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Impact assessment modelling of the matter-less stressors in the context of Life Cycle Assessment

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**A protocol for the
global sensitivity
analysis of
impact assessment
models
in LCA**

A protocol for the global sensitivity analysis of impact assessment models in LCA

Based on:

S. Cucurachi, E. Borgonovo, R. Heijungs. 2014. *Risk Analysis*. Submitted.

Abstract

The Life Cycle Assessment (LCA) framework has established itself as the leading tool for the assessment of the environmental impact of products. It has been claimed that more attention should be paid to quantifying the uncertainties present in the various phases of LCA. Though the topic has been attracting increasing attention of practitioners and experts in LCA, there is still a lack of understanding and a limited use of the available statistical tools. In this work, we introduce a protocol to conduct global sensitivity analysis in LCA. The article focuses on the Life Cycle Impact Assessment (LCIA), and particularly on the relevance of global techniques for the development of trustable impact assessment models. We use a novel characterization model developed for the quantification of the impacts of noise on humans as a test case. We show that global SA is fundamental to guarantee that the modeler has a complete understanding of: (i) the structure of the model; (ii) the importance of uncertain model inputs and the interaction among them.

Keywords

Life Cycle Assessment; LCIA; Global Sensitivity Analysis; Uncertainty importance

1

Introduction

In over thirty years of developments and refinements, Life Cycle Assessment (LCA) has become the reference framework in the sustainability assessment of products and services (EC-JRC 2011). At a policy level, LCA studies are now recommended in a growing number of countries around the world and performed on a vast array of complex product systems (Guinée et al. 2011). As the interest in the methodology has grown, so has done the attention to the trustworthiness of the results of LCA studies.

Results of LCA studies are increasingly used by policy makers. Typical problems are the selection of energy systems for optimal planning, or the discrimination between the environmental performances of products, so that the legislator can establish if any of these products has to be outlawed. A difficulty associated with LCA is cross-comparison and validation of the results obtained. Outcomes are in all cases the result of a modelling process that involves modelling assumptions and uncertain or variable data, which need to be analysed and interpreted in the specific context in which they were made. Since the early days of the methodology, concerns have been expressed about the accuracy and credibility of results, due to the great variability in impacts results also for comparable systems. Even studies compliant with the standard on (ISO. 2006) and dealing with identical systems showed large differences in the assessed impacts (Henriksson et al. 2013). The cross-validation of LCA results is not always straightforward, because assumptions are system- and context- specific. Therefore, there is an urgent need for the LCA community to deploy statistical tools to deal with variability of results and to increase the possibility of objectively evaluate systems.

Sources of variability (e.g. limited data quality, geographic representativeness) need to be reported and analysed to guarantee the reliability of the results of LCA studies. Important for the credibility of LCA is that results are accompanied by adequate uncertainty quantification (Björklund 2002), so to best inform the decision-process (Huijbregts 1998). Reap et al. (Reap et al. 2008a, 2008b) claim that sensitivity and uncertainty analysis tools would improve the representativeness of the whole framework. The importance of sensitivity analysis (SA) has been agreed upon since the beginnings of the development of LCA [e.g. (Heijungs 1996)], and required by the ISO standard (ISO. 2006). The ISO 14044 standard defines SA as “the systematic procedures for estimating the effects of the choices made regarding methods and data on the outcome of a study” (ISO. 2006). In practice, SA has been alternatively interpreted generically as the activity of studying how the output results are sensitive to the variation of the input data, or as a synonym of uncertainty analysis, or as the break-down of output uncertainty in terms of input

uncertainties (Heijungs and Huijbregts 2004; Lloyd and Ries 2007). While in the field of LCA there seems to be an overlapping of concepts falling under the definition of SA, in the risk analysis literature the concept has been formalised and a variety of rigorous statistical techniques have been introduced (Borgonovo 2006; Frey and Patil 2002; Helton and Davis 2002; Helton 1994; Iman and Helton 1988, 1991; Iman and Hora 1990; Patil and Frey 2004; Saltelli 2002).

Internationally, several agencies prescribe sensitivity and uncertainty analysis as part of best practices in the utilization of scientific codes to support decision and policy making. The US EPA [(US - EPA 2009); Appendix D], the European Commission [(European Commission 2009)-section 5.4], the Florida Commission on Hurricane Loss Projection Methodology (FCHLPM)(Iman, Johnson, and Watson 2005), National Institute for Health and Care Excellence in the Great Britain [(Nice 2008); section 5.7], and the "Guidelines for Economic Evaluation of Pharmaceuticals" in Canada [(Canadian Health 2006); section 2.2.6] are just a few examples.

Rabitz [(Rabitz 1989);p.221] observes that *the judicious use of SA techniques appears to be the key ingredient needed to draw out the maximum capabilities of mathematical modelling*. Helton and Oberkampf (Helton and Oberkampf 2004) note that SA should be a fundamental part of any analysis that involves the assessment and propagation of uncertainty.

Characterisation (or impact assessment) models that are used in LCIA can be considered as a specific class of complex integrated assessment models (IAMs). Characterization models are used to calculate science-based conversion factors (characterization factors) to obtain the potential human health and environmental impacts of the resources and releases across a life cycle for a certain stressor [i.e. a set of conditions that may lead to the impact] (EPA 2006; ISO. 2006). Indeed, such models deal with intricate complex phenomena, need to capture elements that vary in different time and space scales, and involve both physical laws and socio-economic aspects (Anderson et al. 2014). Global SA techniques enable us to study the structure of IAMs and their dependence upon the uncertain model inputs, and also to understand which model inputs require additional investigation improve our confidence in the results (Kioutsioukis et al. 2004; Saltelli et al. 2008).

Thus, the provisions concerning the use of global SA that apply in other fields, should also apply for decisions based upon characterization models. However, no shared protocol for the performance of uncertainty and global SA in LCA and, in particular, for the integration of global SA techniques in the process is available to date (Padey et al. 2013). A possible

reason is computational burden, with a high number of model runs required to accurately estimate these sensitivity measures. However, several recent advances have contributed in abating such computational cost, making the techniques, in principle, applicable to a vast class of models. In particular, developments in the post processing or given data directions (Lewandowski, Cooke, and Duintjer Tebbens 2007; Plischke, Borgonovo, and Smith 2013; Storlie et al. 2009) allow analysts to compute global sensitivity measures directly from a Monte Carlo (MC) sample of the model inputs, without the need of a specific design. Then, because several software tools available for LCA studies already include MC subroutines, no additional computational burden with respect to current practice is imposed by post processing schemes.

In this article, we construct a protocol on how to regularly conduct a global SA in impact assessment modelling. We proceed as follows. We cast global SA techniques in the context of LCA characterisation models. We clarify the conceptual differences between SA tools, relating them to the tools that are used in current LCA practice. We introduce sensitivity analysis settings (Andrea Saltelli 2002) in the LCA context. We then define a multi-step protocol for the application of global SA methods to LCIA models. The protocol starts from the identification of the relevant uncertainties and the assignment of distributions, continues with the definition of SA settings and ends with the assessment of the decision-maker's confidence in the estimates.

We illustrate the application of the protocol to a recent LCA model developed to quantify the impact on humans of sound emissions (Cucurachi, Heijungs, and Ohlau 2012; Cucurachi and Heijungs 2014). Two alternative configurations of the same model, at a different level of complexity are analysed using an ensemble of global sensitivity analysis techniques. Numerical findings are discussed in detail. Before concluding, we offer a critical discussion about the proposed protocol, discussion which is also aimed at highlighting the lessons learned and the insights and limitations of the approach that apply within the LCA framework, but also outside it as well.

The remainder of the paper is organised as follows. Section 2 provides an overview of the available SA techniques and gives some insight on the way SA is defined and used in the field of LCA. In section 3, the settings are defined for a global SA design in the context of LCIA. The structure of the noise LCIA model is here analysed together with the importance of its inputs. Section 4 discusses the contribution of global SA for the LCA community. Concluding remarks regarding the empowerment of LCIA models close the article.

2

Literature review: sensitivity analysis and its use in LCA

2.1

The sensitivity analysis setup

The SA standard setup is as follows. One considers the relationship between a quantity of interest (y) [model output] and a set of independent variables (\mathbf{x})

$$y = g(\mathbf{x}), \quad g : \Omega_{\mathbf{x}} \rightarrow \mathbb{R} \quad (1)$$

where $\Omega_{\mathbf{x}} \subseteq \mathbb{R}^k$, with k denoting the number of model inputs (i.e., the size of \mathbf{x}). $\Omega_{\mathbf{x}}$ is the k -dimensional domain of g and it is the Cartesian product of the individual subsets of \mathbb{R} over which each model input is allowed to vary. The model is usually implemented as a scientific code and helps the analyst to forecast the behaviour of y given the values of the model inputs \mathbf{x} .

In a local sensitivity analysis, the analyst is interested in obtaining the response of the output around one point of interest in the model input space $\Omega_{\mathbf{x}}$. Typically, local sensitivity is performed varying one model input at a time (referred to also as OFAT), while the remaining model inputs are kept at a nominal (or base case) value (Saltelli, Tarantola, and Chan 1999). The perturbations of the model inputs can be finite in Tornado diagrams (Eschenbach 1992) and finite change sensitivity indices (Borgonovo and Smith 2011; Borgonovo 2010) or infinitesimal, in differentiation-based methods (Griewank 1995, 2000; Sobol' and Kucherenko 2009). A sensitivity index S_i is calculated through the use of a set of partial derivatives of the output y , with respect to each input X_i :

$$S_i = \frac{\partial g(\mathbf{x})}{\partial x_i} \Big|_{\mathbf{x}=\mathbf{x}^0} \quad (2)$$

In Helton (Helton 1993), partial derivatives are normalized by the nominal value of the factor or by its standard deviation. For instance, if one writes

$$S_i = \frac{\partial y}{\partial x_i} = \frac{\partial y}{\partial x_i} \frac{x_i^0}{y^0}, \quad (3)$$

one obtains the elasticity of the model output with respect to X_i . These two sensitivity measures are particular cases of the differential importance measure [see (Borgonovo 2008) for details].

