necessity of external normalization references. However, these approaches lead to an analysis that is insensitive to magnitude, incapable of identifying tradeoffs (Norris 2001), and incorrectly presented as “unweighted” when in fact they represent *equal* weights that may or may not correspond to decision maker priorities. Thus, relying on default graphical outputs can be misleading. There is an acute need for normalization and weighting (i.e., valuation) methods in Life Cycle Impact Assessment (LCIA) that can guide a comparative decision making process in a transparent and objective manner. This paper introduces a novel approach to normalization and weighting based on Stochastic Multi-Attribute Analysis (SMAA) that uses internal normalization by means of outranking and stochastic exploration of weight sets that do not privilege one impact category over others (Tylock et al. 2012). The method elucidates the trade-offs inherent in a comparative LCA problem, does not rely on external databases, and facilitates a more thorough exploration of uncertainty (including uncertainty and variability in preferences among multiple stakeholders or decision makers). To illustrate application of the new method to a problem in comparative LCA, we present a study in dry versus concentrated liquid laundry detergents using both typical and the novel approach to valuation.

4.2.1 LCA AND DECISION ANALYSIS

Although it is widely understood that problems in comparative LCA present as paradigmatic multicriteria-decision analytic (MCDA) problems under uncertainty, common valuation practices fail to incorporate knowledge from the fields of operations research or decision analysis that might be brought to bear in LCA. Partly this may be due to unresolved controversies within the decision analytic community itself. There are currently two schools of thought: normative and descriptive.

The normative suggests that decision analysis should conform to idealized mathematical or economic representations of how decisions *should* be made, while the descriptive maintains that decision analytics should be representative of the more heuristic and naturalistic processes that people *actually use* when confronting problems unaided. External normalization, as mentioned by ISO, more closely aligns with the *normative* school, while internal normalization in SMAA more closely aligns with the *descriptive* school. Each approach has different assumptions and implications (Prado et al. 2012), as summarized in Table 1.

Table 1. Normative and descriptive assumptions in external and outranking normalization.

	External Normalization in typical valuation	**Outranking in SMAA**
Underlying decision theory	Normative: Models decisions the way they *should* be made according to normative assumptions.	Descriptive: Models decisions more like the way they *are* made.
Type Evaluation/measurement	Absolute	Relative (i.e., comparative)
Sensibility to context	Rigid. Evaluation of alternatives should not change if the options around it change (context independent)	Flexible. If alternatives change the relative evaluation of all alternatives may also change by causing a reframing of the problem (context dependent)
Appropriate application	Improvement assessment LCA	Comparative LCA

Outranking algorithms (and consequently SMAA) use pair-wise comparisons to assess the significance of mutual differences. The comparative performance of multiple alternatives are evaluated against pseudo-criteria called preference (p) and indifference (q) thresholds (Brans and Mareschal 2005), respectively representing the smallest difference between the performance of two alternatives on a single criterion that results in a conclusive preference for one over the other, and the largest difference that is entirely inconclusive (Rogers and Seager 2009). Thus, outranking allows the analyst to discard those categories in which the alternatives are deemed equivalent and focus attention on critical differences. Although internal normalization approaches in the absence of preference and indifference thresholds may result in “absurd” conclusions (Norris 2001), outranking avoids these pitfalls by distinguishing between negligible and significant differences (Prado et al. 2012). Moreover, because outranking relies on comparative pair-wise judgments, analysis can proceed with partially quantitative data, or even qualitative data (Geldermann and Schobel 2011).

SMAA combines outranking normalization with Monte Carlo Analysis (MCA) in weighting (Lahdelma and Salminen 2001; Lahdelma et al. 1998). Specifically, SMAA avoids subjectivity in weighting by allowing for the stochastic exploration of weight spaces (including all possible weight sets, if preferred) rather than point values. This study uses a variation of SMAA, called SMAA-TY, which constrains weight ranges with respect to the relative importance of each criterion for easier weight elicitation (Tylock et al. 2012).

4.3 METHODS

To understand how SMAA-LCIA operates in comparison to other methods, this study compares three approaches to normalization and weighting in a comparative LCA of dry powder and concentrated liquid laundry detergents (Figure 8). These three are: Graphical outputs at characterization (resulting from internal normalization and equal weighting), typical valuation that consists of external normalization relative to national reference datasets, and SMAA-TY style valuation.

The comparative LCA covers the phases of raw material production, product manufacturing, packaging, transportation and disposal of packaging. The use phase, retail and product's end of life is equivalent in both formulations, thus are excluded from the LCA. The functional unit (FU) of the comparison is a standard dose of concentrated liquid and powder detergent. The detergents in this study represent typical market products of double concentration (2X) which can be found in retail stores in the United States.

The inventories of raw materials for the respective products use the ingredient formulations from the *Handbook of Detergents* (Showell 2006). The formulations in this study use point estimates of the content percent by weight of each chemical (See Supplementary Information). Each chemical component is then matched to an appropriate Ecoinvent entry (dataset version 2.2). These entries contain chemical production requirements with respect to electricity, natural gas, and water (Koehler and Wildbolz 2009). For components not found in Ecoinvent, this model uses a proxy. For instance, enzymes in both formulations do not have an Ecoinvent dataset equivalent. Thus, this model uses average datasets of liquid enzyme with enzyme content of 4-6% and a granular enzyme with an enzyme content of 4-6% as proxies (Novozymes 2010). Inventory of packaging materials according to product surveys by The Sustainability Consortium (2011) is also sourced from Ecoinvent (See Appendix).