Differentiation-based approaches compute a value for the sensitivity index S around a fixed nominal point $\mathbf{x}^0 = (x_1^0, x_2^0, \dots, x_k^0)$ (Saltelli, Tarantola, and Campolongo 2000). Thus,

they provide a very limited exploration of the input-output space, if the analysis is limited at a point of interest. Additionally, they ignore probabilistic information in the presence of uncertainty. More generally, because they are OFAT approaches, they are not capable of quantifying the relevance of potential interactions among model inputs (Anderson et al. 2014; Saltelli et al. 2008). However, differentiation-based methods remain appropriate in applications in which the analyst wishes to study how small changes in the input x_i affect the model output around one or more points of interest. When a better exploration of the model input space is sought, then global sensitivity methods are appropriate.

2.2

Global Sensitivity Methods

Global SA methods are used to investigate which model inputs are the most influential in determining the uncertainty of the output of a model, and, after uncertainty analysis, to obtain additional information about the input–output mapping (Anderson et al. 2014). Global SA methods allow analysts to consider the behaviour of the model $g(x)$ in the entire k -dimensional domain, as well as the probability distributions specified to address the variation of the model inputs. Thus, the formal setting sees the enrichment of the model input space Ω_x with the probability space $(\Omega_x, B(\Omega_x), P_x)$, where 1) the capital X denotes that the model inputs are now random variables, 2) P_x denotes the probability distribution that characterizes the analyst’s state of knowledge about the model inputs and $B(\Omega_x)$ is a Borel σ -algebra.

Global SA methods have become the golden standard of sensitivity analysis under uncertainty (Saltelli et al. 2008). A number of global SA techniques have been developed. Due to space limitations, we cannot provide a detailed overview of all methods. For broad reviews, we refer to (Borgonovo 2006; Saltelli et al. 2005, 2012). For details on screening methods, we refer to (Campolongo, Saltelli, and Cariboni 2011; Morris 1991), on non-parametric methods to (Helton and Sallaberry 2009; Helton et al. 2006; Storlie et al. 2009), on expected value of information-based methods to (Felli and Hazen 1998; Oakley 2009; Strong and Oakley 2013). We analyze here in detail the sensitivity measures we are to use in this work, namely, variance-based and distribution-based methods.

As for variance-based techniques, assuming that $g(x)$ in eq. (1) as an integrable function on $(\Omega_x, B(\Omega_x), P_x)$, and if P_x is a product measures, (i.e., we assume that the model inputs are independent), then the following expansion of $g(x)$ holds (Efron and Stein 1981):

$$y = g(\mathbf{x}) = g_0 + \sum_{i=1}^n g_i(x_i) + \sum_{i<j}^n g_{i,j}(x_i, x_j) + \dots + g_{1,2,\dots,k}(x_1, x_2, \dots, x_k) \quad (4)$$

where

$$\begin{cases} g_0 = \int \dots \int_{\Omega_x} g(\mathbf{x}) dP_X = \mathbb{E}[g(x)] \\ g_i(x_i) = \mathbb{E}[g(\mathbf{x}) | X_i = x_i] - g_0 \\ g_{i,j}(x_i, x_j) = \mathbb{E}[g(\mathbf{x}) | X_i = x_i, X_j = x_j] - g_i(x_i) - g_j(x_j) - g_0 \\ \dots \end{cases} \quad (5)$$

In the above equalities, the univariate functions $g_i(x_i)$ represent the first order effects, namely, the part of the response of $g(x)$ due to the individual variation of x_i . Similarly, the $g_{i,j}(x_i, x_j)$ functions account for the residual interaction between pair of variables; etc. [see (Saltelli et al. 2008)].

If, in addition, we assume that $g(x)$ is square integrable, by the orthogonality of the functions in eq. (5), we obtain the complete ANOVA decomposition of the variance of $g(x)$ (Efron and Stein 1981):

$$V[y] = \sum_{s=1}^n \sum_{i_1 < i_2 < \dots < i_s} V_{i_1, \dots, i_s}. \quad (6)$$

where

$$\begin{aligned} V &= \int g^2(\mathbf{x}) d\mathbf{x} - g_0^2, \\ V_{i_1, \dots, i_s} &= \int g^2_{i_1, \dots, i_s}(x_{i_1}, x_{i_2}, \dots, x_{i_s}) dx_{i_1} \dots dx_{i_s}, \end{aligned} \quad (7)$$

Of particular interest are the first and total order sensitivity measures. The first order indices are defined, independently in (Iman and Hora 1990; Sobol' 1993; Wagner 1995):

$$S_i^{FIRST} = \frac{V_i}{V[y]} = \frac{(V[\mathbb{E}(y|x_i)])}{V[y]} \quad (8)$$

They account for expected reduction in variance of the model output when $X_i = x_i$.

We note that if the model output is additive, that is, if $g(\mathbf{x}) = \sum_{j=1}^k h_j(x_j)$, where $h_j(x_j)$ is a univariate function of X_j , then

$$\sum_{j=1}^k V_j = 1 \quad (9)$$

that is, a model is additive if the sum of the first order sensitivity indices is unity. The total order sensitivity indices are defined by

$$S_i^{TOTAL} = \frac{(\mathbb{E}[V(y|x_{-i})])}{V[y]} \quad (10)$$

with the symbol x_{-i} denoting the fact that all variables are fixed but x_{-i} . S_i^{TOTAL} represents the portion of the variance of the model output contributed by X_i individually and through all its interactions with the remaining model inputs.

The presence of interactions indicates that the model is non-additive, that is, its response is not the direct sum of the effects of the individual model input variations. In that case, the total order sensitivity indices equal the first order indices. Knowledge of the first and total order indices allows analysts to obtain information about a structural feature of the model input output mapping.

One of the key assumptions for eqs. (4), (5), (6), and (7) is that the model inputs are independent random variables. Under correlations, the interpretation of V_i remains as the percentage of model output variance that is reduced when we fix X_i , although this does not correspond anymore to the functional contribution of X_i . If correlations are present, Bedford (Bedford 1998) shows that the variance decomposition loses uniqueness and the value of the sensitivity indices becomes dependent on the lexicographical ordering of the variables. Oakley and O'Hagan (Oakley and O'Hagan 2004) highlight that the tidy correspondence of the functional and variance decompositions is lost. This has led authors to introduce sensitivity measures that, while looking at the entire domain, naturally accommodate correlations among model inputs. We consider here moment-independent (also called distribution-based) sensitivity measures. The key-intuition of distribution-based sensitivity measures is to measure the discrepancy between a) $F_Y(y)$, that represents the degree of belief about Y, and b) $F_{Y|X_i=x_i}(y)$ that represents the degree of belief about Y when we receive information that $X_i = x_i$. Then, one can consider the quantity:

$$\delta_i = \mathbb{E}[d\{F_Y(y), F_{Y|X_i}(y)\}] \quad (11)$$

where $d\{F_Y(y), F_{Y|X_i}(y)\}$ is a chosen separation measurement between the conditional and unconditional model output distribution. $d\{\square\square\}$ determines the so-called inner statistic of the global sensitivity measure (Borgonovo et al. 2013).

Depending on the chosen separation measurement, $d\{\square\square\}$, one obtains a specific

sensitivity measure. For instance, for first order variance-based sensitivity measures, the inner statistics is obtained setting

$$d\{F_Y(y), F_{Y|X_i}(y)\} = \mathbb{E}[(Y - \mu_Y)^2 | X_i = x_i] - \mathbb{E}[(Y - \mu_{Y|X_i})^2 | X_i = x_i] \quad (12)$$

where $\mu_Y, \mu_{Y|X_i}$ are respectively the mean and conditional mean of the model output.

Setting:

$$d\{F_Y(y), F_{Y|X_i}(y)\} = \frac{1}{2} \int_{\Omega_Y} |f_Y(y) - f_{Y|X_i}(y)| dy \quad (13)$$

And averaging over the marginal distribution of X_i , we obtain the δ^B importance measure (Borgonovo 2007):

$$\delta_i^B = \frac{1}{2} \mathbb{E} \left[\frac{1}{2} \int_{\Omega_Y} |f_Y(y) - f_{Y|X_i}(y)| dy \right] \quad (14)$$

By setting

$$\delta_i^{KS} = \mathbb{E} \left\{ \sup_y |F_Y(y) - F_{(Y|X_i)}(y)| \right\}, \quad (15)$$

and

$$\delta_i^{KU} = \mathbb{E} \left\{ \sup_y |F_Y(y) - F_{(Y|X_i)}(y)| + \sup_y |F_{(Y|X_i)}(y) - F_Y(y)| \right\}, \quad (16)$$

one sensitivity measures that measure separation between cumulative distribution functions using the Kolmogorov-Smirnov and Kuiper metrics. For the interpretations of these measures, we refer to Baucells and Borgonovo (Baucells and Borgonovo 2013). These three sensitivity measures share the following properties: 1) they are well posed in the presence of correlations; 2) they do not depend on a particular moment of the model output distribution; 3) they are normalized between 0 and 1, 4) they are equal to zero if and only if Y is independent of X_i and 5) they are invariant to monotonic transformation of the output. This last property is particularly convenient when estimation is of concern (Borgonovo et al. 2013).

2.3

Estimation and Global Sensitivity Analysis Settings

The computational cost for computing all V_{i_1, \dots, i_s} in the variance decomposition of eq.

(6) strictly following their definition equals $N^2(2^k - 1)$, with k representing the number of model inputs. This cost makes the calculation rapidly infeasible as N or k increase or when the computational time of the model increases. This cost has been drastically reduced over the last years in a series of works (Homma and Saltelli 1996; Lewandowski et al. 2007; Saltelli 2002; Saltelli et al. 2010). As for estimation, in this work, we use the algorithm in (Saltelli et al. 2010), which enables the estimation of all first and total order indices at a computational cost of $N(k + 2)$ model runs.

However, the fact that all global sensitivity measures rest on a common rationale has two implications. The first, conceptual, is that all their properties depend on the inner statistic. The second is practical. They can all be estimated from the same design, because what we need to estimate them are the conditional and unconditional model output distributions. Using the *given data* logic (Lewandowski et al. 2007; Plischke et al. 2013) one obtains all sensitivity measures for individual model inputs at a cost of N model runs, which is the minimal cost within a MC framework. The given data estimation is based on a sequence of partitions of the same dataset and is not related to a specific design. For instance, in our case, we can use the dataset generated for estimating all first and total order indices according to the scheme of (Saltelli et al. 2010) to obtain also distribution-based sensitivity measures.

Finally, we need to conclude this review of global SA with an important methodological concept for sensitivity analysis introduced in (Saltelli and Tarantola 2002; Andrea Saltelli 2002). For a correct result interpretation and communication of sensitivity analysis results, it is recommended to clearly frame up front the sensitivity analysis exercise. In global SA, this is accomplished using the concept of SA-setting (Saltelli and Tarantola 2002; Andrea Saltelli 2002). A setting is a formulation of the SA goal that allows the analyst to frame the sensitivity exercise in order to identify the most suitable techniques to obtain the desired quantitative insights (Anderson et al. 2014; Borgonovo 2010; Saltelli et al. 2008). In the literature, several SA settings have been defined: factor prioritization, factor fixing, model structure and sign of change (Borgonovo 2007; Saltelli et al. 2008). In this work, we discuss the meaningful settings in the context of LCA.

2.4

Uncertainty quantification in LCA: State of the Art

The distinction that the SA community adopts between local and global approaches has not yet become a standard in the LCA community. Nevertheless, a series of methodological papers have formalised the use of uncertainty evaluation and propagation techniques

in LCA. These techniques serve in some cases the same goal of local SA and global SA without, however, directly contemplating the use of similar tools or jargon.

Among these quantitative tools, we may distinguish three main complementary numerical approaches that have been proposed in LCA (Heijungs 2010):

- uncertainty or error propagation (Heijungs 1994; Lloyd and Ries 2007) or uncertainty analysis (Heijungs and Kleijn 2001), defined as the systematic study of the propagation of uncertainty from input uncertainties to output uncertainties;
- perturbation analysis (Heijungs and Kleijn 2001; Sakai and Yokoyama 2002), or marginal analysis (Heijungs 1994; Heijungs et al. 1992), oriented at analysing how much small marginal perturbation of the model inputs propagate as smaller or larger deviations of the resulting output;
- key-issues analysis (Heijungs 1996) or uncertainty importance (Heijungs 2010; Mutel, de Baan, and Hellweg 2013), defined as the identification of the most influential input that determine the output uncertainty, on which one should focus research efforts to obtain more accurate results.

Looking at the definition of local SA and global SA (Section 2.2), perturbation analysis corresponds conceptually to a local OFAT approach, while uncertainty importance may be considered as a possible class of global SA. According to data availability and according to the focus that a study has, a combination of these techniques may be used. In combination with these techniques, a MC simulation (Robert and Casella 2010) is usually carried out, either using subjective uncertainty estimates, or using uncertainty estimates gathered from the analysis of data.

In the LCA practice, in the few cases where an explicit reference to SA is done, this refers to the comparison of alternative scenarios built varying a set of model inputs around their mean, or built by comparing results obtained using different input values obtained from the literature for selected model inputs, thus to what has been defined as perturbation or marginal analysis, both of which are formally OFAT approaches (Björklund 2002; Huijbregts et al. 2001). Following the OFAT approach, it is up to the practitioner to decide which model input to change and by which amount (Mutel et al. 2013), which may, in turn, lead to misleading results if the scope of the analysis is assign a measure of importance to the model inputs.

Imbeault-Tétréault and colleagues (Imbeault-Tétréault et al. 2013) analyse the output of the life cycle impact assessment (LCIA) phases, considering log-normally distributed model inputs from the ecoinvent database (Frischknecht et al. 2004). For each considered impact category, the analysis aims at defining the model inputs that are likely to be the most influential on the output. The analysis is defined as *sensitivity*, and corresponds to the definition of alternative scenarios and the calculation of sensitivity coefficients, using an OFAT approach.

Geldermann et al. (Geldermann, Spengler, and Rentz 2000) use a set of sensitivity intervals and weights stemming from the use of multi-criteria decision analysis and the fuzzy outranking technique to conduct SA. In (Lewandowska, Foltynowicz, and Podlesny 2004), changes in input data of $\pm 1\%$ and $\pm 10\%$ are applied and the impact of inputs on the output are calculated based on subjectively-defined qualitative sensitivity indicators (e.g., low sensitivity, very high sensitivity). Ardente and colleagues (Ardente et al. 2008), which state that SA can be applied with arbitrarily selected ranges of variation, perform the analysis on the input data of a study on a solar thermal collector. Based on an investigation of the literature, they define alternative scenarios for the key processes of the life cycle (e.g., alternative electricity consumption scenarios, or transportation scenarios with minimum, average and maximum values).

Zhou and Schoenung (Zhou and Schoenung 2007) define a framework with the application of quality management tools (e.g., process mapping, prioritization matrix) and statistical methods (e.g., multi-attribute analysis, cluster analysis) to study the technology of a computer display. Alternative weighting schemes are used as a basis of a SA, which consist, for each impact category considered in the study, in the tabular comparison of the contribution of each impact category to the total impact. Alternative scenarios are defined as SA also in (Martínez et al. 2010), which present as SA the change in impact scores from the variation of single model inputs in four main phases of the lifecycle of a wind turbine, namely maintenance, manufacturing, dismantling, and recycling. Ranges are selected in the contour of the mean of each model input considered.

In the LCA-model development field, the work of Verones et al. (Verones, Pfister, and Hellweg 2013) use SA for the statistical analysis of regionalized fate factors developed for the evaluation of consumptive water use. Once again the SA corresponds to the identification of alternative scenarios, built varying local characteristics in a defined range (e.g. underlying area, hydraulic properties), and to the comparison of the newly obtained fate factor to those obtained in a base average-case.

In Padey et al. (Padey et al. 2013), we find the first available study which uses global SA, as defined in section 2.2, to identify key model inputs explaining the impact variability of wind power systems over their entire life cycle. This work represents the only documented case of the explicit use of a global SA technique in the field of LCA.

3

Global SA and impact assessment models: a protocol and an application to an LCA noise impact assessment model

3.1

LCA as a complex model: interpretation of techniques currently in use

The LCA framework as defined by the ISO standard (ISO. 2006) may be considered in itself as a complex model, which may be analysed by means of SA. In a specific phase of LCA, the interpretation phase, the models and their results are analysed and interpreted. At this stage, significant issues are identified, also regarding the completeness and the variability of data. The ISO standard on LCA recommends performing a sensitivity check on the data and methods as part of the evaluation of the information that is used in a study (ISO. 2006). The standard does not refer to a particular numerical technique, nor addresses the user to a particular approach or way the data should be perturbed, thus leaving it open to the LCA-study performer to select the appropriate technique and interpret the results.

At different stages of an LCA study, uncertainty may be analysed and propagated. Focusing on the LCI and LCIA phases, one may be interested in understanding the uncertainty that propagates from the inventory to the impact scores, and to understand which of the model inputs are important in determining the uncertainty of the output.

Considering a full set of processes and economic flows which are used in LCA, the output variance could well be the result of the variance of thousands of terms. Uncertainty importance or key issues analysis, as defined in (Heijungs 2010), respond to the impossibility of defining a distribution function for the thousands uncertain model inputs of the equation that should be considered, due simply to a lack of sufficient data. In such case, a global SA as formally defined may not be performed, without running the risk of obtaining unrepresentative results. However, this condition does not hold true for the LCIA phase of LCA, in which the LCIA model-developer typically has a full visibility over the model inputs and the input-output mapping. In such a case, it is possible, by analysing the data at hand (e.g. a deposition map, an elevation map), to identify the distribution for the model inputs and apply a global SA approach. Therefore, for the case

of characterisation models it is recommendable to use global SA techniques, which allow to fully evaluating the complex non-linear, non-monotonic models that are used in LCA.

The characterization models and resulting characterisation factors are often a major source of uncertainty for LCA studies (Heijungs et al. 2007). Yet this is a topic that has not attracted sufficient attention from the field of LCA, and especially among model-developers. Together with the evaluation of how to propagate uncertainty in characterisation models, an accurate SA should be conducted and documented. In this study, we focus on the development phase of an impact assessment model and we limit the focus to uncertainty about the way the interaction between technosphere and biosphere has been modelled (Koning et al. 2002). We focus here on how to identify the sources of such uncertainties in the input model inputs, on how to classify them in terms of statistical importance, and on how to apportion the total uncertainty of the output to each of the inputs that are used in characterization models to calculate characterization factors.