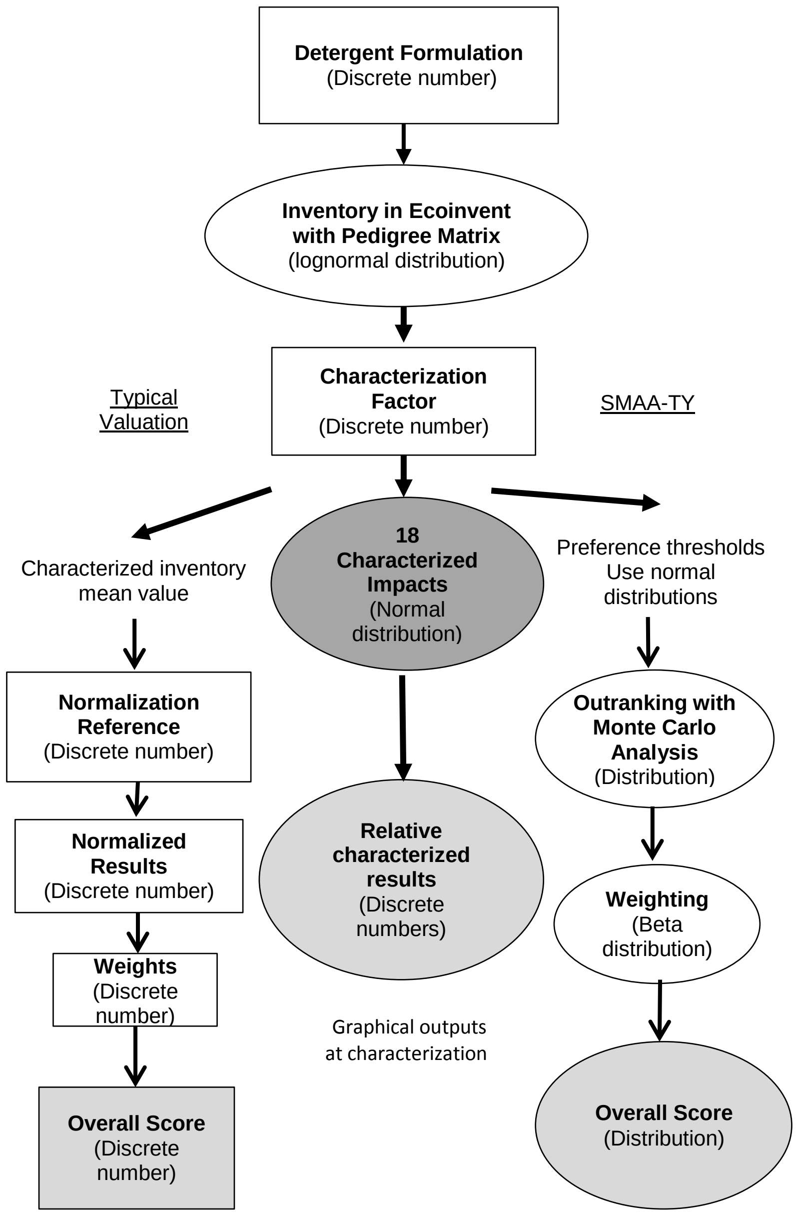

Figure 8 Three interpretation approaches; typical valuation, graphical output at characterization, and SMAA-TY valuation.

Laundry detergent manufacturers double the concentration of their products because it allows for more doses in the same container, and improves storage, distribution and transportation efficiency. Current consumer perceptions (as shaped by marketing messages) are that concentrated detergents save on packaging and transportation costs, and are therefore preferable from an environmental perspective. However, because laundry production is a wet chemical process, production of powder detergents requires an additional drying process prior to packaging – an energy intensive process that may nullify environmental gains in reduced packaging and transportation. Therefore, a comparative LCA can clarify whether the gains in transportation efficiency for powder detergents make up for the additional energy investment required in the manufacturing stage.

After processing, the liquid alternative is packaged in a plastic bottle with a plastic cap and spout, and the powder alternative is packaged in a cardboard container with a plastic scoop (Table 2). Both formulations are then distributed from the manufacturer to major cities across the USA.

Table 2. Material and process inventory of each representative product for the liquid and powder detergent. The powder detergent contains more doses per packaged product.

	Liquid Laundry Detergent	**Powder Laundry Detergent**
Main Packaging-Materials	170 grams of High density polyethylene bottle, and polypropylene cap and spout	355 grams of cardboard box and polyethylene terephthalate scoop
Main Packaging - Processing	Bottle uses stretch blow molding and the cap and spout use an injection molding process	Cardboard box made from virgin material and cap uses injection molding.
Number of FU per packaged product	64	80
Mass of functional unit	49.9 g of liquid detergent plus 2.6 g of combined packaging	34.1 g plus 4.4 grams of combined packaging

Transportation of detergents is based on an illustrative example in the US. According to the US Census Bureau (2012), the largest economic activity in the laundry detergent industry occurs in Ohio. To explore the gains in transportation efficiency versus initial manufacturing energy investments, we model approximately the greatest transportation distance within contiguous United States – from Cincinnati, OH (headquarters of Procter and Gamble, a large laundry detergent manufacturer) to Los Angeles, CA (the most population dense city on the West coast). Thus, we assume the detergents travel approximately 2,300 miles (or 3,700 km) in heavy duty trucks using diesel fuel. Since both products are dense goods, fuel inventories are proportional to weight.

Based on the GREET 1.0 database, a heavy duty truck has a load capacity of 25 short tons with a gas mileage of 5 mpg. We assume each shipment to be at 90% load capacity to take into account further tertiary packaging and pallets. The emissions during transportation depend on the fuel requirements per FU (Table 3). Further distribution to retail stores and use phase transportation is not included in the analysis.

Table 3. Each heavy duty truck contains more doses of powder detergent than liquid. Therefore, the emissions from transportation per FU are about 40% less for the powder detergent. GREET 1.0 emission factors per gallon of diesel combusted can be found in the appendix

	Liquid Detergent	**Powder Detergent**
Weight per unit (includes product and packaging)	3.2 kg	2.7 kg
Number of units in one truck at 90% capacity	7080 bottles	8400 boxes
Number of FU in one truck	453,120	672,000
Diesel fuel requirements for travel per FU	0.025 gal	0.017 gal

Finally, the model includes disposal of the plastic and cardboard packaging of the detergents according to an average US waste scenario. Packaging is disposed of through a municipal solid waste system. Recycling rates according to the EPA (2011) are 19.3% for low-density polyethylene bottles, 8.3% for polypropylene other packaging and 85% of cardboard. There are no recycling credits given in this analysis because the impacts of the recycling process are attributed to the new product. However, this LCA does take into account the impacts of sending the remaining solid waste to landfills in accordance to the Ecoinvent dataset for sanitary landfill disposal. This model assumes no incineration. Finally, the impact of wastewater treatment for the residual laundry product is excluded as the active ingredients in each detergent are biochemically indistinguishable at the treatment plant.

To address uncertainty in the inventory data this study uses the Pedigree Matrix. The Pedigree Matrix assumes a lognormal distribution (represented by arithmetic parameters) for each input in the model. The standard deviation of each distribution is based on six parameters: reliability, completeness, sample size and temporal, geographical and technological correlation (Weidema and Wesnaea 1996). Each parameter in the Pedigree Matrix can be described with a coefficient from 1 to 5. The matrix-based standard deviation captures uncertainties related to the assumptions of the input value. For instance, manufacturing data points tend to have less uncertainty because they are usually tightly controlled. While other inputs, such as transportation, have higher uncertainty because of their dependence on various factors like weather and traffic.

Therefore, this study assigns the Pedigree coefficient to each input in order to model uncertainty. Ecoinvent data already contains the corresponding Pedigree Matrix coefficients that provide a standard deviation to the inventory. Then, a Monte Carlo simulation generates random values for each inventory input to populate the lognormal distribution. This simulation ran 350 scans for all inventories to ensure a complete depiction of the uncertainty values at a 90% confidence level. The resulting inventories were characterized using the ReCiPe method, which multiplies the lognormal distribution of an inventory by a characterization factor represented by a single value. The ReCiPe impact assessment method characterizes the inventory into 18 midpoint impact categories (Table 4).

Table 4. Distributions of characterized results. The mean and standard deviations are both arithmetic, but the distribution is lognormal.

Characterized Impact category	Unit	LIQUID		POWDER	
		Mean	SD	Mean	SD
Metal depletion	kg Fe eq	1.99E-04	2.28E-05	4.43E-03	4.64E-04
Water depletion	m^3	2.66E-03	4.42E-04	1.38E-03	1.74E-04
Terrestrial ecotoxicity	kg 1,4-DB eq	7.06E-04	1.81E-04	2.62E-04	6.97E-05
Agricultural land occupation	m^2	1.02E-02	2.84E-03	2.10E-02	3.80E-03
Ozone depletion	kg CFC-11 eq	9.24E-09	1.49E-09	6.65E-09	7.05E-10
Climate change	kg CO2 eq	9.04E-02	1.00E-02	1.02E-01	8.98E-03
Ionizing radiation	kg U235 eq	6.89E-03	8.91E-03	2.03E-02	1.28E-02
Marine ecotoxicity	kg 1,4-DB eq	5.10E-04	2.43E-04	1.04E-03	6.16E-04
Human toxicity	kg 1,4-DB eq	1.95E-02	1.21E-02	4.10E-02	2.41E-02
Urban land occupation	m^2	1.43E-03	4.75E-04	7.75E-04	6.39E-04
Freshwater ecotoxicity	kg 1,4-DB eq	7.02E-04	2.56E-04	1.17E-03	6.37E-04
Terrestrial acidification	kg SO2 eq	5.12E-04	1.95E-04	4.32E-04	6.54E-05
Marine eutrophication	kg N eq	7.05E-05	1.15E-05	7.93E-05	1.82E-05
Photochemical oxidant formation	kg NMVOC	3.06E-04	3.85E-05	2.89E-04	2.93E-05
Fossil depletion	kg oil eq	3.29E-02	7.44E-03	3.92E-02	1.91E-02
Freshwater eutrophication	kg P eq	3.49E-05	2.12E-05	4.20E-05	1.05E-04
Particulate matter formation	kg PM_{10} eq	1.55E-04	4.32E-05	1.57E-04	1.71E-05
Natural land transformation	m^2	1.95E-05	2.24E-04	1.15E-05	9.53E-05