3.2

A protocol for the LCIA-global SA of a characterization model

3.3

Global sensitivity analysis settings for characterization models

In this section, we demonstrate the use of global SA to develop and study a characterisation model in LCIA. The protocol here proposed is applicable to all other parts of the LCA framework that require the use of complex non-linear IAMs, as well as to other IAMs used in the environmental sciences. We propose a combination of global SA techniques to be applied in the study of impact assessment models developed for LCIA, with particular attention to the case of newly-developed impact categories.

As a starting point for the protocol, let us consider the characterisation model ϑ represented in Figure 1, as part of the impact assessment phase of LCA (ISO. 2006).

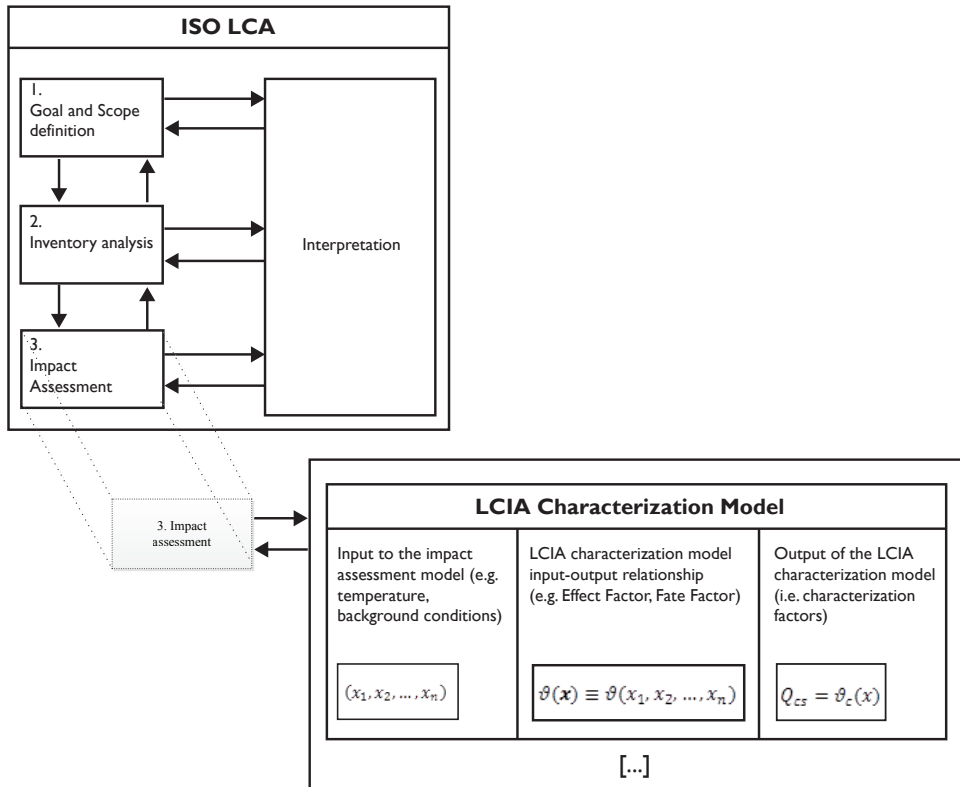


Figure 1. Characterization model in relationship to the LCA framework

The characterisation model is a function of a series of model inputs [e.g. effect factor, fate factor, damage factor; see (Rosenbaum, Margni, and Jolliet 2007)], which are, in turn, dependent on the stressor-specific components that characterise a certain impact category (e.g. temperature, deposition, concentration).

We may define a generic characterisation model for a generic impact category c :

$$Q_{cs} = \vartheta_c(x) \quad (17)$$

where ϑ_c represents the non-linear function representing the characterization model for impact category c , per stressor s and Q_{cs} is the characterisation factor, which is a function of a variety of model inputs x .

At this stage the LCA analyst may consider a generic ϑ that represents a generic characterisation model, of which one wants to understand the behaviour and study the structure, without any *a priori* physical assumption (Rabitz and Aliş 1999) on the nature

of the model input–output relationships. We consider all model inputs that influence the characterization model and are part of its structure. The following steps may be considered as a paradigm of action for any characterisation model in LCIA (see Figure 1).

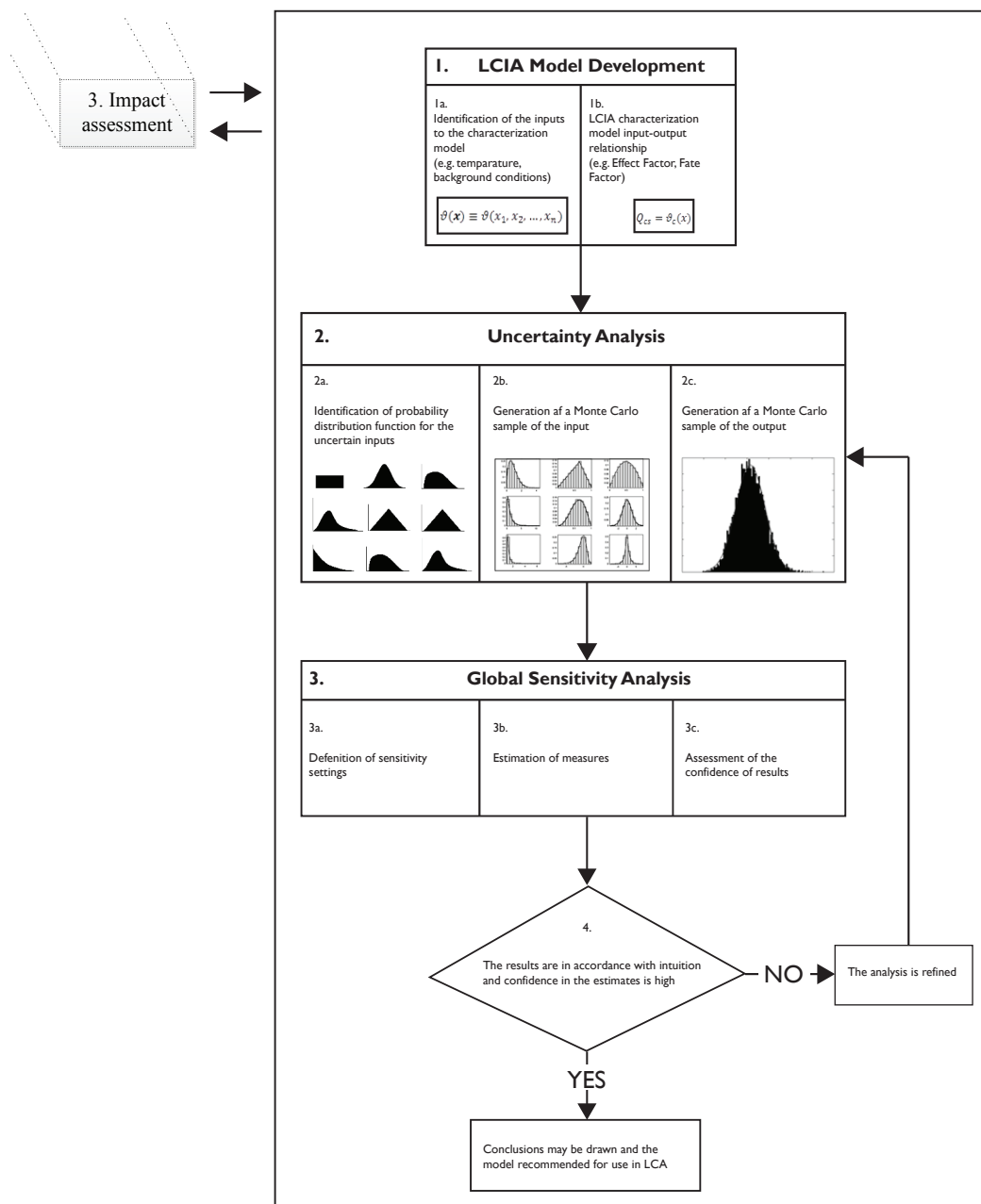


Figure 2. Protocol for the analysis of an LCIA characterization model

The protocol in Figure 2 nests model development with uncertainty analysis and global SA. In the model development phase, the LCA analysis identifies the uncertain model inputs (step 1a in Figure 2), and identifies the input-output programming of the LCIA characterization model (1b; i.e. the LCIA model input-output relationships).

Step 2 deals with what is commonly identified as uncertainty analysis (or uncertainty propagation). The analyst identifies the probability distribution functions for the uncertain model inputs (2a). The distributions can be obtained from expert opinions or from available data (which can be collected either in the literature, or from the analysis of spatially-explicit data in GIS collected during the model development exercise). A MC sample of the model inputs is generated (2b). This generation can be obtained using a crude MC generator. However, for a more efficient exploration of the model input space a Latin Hypercube or a quasi-random design is preferred [the reviewer is referred to (Helton and Davis 2002; Owen 1998, 2006; Sobol' et al. 1992) for additional details]. The following step (2c) consists in the evaluation of the model in correspondence of the generated sample to obtain the model output distribution.

In step 3, the analyst establishes the sensitivity analysis settings, that is, she formulates the sensitivity questions and identifies the sensitivity measures for obtaining the consistent answers. If computational time allows, the model can be run according to specific designs to obtain the appropriate sensitivity measures. Otherwise, the dataset generated by MC simulation is post-processed to obtain the required sensitivity measures. Before coming to conclusions and recommendations, it is suggested to assess the confidence in the estimates of the sensitivity measures. This can be done, for instance, using bootstrapping (Archer, Saltelli, and Sobol 1997).

If the results are in accordance with intuition and confidence in the estimates allows, conclusions can be drawn and the model can be given to decision makers and used in LCA (step 4). If not, one needs to repeat the analysis. In the case repetition is due to results not in accordance with intuition, then the analyst needs to establish whether the sensitivity results reveal some hidden phenomenon that was not taken into account or a numerical error is present in the code or in the distribution assignment (in this case, we are in a debugging mode). The remedy is to intervene on the code or on the model input distributions. If the repetition is due to low confidence in the estimates, then the remedy is an analysis at a larger sample size, if computing time permits.

3.4

Application of LCIA-global SA protocol to the noise characterization model

The protocol is here applied to a characterisation model developed for the quantification of the impacts on humans of sound emissions from various classes of sources in a life cycle [noise-model, from now on; (Cucurachi et al. 2012; Cucurachi and Heijungs 2014)]. Cucurachi et al. (Cucurachi et al. 2012) define a theoretical framework for the inclusion of the impacts of noise on humans in LCA studies. In Cucurachi and Heijungs (Cucurachi and Heijungs 2014), the methodology has been operationalized and characterisation factors are provided to be used in LCA studies. In the following, the protocol is applied to the two acceptations of this IAM.

Step I: Noise-model definition

The noise-model is based on the quantification of the noise impacts of sound emitted by any source operating in a life cycle (Cucurachi et al. 2012). The sound power emitted by a source, or combination thereof, at the emission compartment determines a change in sound pressure at the exposure compartment. A series of conditions intervene to attenuate or propagate the trajectory of sound waves, thus influencing the way the sound emissions are perceived eventually as noise by human targets that are exposed to them. Generic characterisation factors are calculated according to the formula:

$$Q_{cs} = \frac{20}{\sqrt{W_{amb}}} \times Nf \times 10^{\frac{(D-A_{att})}{20}} \times 10^{\frac{(\alpha+\beta)}{20}} \quad (18)$$

where W_{amb} represents the environmental sound power at the emission compartment, thus assuming that some sound emissions are already present in the environment, Nf represents the number of targets that are exposed to the sound power, D is a directivity factor that determines the direction of propagation, A_{att} defines a series of attenuations factors that intervene and limit the propagation of sound waves between emitting source and receiver, α is a specific factor related to the frequency of emission, β refers to a penalty added according to the time of the day the emission takes place. Furthermore, A_{att} may be expanded into:

$$A_{att} = A_{div} + A_{atm} + A_{ground} + \dots A_{other} \quad (19)$$

thus it represents a series of context-specific attenuation factors that are a function of the distance between source and receiver (A_{div}), the atmospheric conditions (A_{atm}), the ground composition (A_{ground}), and any other attenuation that may be relevant to the system under study (A_{other}). For the sake of simplicity, we omit in the characterisation

factors formulas the indexes used in LCA to define the compartments of emission and exposure and refer to (Cucurachi et al. 2012; Cucurachi and Heijungs 2014) for more details on the model.

We may consider the complete formula for the calculation of the characterisation factors as the input-output-noise-model to which we want to apply the LCIA-global SA settings, and the model inputs reported below in eqs. (18) and (19) as the uncertain variables that will be analysed (step 1a in Figure 2). We considered two alternative configurations of the noise-model:

- **Simple model**, based on eq. (18), and considering A_{att} as an uncertain model input with a given distribution (see table I):

$$y_{SM} = g_{SM}(\mathbf{x}) = f(W_{amb}, D, A_{att}, Nf, \alpha, \beta) \quad (20)$$

- **Extended model**, including the expansion of A_{att} to be, in turn, a function of the specific local conditions of e.g. temperature, humidity (see Table IV),

$$y_{EM} = g_{EM}(\mathbf{x}) = f(W_{amb}, D, A_{att}[T, Prs, RelHum, fm, d, G], Nf, \beta) \quad (21)$$

In the extended model, A_{att} is calculated by an iterative process involving a combination of intermediate calculation model inputs and uncertain variables, on which A_{att} depends ($[T, Prs, RelHum, fm, d, G]$; see Table IV). In the simple model the analysis is limited to assigning a probability distribution to A_{att} based on the a priori knowledge of the model. A series of additional model inputs is introduced, and compared in the analysis with the simple model composition. Model input α (i.e., frequency component) is excluded from the extended model, because it becomes dependent on fm . The two alternative configurations refer to two different times of the process of development of an LCIA model. Respectively, the simple configuration refers to the phase of theoretical definition of the model, the extended configuration to a later phase in which the modeler has already a deeper knowledge of the functioning of the model and more data is available on the variables that are used.

We then proceeded according to the protocol and a computer model was created to encode the input-output mapping for the simple and extended model configurations (step 1b of the protocol in Figure 2).

Step 2: Uncertainty analysis

In order to identify the most-representative distributions for the model inputs (step 2a of the protocol; see Figure 2), the data provided in Cucurachi and Heijungs (Cucurachi and Heijungs 2014) were confronted with data from the noise literature. In Table IV below, the distributions are defined for the input variables for both the simple and the extended configurations. Similar distributions were chosen for variables that appear in both the simple and extended noise-model.

Table IV. Uncertain inputs in the noise-model in the two alternative configurations

Simple model		
Variable	Probability distribution function	
W_{amb}	Background sound power level [dB]	Lognormal (meanlog=2.3, sdlog=1.09)
D	Directivity component [dB]	Normal (mean=3, standard deviation=1)
A_{att}	Attenuation factors [dB]	Normal (mean=5, standard deviation=1)
Nf	Population level	Lognormal (meanlog=2.3, sdlog=1.09)
α	Perceived frequency model input [dB]	Uniform (min=-26.2,max=2)
β	Penalty for time of the day [dB]	Triangular (0;10;5)
Extended model		
Variable	Probability distribution function	
W_{amb}	Background sound power level [dB]	Lognormal (meanlog=2.3, sdlog=1.09)
D	Directivity component [dB]	Normal (mean=3, standard deviation=1)
Nf	Population level	Lognormal (meanlog=2.3, sdlog=1.09)
β	Time of the day penalty [dB]	Triangular (0;10;5)
T	Temperature [°C]	Normal (mean=15, standard deviation=5)
Prs	Ambient pressure [Pa]	Uniform (min=2000,max=101325)
$RelHum$	Relative humidity [%]	Uniform (min=10,max=100)
f_m	Frequency of the emission [Hz]	Triangular (63;8000;4000)
d	Distance from source to receiver [m]	Lognormal (meanlog=3.9, sdlog=1.09)
G	Ground composition factor	Triangular (0;1;0.5)

Given the low calculation time required by the running of the two configurations of the model a MC sample of $N=120000$ was selected. Sobol' quasi-random sequences (Bratley and Fox 1988; Sobol 1998, 2001) were used to generate the sample for the uncertain inputs (step 2b). Data was stored and used for the calculation of the two outputs y_{SM} and y_{EM} , according to the defined computational model (step 2c).

Step 3: Global Sensitivity Analysis

The analysis proceeded with definition of the global SA settings (step 3a). The following settings were defined as a basis of the global SA of the noise-model:

1. **LCIA Model Structure:** to determine whether the behaviour of the quantity of interest (model output) is the result of individual effects or of interactions among the model outputs. This goal is reached by estimating first order sensitivity indices and comparing their value to unity (see section 2.2). Possibly, if computing time allows, one can estimate also the total order sensitivity indices or higher order indices.
2. **Factor prioritization:** to determine key uncertainty drivers in the impact assessment model, namely the model outputs on which to put resources to reduce uncertainty. The process can possibly identify those model inputs that can be fixed to a nominal value without the risk of adding extra uncertainty to the model. For the LCIA-global SA of a characterization model, the estimation of the important measures defined in section 2.2 offers a valuable piece of information on the importance of a certain model input in a characterization model.

Based on the settings, we proceeded with estimating the global SA measures presented in section 2.2. As mentioned in section 2.3, first order variance based sensitivity indices and the sensitivity measures δ^B , δ^{KS} and δ^{KU} can be estimated from the same MC sample with no additional model evaluations, while a specific design is necessary to estimate total indices. We used the `sobolj2007` function of the package `sensitivity` of the software [R] (Cran-R n.d.). The function allows implementing MC estimations of both first- and total-order sensitivity indices simultaneously, at a computational cost of $N(k+2)$ (Saltelli et al. 2010). The same MC sample was used both to estimate the total indices in the required specific design and for the estimation of the sensitivity measures in eqs. (8), (14), (15), and (16).

Setting 1: LCIA Model Structure. In order to study the structure of the model, first and total order indices were calculated for the simple and the extended noise-model. In Table V, the results are reported for both configurations (step 6 of the protocol).

Table V. First order and Total order sensitivity indices ^a

Simple model			
		Analysis of model structure	
Variable		First Order	Total order
W_{amb}	Background sound power level [dB]	0.021	0.296
D	Directivity component [dB]	0.002	0.047
A_{att}	Attenuation factors [dB]	0.002	0.052
Nf	Population level	0.175	0.858
α	Perceived frequency model input [dB]	0.026	0.183
β	Penalty for time of the day [dB]	0.003	0.062
Extended model			
Variable		First Order	Total order
W_{amb}	Background sound power level [dB]	0.003	0.422
D	Directivity component [dB]	0.009	0.009
Nf	Population level	0.003	0.932
β	Time of the day penalty [dB]	0.006	0.978
T	Temperature [°C]	0.003	0.003
Prs	Ambient pressure [Pa]	0.003	0.517
$RelHum$	Relative humidity [%]	0.003	0.003
f_m	Frequency of the emission [Hz]	0.003	0.261
d	Distance from source to receiver [m]	0.004	0.946
G	Ground composition factor	0.003	0.068

^a Top contributors in bold

Table V shows that, in the simple model configuration, the highest contributor to the output variance is Nf the population level, which contributes for about 18% of the output variance. The total sum of the first order indices adds up to around 20%, suggesting the presence of strong interactions between model inputs even in the simple model configuration. The results of the total order indices show that Nf explains 85% of the output variance when all interactions with other inputs are considered.