4.4 RESULTS

4.4.1 TYPICAL SOFTWARE OUTPUT

Most comparative LCAs stop at the characterization stage to avoid subjectivity risks associated with valuation. However, avoiding valuation can lead to a misinterpretation of data. Uncertain characterized results are notoriously difficult to interpret unaided because of the large amount and disparate range of units and data ranges (as shown in Table 4). To speed interpretation of results, the many studies represent characterized results in a single figure according to their relative performance normalized to 100% . Figure 9 shows the relative performances of the liquid and powder detergent in 18 characterized impacts, where the better performing alternative is normalized relative to the poorer performer on a category-by-category basis. This type of graph is also the main output from comparative analysis in most LCA software packages.

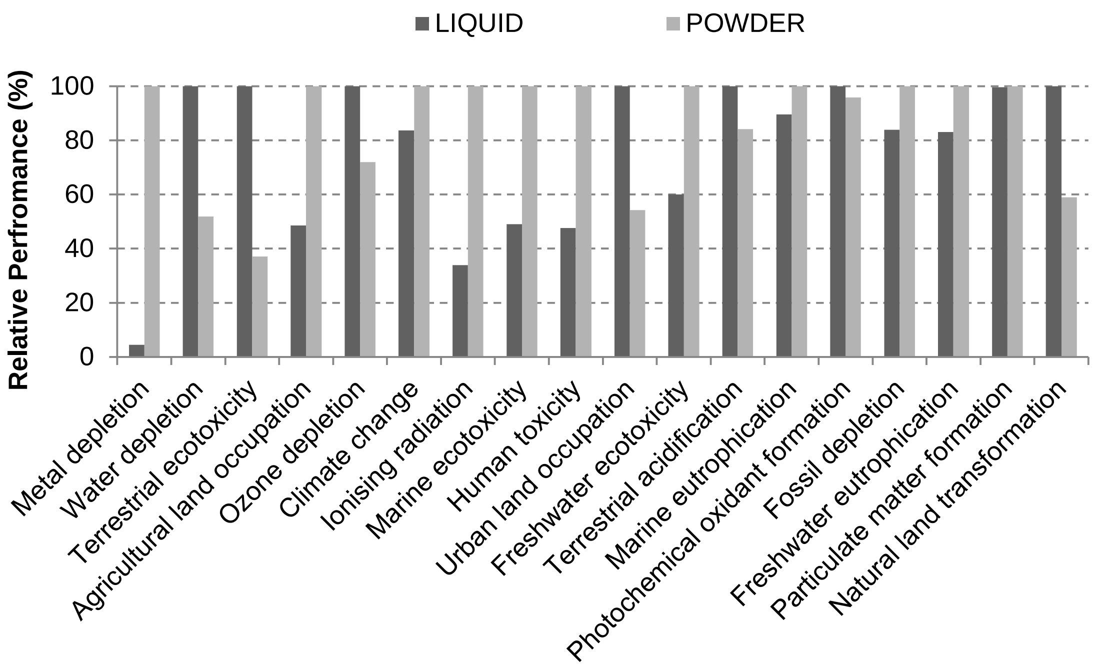

Figure 9 Eighteen characterized impact categories normalized to the worst in each category. Here, the liquid detergent performs relatively better in 11 of the 18 categories while the powder alternative performs best in the remaining 7 impact categories. This graph lacks preference thresholds that measure the significance of "wins" and "losses".

Figure 9 is insensitive to the magnitude (or significance) of each impact category, graphically depicting the worst performer in all categories as 100% regardless of the absolute scale of emissions in any category. This graph can easily be misinterpreted because it suggests an approach of counting winners and losers in each category without any notion regarding the significance of those wins or losses. Without preference or indifference thresholds, this graph is unable to distinguish those differences that are important to decision-makers from those that have such a small magnitude that they may reliably be ignored.

Even though this analysis is performed when *avoiding* valuation, there is an inherent valuation in Figure 9 that analysts often fail to make explicit. While it is sometimes reported that output such as Figure 9 is "unweighted", in fact the graphical depiction represents *equal* weights applied to each impact category (which is itself a subjective judgment). As a result, there is a need for valuation methods that process data in a way that highlights salient aspects without introducing subjectivity.

4.4.2 TYPICAL VALUATION: EXTERNAL NORMALIZATION AND SINGLE VALUE WEIGHTS

In accordance with ISO recommendations, characterized inventory data can be normalized relative to an external normalization reference. These references are single values and report no uncertainty. Figure 10 reports the results of applying normalization factors inherent in the ReCiPe Midpoint Hierarchist methodology on a European scale within the SimaPro software package for the liquid and powder detergent.

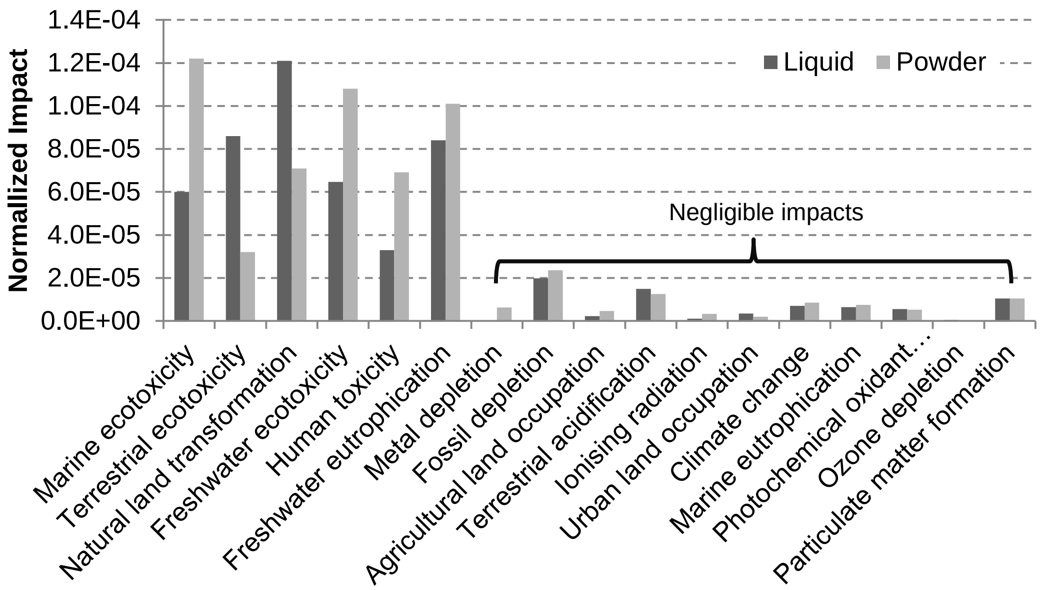

Figure 10 Normalized impacts according to the ReCiPe Midpoint Hierarchist model (values in supplementary information). There is no normalization reference available that quantifies the regional water resources, thus it is not possible to include the Water Depletion category in the analysis of typical valuation (another drawback of relying in external databases). The impacts to the left of Freshwater Eutrophication have the greatest contributions, while the impacts to the right are negligible.

Normalization is followed by weighting that evaluates multiple indicators according to the priorities of the decision makers' agendas. Weights are typically represented as single values without uncertainty, and are entirely subjective because they depend on the individual priorities of decision makers (Schmidt and Sullivan 2002). We apply equal weights for the seventeen impact categories for which normalization references are available, weighting each at 5.88% to give impacts the same level of priority. Overall scores follow Equation 2 and utilize mean values of the characterized inventory. However, because categories are equally weighted, the relative size of the weighted impacts is the same as the normalized impacts.

$$Single\ score = \sum \frac{Characterized\ Impact_i}{Normalization\ Reference_i} \times Weight_i$$

Figure 11a shows that in average, the liquid alternative likely has a lesser overall environmental impact. Furthermore, the combined mean scores of 11 impact categories (labeled as "Others") has a joint contribution of approximately 15%, and the remaining 6 impact categories drive majority of the results. Therefore, the use of normalization references is masking 11 out of the 17 impact categories. Figure 4b shows the lognormal distribution of scores. Even though mean values favor the liquid alternative, the probability distributions overlap, indicating instances in which the liquid detergent performs worse than the powder detergent. However, this overlap is not visible when reporting single scores.

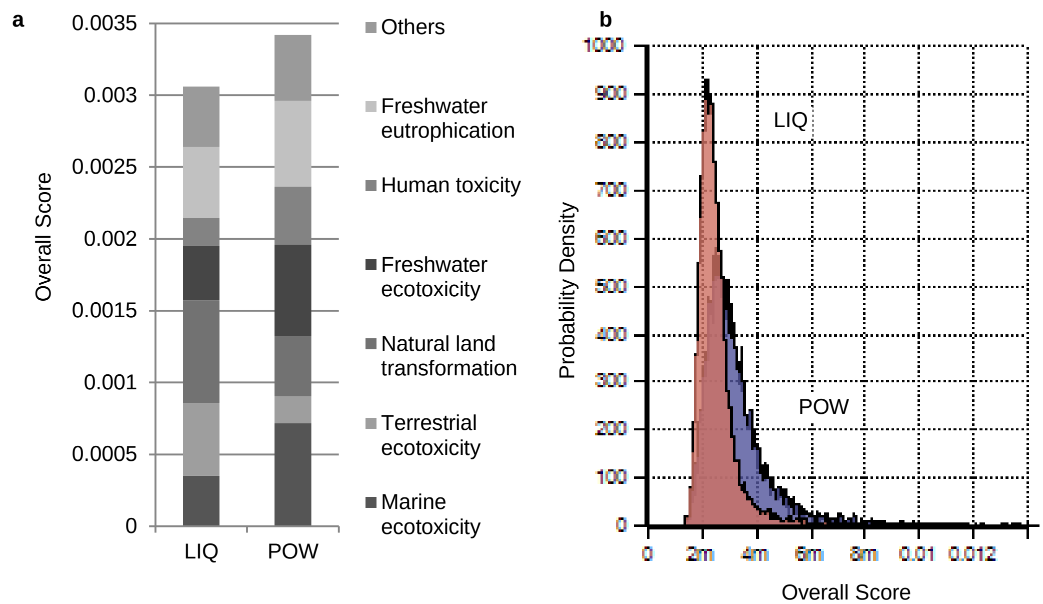

Figure 11a-b Overall average and probabilistic scores for liquid (LIQ) and powder (POW) detergent according to the typical valuation method. The category "Others" is composed of Metal depletion, Fossil depletion, Agricultural land occupation, Terrestrial acidification, Ionizing radiation, Urban land occupation, Climate change, marine eutrophication, Photochemical oxidant formation, Ozone depletion, and Particulate matter formation. Probability distribution in Figure 11b is a representation of the lognormal distribution of characterized impacts in Table 4.

4.4.3 STOCHASTIC MULTI-ATTRIBUTE ANALYSIS TY

Stochastic Multi-attribute TY (SMAA-TY), a modified version of SMAA, consists of outranking normalization (Figure 12) and relative probabilistic weights (Tylock et al. 2012). Conventional SMAA methods examine the entire feasible weight space or a range, but SMAA-TY elicits weights in terms of the relative importance of each criterion according to six levels of importance: Well Above Average, Above Average, Average, Below Average and Well Below Average. This feature is unique to SMAA-TY. Instead of translating preferences directly into numeric values, SMAA-TY elicits weights qualitatively from decision makers. The choices by decision makers are then converted into a probability distribution as a function of the level of priority given, the total number of criteria and the confidence level. The confidence level in SMAA-TY is another unique feature and it ranges from Fair to Precise. The more confidence in a weight (i.e. the more precise), the more clustered the distribution. Likewise, if the confidence level is Fair, the distribution is wider.

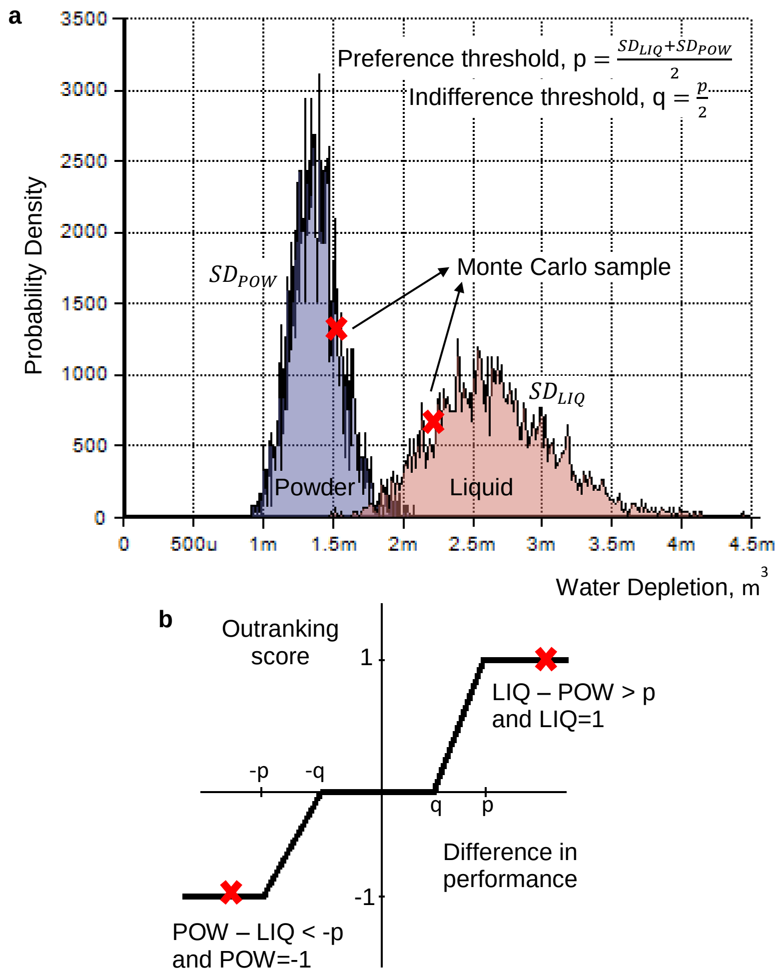

Figure 12 shows the probabilistic performance of liquid and powder in the Water Depletion characterized impact category, and the outranking function indicating the preference and indifference thresholds. Preference thresholds in this study equal the average between standard deviations, and the indifference threshold is half of the preference threshold. The difference in performance in each criterion in Figure 12a is evaluated with the preference threshold (p) and the indifference threshold (q) in Figure 12b. The outranking score ranges from -1 to 1 for each of the Monte Carlo runs (shown by the red "x"). This study performs 2,000 Monte Carlo simulations.