In the extended model configuration, Table V shows that the highest contributors are, respectively, D , β , and d . However, the total sum of the first order indices adds to less than 1%, thus suggesting that interactions strongly influence the model behaviour. Thus, as far as this setting is concerned, we can conclude that the model is non-additive, and interaction effects dominate over individual effects.

We then come to the analysis of the *Key-Uncertainty Drivers*.

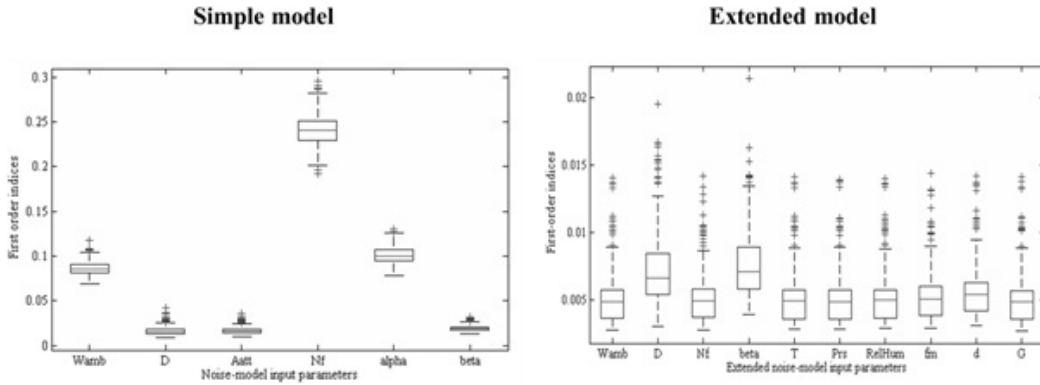


Figure 8. Result of 500 bootstrap runs of the calculation of first order indices for the simple and the extended model

For the model at hand interaction effects strongly influence the model behaviour, limiting the possibility of extracting conclusive information from first order variance-based indices. The total order indices suggest that, for a number of model inputs (in bold in Table V), the contribution to the output variance is almost totally due to interactions. At the same time the extremely low values for model inputs *D*, *T*, and *RelHum* may again suggest a methodological issue in the estimation of variance-based measure in the presence of a multiplicative function. The estimation of first order indices becomes particularly challenging in the presence of nonlinearities and interaction, e.g., multiplications, between model outputs [(Borgonovo et al. 2013);^{p. 3}; see also the multiplicative model in (Borgonovo et al. 2013), for which estimation of variance based sensitivity measures results inaccurate].

We then used bootstrapping (Archer et al. 1997) to assess our confidence in the estimates. For the case of the total order indices, such analysis could not be conducted due to the specific design that was used. On the other hand, it was possible to use the generated MC sample to obtain confidence intervals for the first order indices. Figure 3 displays the confidence intervals obtained using 500 bootstrap replicates.

Figure 3 shows that for the simple model we have limited variability in the estimates, and, therefore, we are confident about the ranking obtained with S_i^{FIRST} . Conversely, a great variability is obtained for the calculation of the first order variance-based sensitivity indices for the extended model. This variability should lead an analyst to a diminished confidence in the obtained ranking.

Based on the results of the confidence test and on the considerations above, we used an ensemble of sensitivity measures to reinforce the analysis. As described in section 2.3, from the same dataset used to compute the first and total order indices, it is possible to estimate also the importance measures δ^B , δ^{KS} and δ^{KU} . The values are reported in Table VI (step 7 of the LCIA-global SA).

The confidence of the results was tested, once again, by means of bootstrapping. We show the results of 500 bootstrap runs for the δ^B importance measure (see Figure 9). For both configurations of the noise-model we have limited variability of the estimates, thus suggesting that the distance-based importance measures are better able to deal with the noise-model interactions.

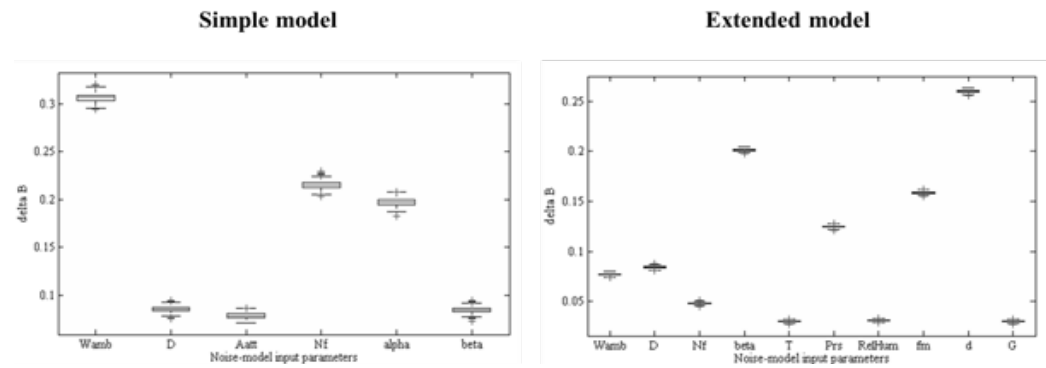


Figure 9. Result of 500 bootstrap runs of the calculation of δ^B for the simple and the extended model

In the simple configuration, the most influential factors are Nf (population level) and W_{amb} (background sound power level) according to all of the three distance-based measures used. The importance of W_{amb} had not been spotted by the variance-based indices estimated in section 0. Other model outputs have an intermediate influence on the output. According to distance-based sensitivity measures, the background context of emission is the model input to focus the attention for model development if the attenuations were not considered in the full specification, together with the number of targets that are exposed to a level of sound emissions that may be perceived as noise (Cucurachi et al. 2012).

Table VI. Importance measures for the simple and extended noise-model configurations

Simple model				
Variable		Importance measure		
		δ^B	δ^{KS}	δ^{KU}
W_{amb}	Background sound power level [dB]	0.29	0.27	0.29
D	Directivity component [dB]	0.13	0.05	0.08
A_{att}	Attenuation factors [dB]	0.12	0.05	0.07
Nf	Population level	0.31	0.29	0.32
α	Perceived frequency model input [dB]	0.17	0.16	0.18
β	Penalty for time of the day [dB]	0.01	0.06	0.08
Extended model				
Variable		Importance measure		
		δ^B	δ^{KS}	δ^{KU}
W_{amb}	Background sound power level [dB]	0.13	0.04	0.06
D	Directivity component [dB]	0.15	0.11	0.13
Nf	Population level	0.12	0.08	0.09
β	Time of the day penalty [dB]	0.30	0.27	0.29
T	Temperature [°C]	0.15	0.03	0.05
Prs	Ambient pressure [Pa]	0.14	0.12	0.13
$RelHum$	Relative humidity [%]	0.15	0.03	0.05
f_m	Frequency of the emission [Hz]	0.20	0.19	0.20
d	Distance from source to receiver [m]	0.22	0.20	0.21
G	Ground composition factor	0.15	0.03	0.05

In the extended configuration, β (time of the day penalty) and d (distance of propagation) become the most influential factors. The importance of β had not been spotted by the first order variance-based indices, but is revealed by the total indices.

The results in Table VI suggest that, if more resources were to be available, a modeller would have to investigate the exact time of the day an emission is taking place, and the exact distance between the source of the sound emission and the receiver/receivers. Such information also provides a way of prioritizing the recording of information at the LCI phase of an LCA study, expanding on the information gathered using the variance-based techniques.

Step 4: Results Evaluation

With these results in mind, following the final decision step 4 of the protocol presented in Figure 2, we decided that the results provide sufficient information to judge the noise-model. It was resolved that no further analyses were needed and that the N selected was suitable to obtain accurate estimates. We turned, then, to the investigation of the extent to which measures agree/disagree in the identification of key uncertainty drivers (Kleijnen and Helton 1999). The inputs for both configurations of the model did not have the same influence with respect to the global sensitivity measures used. The calculation of the correlation coefficient among Savage scores allows us to study the accordance among different rankings [see (Borgonovo, Gatti, and Peccati 2010)]. Such a technique emphasizes the agreement/disagreement for the most important variables and places reduced weight on agreement/disagreement for the variables of low importance [(Kleijnen and Helton 1999); p. 166]. Table VII displays the resulting correlations among Savage scores are presented.

Table VII. Correlation among Savage scores across global sensitivity measures

Simple model					
	First Order	Total order	δ^B	δ^{KS}	δ^{KU}
First Order	1	0.93	0.46	0.51	0.51
Total order	0.93	1	0.68	0.72	0.72
δ^B	0.46	0.68	1	0.96	0.96
δ^{KS}	0.51	0.72	0.96	1	1
δ^{KU}	0.51	0.72	0.96	1	1
Extended model					
	First Order	Total order	δ^B	δ^{KS}	δ^{KU}
First Order	1	0.68	0.59	0.60	0.62
Total order	0.68	1	0.66	0.73	0.72
δ^B	0.59	0.66	1	0.98	0.99
δ^{KS}	0.60	0.73	0.98	1	0.99
δ^{KU}	0.62	0.72	0.99	0.99	1

In the simple configuration of the model, the correlation coefficients suggest that most measures agree with the ranking of inputs. The Savage scores for the measures δ^B , δ^{KS} and δ^{KU} strongly correlate to one another (~ 1). A lower positive correlation of Savage scores is obtained comparing the measure δ^B with both first and total order indices. For the extended model, the rankings between variance-based and the other importance measures put forward a similar picture. Greater differences are highlighted between the invariant importance measures and the first and total order indices, with δ^B once again presenting the lowest correlation value.