Outranking scores are unitless numbers between -1 and +1, where +1 is complete preference, and 0 is indifference. The preference threshold (p) is the smallest difference between the two alternatives for which a complete preference may be inferred. In this case, a complete preference of +1 signifies an alternative that performs worse than the other in a given impact category. A score of -1 indicates superior comparative environmental performance.

Indifference is determined by the *indifference threshold (q)*, the largest deviation considered negligible. Strict indifference occurs when both alternatives performances are within a negligible difference from each other (between –q and +q), and both receive a 0. A weak preference is when the difference in performance lies between the indifference and preference threshold and it results in an interpolated value between -1 and +1. A weak preference means that an alternative is better than the other, but not enough to be a strict preference. Preference and Indifference thresholds can be selected through expert elicitation or with respect to the uncertainty of a given criteria (Linkov et al. 2007; Rogers and Bruen 1998; Rogers and Seager 2009). This study instead utilizes uncertainty in the data to calculate preference and indifference thresholds (Figure 12a). Note that negative scores do not mean a negative impact (i.e. environmental benefit). Similar to typical valuation scores, a higher outranking score represents a greater environmental impact.

Before weighting, SMAA-TY winnows the alternatives to a maximum of eight impact categories in which the differences are the greatest and most significant. To evaluate this significance in the 18 characterized impact categories in Table 4, we use the *relevance parameter* (r) derived from the outranking algorithm in Equation 3.

$$r_i = \frac{\left|\mu_{LIQ} - \mu_{POW}\right|_i}{\frac{1}{2}\left(SD_{LIQ} + SD_{POW}\right)_i}$$

The numerator in Equation 3 represents the absolute difference between the means for each impact category, and the denominator represents the average of the arithmetic standard deviations for each impact category (i.e. the preference threshold). A large relevance parameter means that the detergents mutual difference in performance is significant. It is important to include the standard deviations otherwise the absolute differences in mean values alone will favor those categories with greater magnitudes, when in fact their mutual difference might not be significant. Figure 13 shows the relevance parameter of the 18 characterized impact categories. Since the relevance parameter is a function of the mutual differences, there is one indicator per impact category.

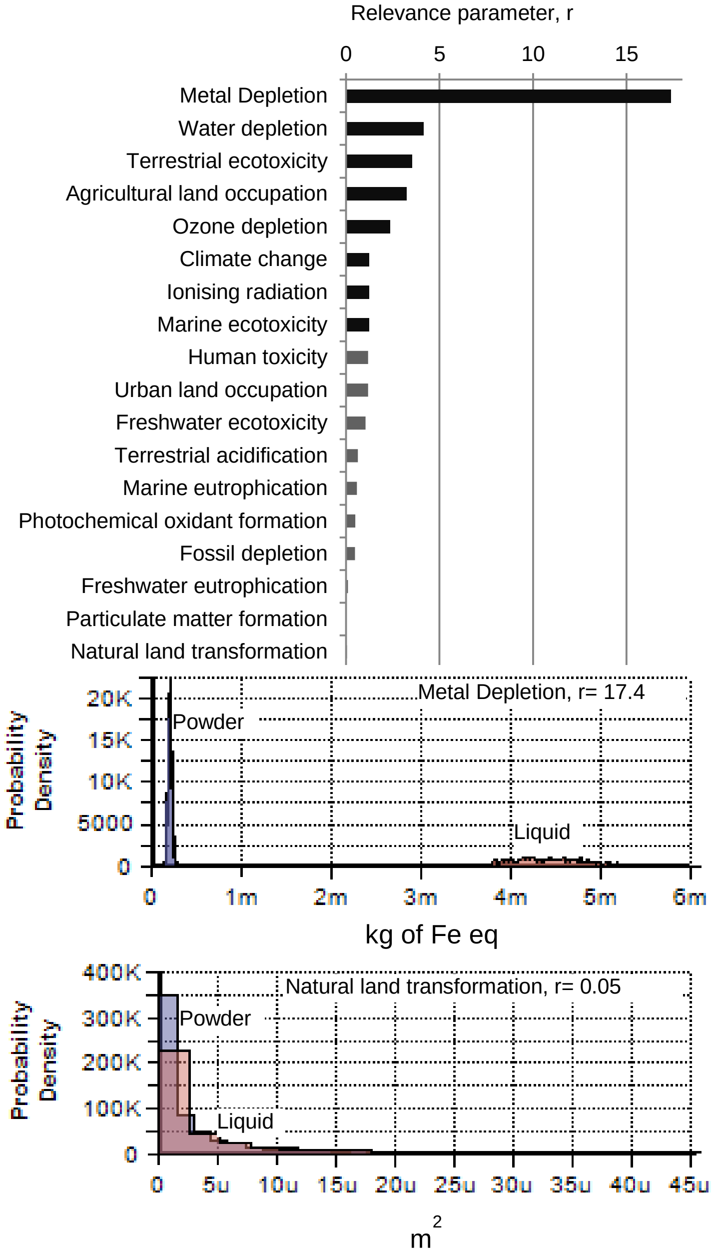

Figure 13 shows the relevance parameter of impact categories and a graphical representation of the most and least relevant categories (metal depletion and natural land transformation respectively). Therefore, when probability distributions overlap the difference in performances is irrelevant because there is not enough certainty that one outperforms the other.

From this point forward there is a clear difference between typical valuation and

SMAA-TY. Even though the mutual difference between the detergents is very significant for the Metal Depletion category (Figure 13), its impact is masked when dividing it by an external normalization reference (Figure 10). Therefore, evaluating performance with respect to a normalization reference fails to identify key tradeoffs among alternatives. In addition, the Water Depletion impact category which is not evaluated past characterization, in this case by ReCiPe, happens to be the second most relevant impact category - a significant impact that is excluded when there is a lack of a specific normalization reference.

SMAA-TY performs 20,000 outranking Monte Carlo simulations for each of the eight impact categories and gathers outranking scores in terms of a probability distribution. Scores from the pair-wise comparisons are multiplied by the probabilistic weights selected by the simulation for each impact category. All weight parameters were set at a relative importance of “Average” with a confidence level of “Fair”. (See the stochastic weight representation in Appendix). Finally, SMAA-TY generates a probability distribution for the overall environmental score of each detergent (Figure 14). The overall score reflects environmental impact, therefore the powder detergent, which is further to the right, is more likely to have a greater environmental impact. Scores are entirely relative to one another. Therefore, a negative score means a lower score with respect to other alternatives, not an environmental benefit. From this analysis, it can be calculated that the powder is 83% likely to be worse than the liquid alternative. Alternatively, 17% of the time the liquid detergent is worse than the powder alternative. The probabilistic score contributions in Figure 14 show that five out of the eight most relevant impact categories evaluated in SMAA-TY can be masked by the use of normalization references. An additional category, Water Depletion, lacks normalization references in the ReCiPe method, so is not evaluated by the typical valuation approach.

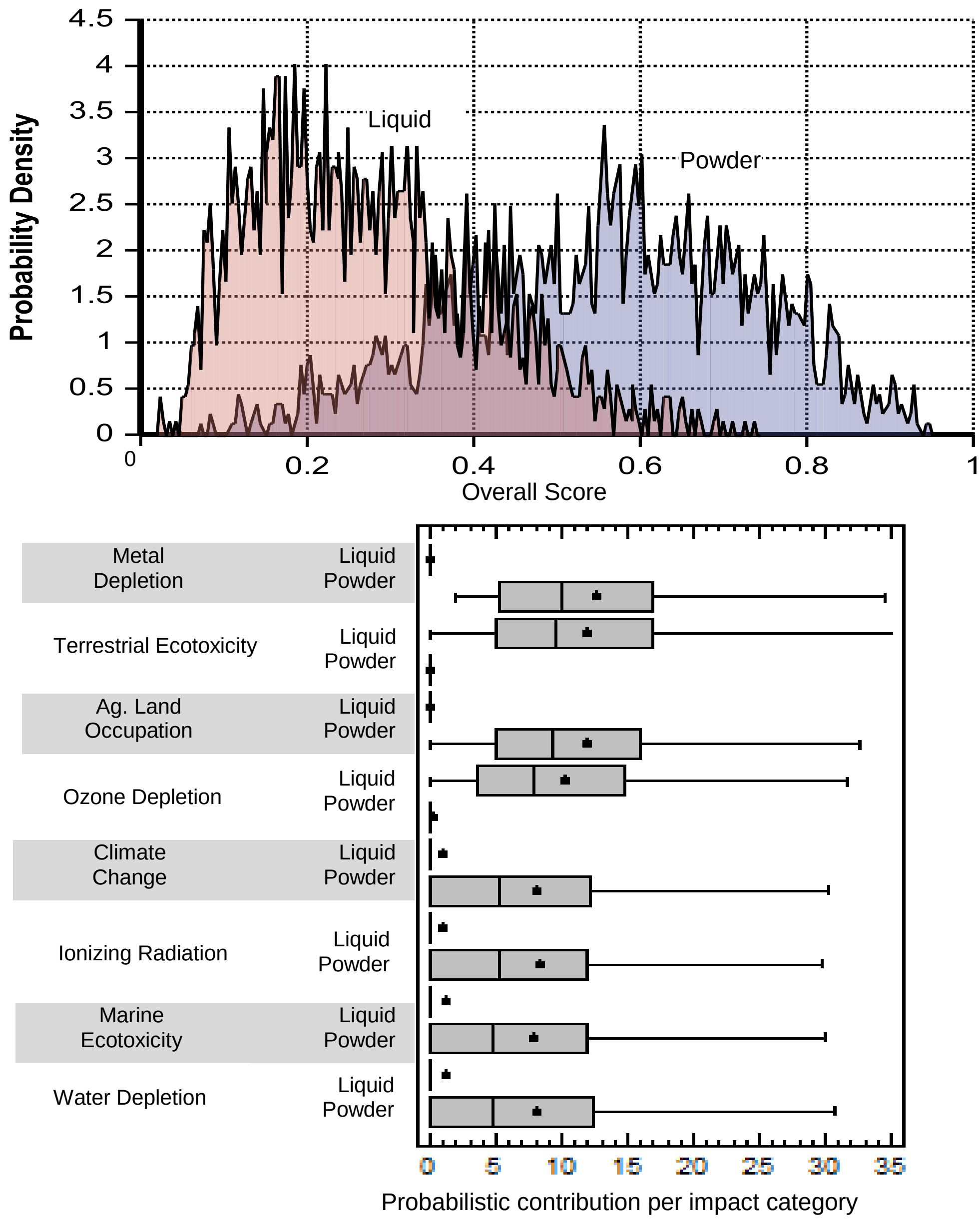

Figure 14 Shows the probability distribution and contribution of the overall scores for the liquid and powder detergent according to SMAA-TY.

4.5 DISCUSSION

Both valuation methods recommend the liquid over the powder detergent, suggesting that the additional energy footprint during processing of the powder detergent exceeded the gains in transportation efficiency. However, the results shown in this paper are not intended to give a definite recommendation on laundry detergents. Rather, they showcase the capabilities of different interpretation approaches.

The first approach consists of showing characterized impacts in relation to one another (Figure 9). These results have inherent normalization and weighting which, according to ISO guidelines, weighting should not be applied when sharing LCA results to the public. In addition, they are insensitive to magnitude and oblivious to negligible and significant differences between impact categories. Thus, this type of analysis has severe limitations in terms of decision support.

Results from typical valuation in Figure 11 show the overall scores resulting from external normalization on a European scale with single value egalitarian weighting. Results show that the categories accounting for at least 80% of both total scores are: Marine Ecotoxicity, Terrestrial Ecotoxicity, Natural Land Transformation, Freshwater Ecotoxicity, Human Toxicity, and Freshwater Eutrophication. The remaining *eleven* categories have little influence on both detergents. However, single scores are a poor representation of life cycle data because environmental performance is not a single indicator, nor it is a discrete value. Figure 11b shows the uncertainty in the overall scores of the typical valuation method. However, these scores remain distorted by normalization references.

Alternatively, the results from SMAA-TY show the probability distributions of the overall scores indicating the powder detergent is 83% more likely to have a greater impact than the liquid detergent (Figure 14). The individual contribution from each weighted characterized impact category is also a distribution composed of 2,000 Monte Carlo runs represented by Box-and-Whisker plots. The breakdown by category in Figure 14 shows that most impact categories contribute more to the powder detergent than to the liquid detergent. However, the liquid detergent has a greater impact in Terrestrial ecotoxicity and Ozone depletion. Five out of eight of the categories evaluated by SMAA-TY show a negligible contribution in the results from typical valuation in Figure 11.

Out of the total eighteen characterized impact categories generated by ReCiPe in Table 4, six impact categories drove the majority of the results in the typical valuation, and eight impact categories drove the results in SMAA-TY. However, SMAA-TY focuses the analysis in the categories with the most tradeoffs - something that typical valuation and truncation at characterization fails to evaluate.

4.6 CONCLUSION

There is an acute need for interpretation methods in comparative LCAs that help understand the significance of mutual performances even before weighting. Graphical outputs at characterization fail at evaluating tradeoffs at the characterization stage, and typical practices in valuation, although in accordance to ISO guidelines, further distort data at normalization and weighting. This method conceals most impact categories due to the use of external normalization references. Therefore, it allows for a small fraction of the categories to dominate both scores and it does not present a robust platform for decision makers. Such high bias overcomes earlier efforts of data collection, impact assessment and inputs from decision makers. An ideal valuation method is capable of guiding the decision making process by revealing all aspects and dimensions of the problem in a transparent and concise way. A descriptive approach to interpretation that implements preference thresholds distinguishes between negligible and significant differences and can better highlight existing tradeoffs. We propose utilizing SMAA-TY based valuation applicable in all comparative LCAs. This novel method avoids masking criteria, is independent of external databases, includes multiple perspectives, and generates results that better inform decision makers.

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Chapter 5

KEY FINDINGS

Existing LCA research efforts in valuation call attention to inconsistencies within normalization references, including incomplete datasets, geospatial variability, and non-stationarity of technology. However, regardless of data completion and availability, current valuation practices have fundamental issues when applied to comparative LCAs. This study demonstrates fundamental flaws in existing comparative LCA interpretation practices, and demonstrates the application of stochastic decision analysis methods, namely, SMAA, for a more robust decision platform.