In summary, the calculation of the correlation of Savage scores and the use of bootstrap sampling further helps the LCA modeler to study and understand the developed model, and it is advised as a supporting analysis for the protocol presented in the previous sections. In our case, the analysis shows that the factors W_{amb} and Nf can confidently be considered as the key uncertainty drivers for the simple model, while factors d and β are the key drivers in the extended configuration.

4

Discussion: striving towards improved life cycle assessment models

The LCA community is recognizing the need of improving its methods for the sensitivity and uncertainty analyses of LCA codes. Our work has investigated this issue, unveiling several aspects. First, we have seen that the complexity of LCA models might make it impossible to perform a fully blown global SA at the whole LCA scale, due to its complexity. However, we have seen that global SA is applicable in portions of the evaluation and, in particular, in the crucial LCIA phase, where performing a full-fledged global SA not only becomes possible, but is capable of producing insights for the analyst that would otherwise go lost. The SA measures are responsive to non-linearities in LCIA models, also in the presence of correlated inputs. The ability to capture dependencies among factors and the importance of factors to the output of the model makes the protocol extendable to other phases of LCA, in which input are used to calculate an output. For instance, at the inventory phase the influence of inventory items on the output of a study may be also evaluated taking into account model-structure measures and importance measures.

The protocol proposed here allows extracting information on a model (LCIA or otherwise) directly from the results of a MC simulation, without the need to obtain a specific design. This is advantageous, because most of the software packages that are used

to conduct LCA studies already contain MC subroutines* . MC simulation alone, however, does not allow the analyst to identify key drivers of uncertainty, and to understand the structure of the input-output model (Anderson et al. 2014). In this respect, an issue is represented by the need to define a joint distribution function that truly represents the decision-maker's degree of belief about the model inputs. In the context of LCIA model development, modellers typically have sufficient data to define how the model inputs are distributed.

In the preliminary phases of the analysis, global SA can help gathering focus on important factors based on estimates and expert judgement. Later, a complete global SA can be performed when a better coverage of data is available. In our application, we considered two different configurations of the same model that correspond to two model development stages. As noted, even though some inputs had the same distribution function in both configurations, their importance changed.

Finally, a combination of measures is recommended for the identification of key uncertainty drivers. Using an ensemble of sensitivity measures allows an analyst to overcome the limitations of each single method and to obtain a robust ranking of model outputs. Then, an analyst has information about which values is possible to fix in the remainder of the analysis. This is particularly relevant in the context of LCIA modelling, where it is common to use characterisation factors that are often representative of certain average conditions (e.g. a certain geographical location is taken as representative of a wide area). Here, the protocol can guide the modeller in deciding which model inputs could be averaged without affecting the uncertainty of the model. Once the modeller has a clear idea of the structure of the model and of the key input drivers, it is also possible to further evaluate the need to produce geographically-explicit characterisation factors with high level of spatial resolution. For all LCIA models for which only few inputs would be determinant in varying the output, it would be a questionable use of resources to define characterisation factors that are specific to highly-localised conditions. Those model inputs with the largest values of all measures should be prioritized and further analysed and localised.

* Also, fully-documented computer subroutines are freely available for the most used global sensitivity tools, allowing for a straightforward application of the measures to any context, including that of LCA, without any additional modelling time. For the calculation of sensitivity measures in this article both [R] and Matlab® (MathWorks 2013) subroutines were used.

5

Conclusions

This article has discussed the use of global SA techniques to increase the trust in LCIA models, thus of LCA as a tool of sustainability assessment. The application of the proposed global SA techniques would increase the confidence of decision makers and users of existing LCIA models, and also of any future developments of novel impact assessment models and characterisation factors. Relying on an ensemble of sensitivity measures, the protocol provides the LCA modeller with a series of powerful tools that increase the validity of the LCA framework, and particularly the transparency of the modelling phase of LCIA characterisation models.

The insights of this work can be extended to all other tools of the environmental, climate change and risk sciences in which complex models are used and where global SA is a key-ingredient to increase model validity and reliability.

References

- Anderson, B., E. Borgonovo, M. Galeotti, and R. Roson. 2014. "Uncertainty in Climate Change Modelling: Can Global Sensitivity Analysis Be of Help?" *Risk Analysis* 34(2):271–93.
- Archer, G. E. B., A. Saltelli, and I. M. Sobol. 1997. "Sensitivity Measures, ANOVA-like Techniques and the Use of Bootstrap." *JOURNAL OF STATISTICAL COMPUTATION AND SIMULATION* 58(2):99–120. Retrieved (<http://www.tandfonline.com/doi/abs/10.1080/00949659708811825>).
- Ardente, F., M. Beccali, M. Cellura, and V. Lofrano. 2008. "Energy Performances and Life Cycle Assessment of an Italian Wind Farm." *Renewable and Sustainable Energy Reviews* 12(1):200–217. Retrieved August 3, 2010 (<http://linkinghub.elsevier.com/retrieve/pii/S136403210600075X>).
- Baucells, Manel, and Emanuele Borgonovo. 2013. "Invariant Probabilistic Sensitivity Analysis." *Management Science* 59(11):2536–49. Retrieved (<http://www.scopus.com/inward/record.url?eid=2-s2.0-84888863510&partnerID=tZOtx3y1>).
- Bedford, T. 1998. "Sensitivity Indices for (Tree)- Dependent Variables." *Proceedings of the Second International Symposium on Sensitivity Analysis of Model Output, Venice* (1:17–20).
- Björklund, Anna E. 2002. "Survey of Approaches to Improve Reliability in Lca." *The International Journal of Life Cycle Assessment* 7(2):64–72.
- Borgonovo, E. 2007. "A New Uncertainty Importance Measure." *Reliability Engineering and System Safety* 92(6):771–84.
- Borgonovo, E. 2010. "Sensitivity Analysis with Finite Changes: An Application to Modified EOQ Models." *European Journal of Operational Research* 200(1):127–38.
- Borgonovo, E. 2010. "Sensitivity Analysis with Finite Changes: An Application to Modified EOQ Models." *European Journal of Operational Research* 200(1):127–38.
- Borgonovo, E., S. Gatti, and L. Peccati. 2010. "What Drives Value Creation in Investment Projects? An Application of Sensitivity Analysis to Project Finance Transactions." *European Journal of Operational Research* 205(1):227–36.
- Borgonovo, E., and C. L. Smith. 2011. "A Study of Interactions in the Risk Assessment of Complex Engineering Systems: An Application to Space PSA." *Operations Research* 59(6):1461–76.
- Borgonovo, E., S. Tarantola, E. Plischke, and M. D. Morris. 2013. "Transformation and Invariance in the Sensitivity Analysis of Computer Experiments." *Journal of the Royal Statistical Society Series B* (DOI: 10.1111/rssb.12052).
- Borgonovo, Emanuele. 2006. "Measuring Uncertainty Importance: Investigation and Comparison of Alternative Approaches." *Risk analysis : an official publication of the Society for Risk Analysis* 26(5):1349–61.
- Borgonovo, Emanuele. 2008. "Sensitivity Analysis of Model Output with Input Constraints: A Generalized Rationale for Local Methods." *Risk analysis : an official publication of the Society for Risk Analysis* 28(3):667–80.
- Bratley, Paul, and Bennett L. Fox. 1988. "ALGORITHM 659: Implementing Sobol's Quasirandom Sequence Generator." *ACM Transactions on Mathematical Software (TOMS)* 14(1):88–100.
- Campolongo, Francesca, Andrea Saltelli, and Jessica Cariboni. 2011. "From Screening to Quantitative Sensitivity Analysis. A Unified Approach." *Computer Physics Communications* 182(4):978–88.
- Canadian Health. 2006. *Guidelines for the Economic Evaluation of Health Technologies, 3rd Edition, 2006*. Retrieved (http://www.cadth.ca/media/pdf/186_EconomicGuidelines_e.pdf).