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APPENDIX A

SUPPLEMENTARY INFORMATION FOR CHAPTER 4

S1. Liquid laundry detergent Life Cycle Inventory

Ingredients	% of total mass	Inventory Dataset	Uncertainty	
			Pedigree Matrix	SD Value
C11-C13 Linear Alkyl Benzene Sulfonate	12.00%	Alkylbenzene sulfonate, linear, petrochemical, at plant/RER	(1,3,3,5,3,4)	1.29
C14-C15 Alkyl Ethoxy (E2.5) Sulfate	12.00%	Fatty alcohol sulfate, palm oil, at plant/RER	(1,3,3,5,4,4)	1.56
C12-C13 Alcohol Ethoxylate (E7)	3.00%	Ethoxylated alcohols (ae7), palm kernel oil, at plant/RER	(1,3,3,5,3,4)	1.29
C12-C14 Fatty Acids	2.00%	Fatty alcohol sulfate, palm oil, at plant/RER	(1,3,3,5,4,4)	1.56
Citric Acid	3.00%	Edta, ethylenediaminetetraacetic acid, at plant/RER	(1,3,3,5,4,4)	1.56
Sodium Cumene Sulfonate	4.00%	Sodium tripolyphosphate, at plant/RER	(1,3,3,5,4,4)	1.56
Sodium Hydroxide	6.00%	Sodium hydroxide, production mix, at plant/kg NREL /RNA	(1,3,3,5,3,4)	1.29
1,2 Propanediol	3.00%	Propylene glycol, liquid, at plant	(1,3,3,5,4,4)	1.56
Monoethanolamine	3.00%	Monoethanolamine, at plant/RER	(1,3,3,5,3,4)	1.29
Protease	0.80%	Detergent enzyme, at plant	(1,3,3,5,3,4)	1.29
Polyester-based release polymer	0.20%	Polyester resin, unsaturated, at plant/RER	(1,3,3,5,4,4)	1.56
Water	51.00%	Water, completely softened, at plant	(1,3,3,5,3,4)	1.29
Production Inputs	**Required per load**	**Inventory Dataset**	**Uncertainty**	
			Pedigree Matrix	**SD Value**
Electricity supply	2.78E-03 MJ eq	Electricity, high voltage, at grid	(2,4,2,5,3,3)	1.28
Heat (natural gas) supply	3.92E-03MJ eq	Natural gas, burned in power plant	(2,4,2,5,3,3)	1.28
Water used	7.54E-02 kg	Water, completely softened, at plant/RER	(2,4,2,5,3,3)	1.28
Packaging type	**Required per load**	**Inventory Dataset**	**Uncertainty**	
			Pedigree Matrix	**SD Value**

LDPE, virgin	2.43E-03 kg	Polyethylene, LDPE, granulate, at plant/RER	(2,3,2,5,3,3)	1.26
PP, virgin	2.38E-04 kg	Polypropylene, granulate, at plant/RER	(2,3,2,5,3,3)	1.26
Plastic processing, PP	2.39E-04 kg	Extrusion, plastic pipes/RER	(4,3,2,5,3,3)	1.34
Plastic processing, LDPE	2.44E-03 kg	Injection moulding/RER	(4,3,2,5,3,3)	1.34
Disposal	**Required per load**	**Inventory Dataset**	**Uncertainty**	
			Pedigree Matrix	**SD Value**
LDPE, virgin	1.96E-03 kg	Disposal, polyethylene, 0.4% water, to sanitary landfill/CH	(4,2,3,5,3,3)	1.35
PP, virgin	2.18E-04 kg	Disposal, polypropylene, 15.9% water, to sanitary landfill/CH	(4,2,3,5,3,3)	1.35

S2. Powder laundry detergent Life Cycle Inventory

Ingredients	% of total mass	Inventory Dataset	Uncertainty	
			Pedigree Matrix	SD Value
C11-C13 Linear Alkyl Benzene Sulfonate	10%	Alkylbenzene sulfonate, linear, petrochemical, at plant/RER	(1,3,3,5,3,4)	1.29
C14-C15 Alkyl Sulfate	7%	Fatty alcohol sulfate, palm oil, at plant/RER	(1,3,3,5,4,4)	1.56
C14-C15 Alkyl Ethoxy (E2) Sulfate	1%	Fatty alcohol sulfate, palm oil, at plant/RER	(1,3,3,5,4,4)	1.56
C14-C15 Alcohol Ethoxylate (E7)	1%	Ethoxylated alcohols (AE7), palm kernel oil, at plant/RER	(1,3,3,5,3,4)	1.29
Zeolite	22%	Zeolite, powder, at plant/RER	(1,3,3,5,3,4)	1.29
Carbonate	19%	Polycarboxylates, 40% active substance, at plant/RER	(1,3,3,5,4,4)	1.56
Silicate	1%	Layered sodium silicate, SKS-6, powder, at plant/RER	(1,3,3,5,3,4)	1.29
Sodium Sulfate	10%	Sodium sulphate, powder, production mix, at plant/RER	(1,3,3,5,3,4)	1.29
Sodium Perborate Tetrahydrate	1%	Sodium perborate, tetrahydrate, powder, at plant/RER	(1,3,3,5,3,4)	1.29
TAED	4%	DTPA, diethylenetriaminepentaacetic acid, at plant/RER	(1,3,3,5,4,4)	1.56
DTPA	0.40%	DTPA, diethylenetriaminepentaacetic acid, at plant/RER	(1,3,3,5,3,4)	1.29
Protease	0.30%	Detergent enzyme, granulated	(1,3,3,5,3,4)	1.29
Amylase	0.10%	Detergent enzyme, granulated	(1,3,3,5,3,4)	1.29
Acrylic/maleic copolymer	1%	Maleic anhydride, at plant/RER	(1,3,3,5,4,4)	1.56
Polyester-based soil release polymer	0.40%	Polyester resin, unsaturated, at plant/RER	(1,3,3,5,4,4)	1.56
Water	51%	Water, completely softened, at plant	(1,3,3,5,3,4)	1.29

Production Inputs	Required per load	Inventory Dataset	Uncertainty	
			Pedigree Matrix	SD Value
Electricity supply	2.77E-02 MJ	Electricity, high voltage, at grid/US	(2,4,2,5,3,3)	1.28
Heat (natural gas) supply	3.81E-02 MJ	Natural gas, burned in power plant/US	(2,4,2,5,3,3)	1.28
Water used	1.03E-01 kg	Water, completely softened, at plant/RER	(2,4,2,5,3,3)	1.28
Packaging type	**Required per load**	**Inventory Dataset**	**Uncertainty**	
			Pedigree Matrix	**SD Value**
Cardboard, fresh fiber	2.45E-03 kg	Corrugated board, fresh fiber, single wall, at plant/RER	(2,3,2,5,3,3)	1.26
PET, bottle grade	4.30E-03 kg	Polyethylene terephthalate, granulate, bottle grade, at plant/RER	(2,3,2,5,3,3)	1.26
Plastic processing	4.39E-03 kg	Stretch blow moulding/RER	(4,3,2,5,3,3)	1.34
Disposal	**Required per load**	**Inventory Dataset**	**Uncertainty**	
			Pedigree Matrix	**SD Value**
Cardboard, fresh fiber	3.67E-04 kg	Disposal, packaging cardboard, 19.6% water, to sanitary landfill/CH	(4,2,3,5,3,3)	1.35
PET, bottle grade	4.30E-03 kg	Disposal, polyethylene terephtalate, 0.2% water, to sanitary landfill/CH	(4,2,3,5,3,3)	1.35

S3. GREET 1.0 Emission factors per gallon of diesel

Pollutant	Emission factor (grams of pollutant/ gallon of diesel)
volatile organic carbons	1.1
carbon monoxide	4.5
nitrogen oxides	13.4
particulate matter of 10 micros (PM_{10})	0.5
particulate matter of 2.5 microns ($PM_{2.5}$)	0.4
sulfur oxides	1.3
methane	0.05
nitrous oxide	0.2
carbon dioxide	10,732

S4. Normalized Impacts, weighted impacts and Error propagation

Table S4.1 Normalized impact categories

	Liquid		Powder	
Impact category	Mean	SD	Mean	SD
Marine ecotoxicity	0.00006	2.85E-05	0.000122	7.25E-05
Terrestrial ecotoxicity	0.000086	0.000022	0.000032	8.5E-06
Natural land transformation	0.000121	0.00139	0.000071	0.00059
Freshwater ecotoxicity	6.46E-05	2.35E-05	0.000108	5.86E-05
Human toxicity	0.000033	2.04E-05	6.92E-05	4.07E-05
Freshwater eutrophication	8.41E-05	5.11E-05	0.000101	0.000253
Metal depletion	2.79E-07	3.19E-08	6.22E-06	6.51E-07
Fossil depletion	1.98E-05	4.47E-06	2.36E-05	1.15E-05
Agricultural land occupation	2.25E-06	6.27E-07	4.65E-06	8.42E-07
Terrestrial acidification	1.49E-05	5.67E-06	1.26E-05	1.9E-06
Ionizing radiation	1.1E-06	1.43E-06	3.25E-06	2.05E-06
Urban land occupation	3.52E-06	1.17E-06	1.9E-06	1.57E-06
Climate change	7.08E-06	8.92E-07	8.46E-06	8.01E-07
Marine eutrophication	6.45E-06	1.14E-06	7.48E-06	1.8E-06
Photochemical oxidant formation	5.47E-06	7.24E-07	5.25E-06	5.51E-07
Ozone depletion	4.2E-07	6.76E-08	3.02E-07	3.2E-08
Particulate matter formation	1.04E-05	2.9E-06	1.05E-05	1.15E-06

S5. Relevance parameter

		Characterized Impacts						
		Liquid		Powder				
Impact category	Unit	Mean	SD	Mean	SD	p	q	r (Eq. 2)
Metal depletion	kg Fe eq	0.000199	2.28E-05	0.00443	0.000464	0.000243	0.000122	18.20049
Water depletion	m3	0.00266	0.000442	0.00138	0.000174	0.000308	0.000154	4.155844
Terrestrial ecotoxicity	kg 1,4-DB eq	0.000706	0.000181	0.000262	6.97E-05	0.000125	6.27E-05	3.542082
Agricultural land occupation	m2a	0.0102	0.00284	0.021	0.0038	0.00332	0.00166	3.253012
Ozone depletion	kg CFC-11 eq	9.24E-09	1.49E-09	6.65E-09	7.05E-10	1.1E-09	5.49E-10	2.359909
Climate change	kg CO_2 eq	0.090378177	0.01	0.102304355	0.00898	0.00949	0.004745	1.25671
Ionising radiation	kg U235 eq	0.00689	0.00891	0.0203	0.0128	0.010855	0.005428	1.235375
Marine ecotoxicity	kg 1,4-DB eq	0.00051	0.000243	0.00104	0.000616	0.00043	0.000215	1.233993
Human toxicity	kg 1,4-DB eq	0.0195	0.0121	0.041	0.0241	0.0181	0.00905	1.187845
Urban land occupation	m2a	0.00143	0.000475	0.000775	0.000639	0.000557	0.000279	1.175943
Freshwater ecotoxicity	kg 1,4-DB eq	0.000702	0.000256	0.00117	0.000637	0.000447	0.000223	1.048152
Terrestrial acidification	kg SO_2 eq	0.000518689	0.000195	0.000436512	6.54E-05	0.00013	6.51E-05	0.631164
Marine eutrophication	kg N eq	7.05104E-05	1.15E-05	7.92817E-05	1.82E-05	1.49E-05	7.43E-06	0.590656
Photochemical oxidant formation	kg NMVOC	0.000306118	3.85E-05	0.000289197	2.93E-05	3.39E-05	1.7E-05	0.49916
Fossil depletion	kg oil eq	0.0329	0.00744	0.0392	0.0191	0.01327	0.006635	0.474755
Freshwater eutrophication	kg P eq	0.0000349	2.12E-05	0.000042	0.000105	6.31E-05	3.16E-05	0.11252
Particulate matter formation	kg PM10 eq	0.000159255	4.32E-05	0.00015987	1.71E-05	3.02E-05	1.51E-05	0.020388
Natural land transformation	m^2	0.0000195	0.000224	0.0000115	9.53E-05	0.00016	7.98E-05	0.05011

S6. Summary Statistics of box-and-whisker plots in Figure 8.

	Average	Standard deviation	Coeff. of variation	Min	Max	Stnd, Skewness	Stnd. Kurtosis
Metal Depletion LIQUID	0	0		0	0	-	-
Metal Depletion POWDER	12.5749	9.30874	74.0262%	2.01106	63.2514	24.7071	19.3314
Terrestrial Ecotoxicity LIQUID	11.9968	9.23777	77.0018%	0	56.8079	22.934	15.3589
Terrestrial Ecotoxicity POWDER	0.0283343	0.51292	1810.24%	0	13.0137	361.666	3764.72
Agricultural Land Occup. LIQUID	0.0201122	0.47941	2383.67%	0	18.8601	601.951	11180.8
Agricultural Land Occup. POWDER	11.8027	9.17579	77.7429%	0	58.4434	24.4907	17.8069
Ozone Depletion LIQUID	10.285	9.26214	90.0549%	0	54.331	24.5792	17.7638
Ozone Depletion POWDER	0.201757	1.59945	792.762%	0	27.5305	197.222	1226.46
Climate Change LIQUID	1.05685	4.05926	384.089%	0	51.2206	102.499	368.702
Climate Change POWDER	8.07458	9.36653	116.0%	0	56.7676	29.3302	26.5967
Ionizing Radiation LIQUID	1.0362	4.15804	401.279%	0	51.593	105.892	387.763
Ionizing Radiation POWDER	8.25338	9.60312	116.354%	0	62.1913	29.4062	25.7677
Marine Ecotoxicity LIQUID	1.25335	4.56084	363.893%	0	43.5256	86.3565	231.847
Marine Ecotoxicity POWDER	7.85316	9.35932	119.179%	0	59.4454	28.5187	24.4123
Water Depletion LIQUID	1.16532	4.32966	371.544%	0	44.6004	90.9951	264.304
Water Depletion POWDER	7.98374	9.54312	119.532%	0	58.6613	28.9338	25.1148

S7. Stochastic weighting

Figure S7 shows the beta distribution of the weights for eight impact categories. The vertical axis is the probability density and the horizontal axis is the weight value in percent. Since all impacts have the same priority level, the probability distributions overlap. At any given point the sum of all weights must equal 100, thus the probability of weights is higher at lower values. For more information on the weight calculation procedure see Tylock et al, 2012.