- Cran-R. n.d. "Package 'sensitivity'." Retrieved March 24, 2014 (Available online at: <http://cran.r-project.org/web/packages/sensitivity/sensitivity.pdf>).
- Cucurachi, S., and R. Heijungs. 2014. "Characterisation Factors for Life Cycle Impact Assessment of Sound Emissions." *Science of the Total Environment* 468-469:280–91.
- Cucurachi, Stefano, Reinout Heijungs, and Katrin Ohlau. 2012. "Towards a General Framework for Including Noise Impacts in LCA." *The International Journal of Life Cycle Assessment* 17(4):471–87.
- EC-JRC. 2011. *ILCD Handbook - General Guide on LCA - Detailed Guidance*. Retrieved (<http://eplca.jrc.ec.europa.eu/uploads/2014/02/JRC-Reference-Report-ILCD-Handbook-Towards-more-sustainable-production-and-consumption-for-a-resource-efficient-Europe.pdf>).
- Efron, B., and C. Stein. 1981. "The Jackknife Estimate of Variance." *The Annals of Statistics* 9(3):586–96.
- EPA. 2006. "Life Cycle Impact Assessment." Pp.46–53 in *Life Cycle Assessment: Principles and Practice*. Scientific Applications International Corporation (SAIC). Retrieved (<http://www.springerlink.com/index/M5342P55737M7016.pdf>)<http://www.cs.ucsb.edu/~chong/290N-W10/EPAonLCA2006.pdf>).
- Eschenbach, Ted G. 1992. "Spiderplots versus Tornado Diagrams for Sensitivity Analysis." *Interfaces* 22(6):40–46.
- European Commission. 2009. *European Commission*. Retrieved (http://ec.europa.eu/smart-regulation/impact/commission_guidelines/docs/iag_2009_en.pdf).
- Felli, J. C., and G. Hazen. 1998. "Sensitivity Analysis and the Expected Value of Perfect Information." *Medical Decision Making* 18:95–109.
- Frey, H. Christopher, and Sumeet R. Patil. 2002. "Identification and Review of Sensitivity Analysis Methods." *Risk Analysis* 22(3):553–78.
- Frischknecht, Rolf et al. 2004. "The Ecoinvent Database: Overview and Methodological Framework (7 Pp)." *The International Journal of Life Cycle Assessment* 10(1):3–9. Retrieved (<http://www.springerlink.com/index/10.1065/lca2004.10.181.1>).
- Geldermann, Jutta, Thomas Spengler, and Otto Rentz. 2000. "Fuzzy Outranking for Environmental Assessment. Case Study: Iron and Steel Making Industry." *Fuzzy Sets and Systems* 115(1):45–65.
- Griewank, A. 2000. *Evaluating Derivatives, Principles and Techniques of Algorithmic Differentiation*. Philadelphia: SIAM.
- Griewank, Andreas. 1995. *Automatic Directional Differentiation of Nonsmooth Composite Functions*.
- Guinée, Jeroen B. et al. 2011. "Life Cycle Assessment: Past, Present, and Future." *Environmental science & technology* 45(1):90–96.
- Heijungs, R. 1994. "A Generic Method for the Identification of Options for Cleaner Products." *Ecological Economics* 10(1):69–81.
- Heijungs, Reinout et al. 1992. "Environmental Life Cycle Assessment of Products: Guide and Backgrounds (Part 2)."
- Heijungs, Reinout. 1996. "Identification of Key Issues for Further Investigation in Improving the Reliability of Life-Cycle Assessments." *Journal of Cleaner Production* 4(3-4):159–66.
- Heijungs, Reinout. 2010. "Sensitivity Coefficients for Matrix-Based LCA." *The International Journal of Life Cycle Assessment* 15(5):511–20.
- Heijungs, Reinout, Jeroen Guinée, René Kleijn, and Vera Rovers. 2007. "Bias in Normalization: Causes, Consequences, Detection and Remedies." *The International Journal of Life Cycle Assessment* 12(4):211–16.

Heijungs, Reinout, and Mark A. J. Huijbregts. 2004. "A Review of Approaches to Treat Uncertainty in LCA." P. 8 in iEMSs 2004 International Congress. Retrieved (<http://www.iemss.org/iemss2004/pdf/lca/heijarev.pdf>).

Heijungs, Reinout, and René Kleijn. 2001. "Numerical Approaches towards Life Cycle Interpretation Five Examples." *The International Journal of Life Cycle Assessment* 6(3):141–48.

Helton, J. C. 1994. "Treatment of Uncertainty in Performance Assessments for Complex Systems." *Risk Analysis* 14:483–511.

Helton, J. C., J. D. Johnson, C. J. Sallaberry, and C. B. Storlie. 2006. "Survey of Sampling-Based Methods for Uncertainty and Sensitivity Analysis." *Reliability Engineering & System Safety* 91(10-11):1175–1209.

Helton, J. C., and W. L. Oberkampf. 2004. "Alternative Representations of Epistemic Uncertainty." Pp. 1–10 in *Reliability Engineering and System Safety*, vol. 85.

Helton, J., and F. J. Davis. 2002. "Illustration of Sampling-Based Methods for Uncertainty and Sensitivity Analysis." *Risk Analysis* 22(3):591–622.

Helton, Jon C. 1993. "Uncertainty and Sensitivity Analysis Techniques for Use in Performance Assessment for Radioactive Waste Disposal." *Reliability Engineering and System Safety* 42(2-3):327–67.

Helton, Jon C., and Cedric J. Sallaberry. 2009. "Computational Implementation of Sampling-Based Approaches to the Calculation of Expected Dose in Performance Assessments for the Proposed High-Level Radioactive Waste Repository at Yucca Mountain, Nevada." *Reliability Engineering & System Safety* 94(3):699–721.

Henriksson, Patrik John Gustav, Jeroen Bartholomeus Guinée, Reinout Heijungs, Arjan Koning, and Darren Michael Green. 2013. "A Protocol for Horizontal Averaging of Unit Process Data—including Estimates for Uncertainty." *The International Journal of Life Cycle Assessment* 19(2):429–36. Retrieved (<http://link.springer.com/10.1007/s11367-013-0647-4>).

Homma, Toshimitsu, and Andrea Saltelli. 1996. "Importance Measures in Global Sensitivity Analysis of Nonlinear Models." *Reliability Engineering & System Safety* 52(1):1–17.

Huijbregts, Mark A. J. 1998. "Uncertainty in LCA LCA Methodology Application of Uncertainty and Variability in LCA Part I: A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment." 3(5):273 – 280.

Huijbregts, Mark A. J. et al. 2001. "Framework for Modelling Data Uncertainty in Life Cycle Inventories." *The International Journal of Life Cycle Assessment* 6(3):127–32.

Iman, R. L., and J. C. Helton. 1988. "An Investigation of Uncertainty and Sensitivity Analysis Techniques for Computer Models." *Risk Analysis* 8:71–90.

Iman, R. L., and J. C. Helton. 1991. "The Repeatability of Uncertainty and Sensitivity Analyses for Complex Probabilistic Risk Assessments." *Risk Analysis* 11(4):591–606.

Iman, R. L., and S. C. Hora. 1990. "A Robust Measure of Uncertainty Importance for Use in Fault Tree System Analysis." *Risk Analysis* 10:401–6.

Iman, R. L., M. E. Johnson, and C. C. J. R. Watson. 2005. "Sensitivity Analysis for Computer Model Projections of Hurricane Losses." *Risk Analysis* 25 (5):1277–98.

Imbeault-Tétrault, Hugues, Olivier Jolliet, Louise Deschênes, and Ralph K. Rosenbaum. 2013. "Analytical Propagation of Uncertainty in Life Cycle Assessment Using Matrix Formulation." *Journal of Industrial Ecology* 17(4):485–92.

ISO. 2006. "ISO 14044: Environmental Management — Life Cycle Assessment — Requirements and Guidelines." *Environmental Management* 3:54. Retrieved (http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=38498).

- Kioutsoukis, Ioannis, Stefano Tarantola, Andrea Saltelli, and Debora Gatelli. 2004. "Uncertainty and Global Sensitivity Analysis of Road Transport Emission Estimates." *Atmospheric Environment* 38(38):6609–20.
- Kleijnen, J. P. C., and J. C. Helton. 1999. "Statistical Analyses of Scatterplots to Identify Important Factors in Large-Scale Simulations, 2: Robustness of Techniques." *Reliability Engineering & System Safety* 65(2):187–97.
- Koning, Arjan De, Jeroen Guinée, David Pennington, Anneke Sleeswijk, and Diederik Schowanek. 2002. "Methods and Typology Report Part A : Inventory and Classification of LCA Characterisation Methods for Assessing Toxic Releases Contribution to Work-Package 7 of the OMNIITOX Project as Part A of Appropriate Deliverable D11." Methods.
- Lewandowska, Anna, Zenon Foltynowicz, and Andrzej Podlesny. 2004. "Comparative Lca of Industrial Objects Part I: Lca Data Quality Assurance — Sensitivity Analysis and Pedigree Matrix." *The International Journal of Life Cycle Assessment* 9(2):86–89.
- Lewandowski, Daniel, Roger M. Cooke, and Radboud J. Duintjer Tebbens. 2007. "Sample-Based Estimation of Correlation Ratio with Polynomial Approximation." *ACM Transactions on Modeling and Computer Simulation* 18(1):3:1–3:16.
- Lloyd, Shannon M., and Robert Ries. 2007. "Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment." *Journal of Industrial Ecology* 11(1):161–79.
- Martínez, E., E. Jiménez, J. Blanco, and F. Sanz. 2010. "LCA Sensitivity Analysis of a Multi-Megawatt Wind Turbine." *Applied Energy* 87(7):2293–2303. Retrieved August 13, 2010 (<http://linkinghub.elsevier.com/retrieve/pii/S0306261909005121>).
- MathWorks. 2013. "MatLab Central." <http://www.mathworks.com/matlabcentral/fileexchange>.
- Morris, M. D. 1991. "Factorial Sampling Plans for Preliminary Computational Experiments." *Technometrics* 33(2):161–74.
- Mutel, Christopher L., Laura de Baan, and Stefanie Hellweg. 2013. "Two-Step Sensitivity Testing of Parametrized and Regionalized Life Cycle Assessments: Methodology and Case Study." *Environmental science & technology* 47(11):5660–67. Retrieved (<http://www.ncbi.nlm.nih.gov/pubmed/23656506>).
- Nice. 2008. "Guide to the Methods of Technology Appraisal." *Regulation* 26(June):76. Retrieved (<http://www.nice.org.uk/media/B52/A7/TAMethodsGuideUpdatedJune2008.pdf>).
- Oakley, J. E. 2009. "Decision-Theoretic Sensitivity Analysis for Complex Computer Models." *Technometrics* 51(2):121–29.
- Oakley, Jeremy E., and Anthony O'Hagan. 2004. "Probabilistic Sensitivity Analysis of Complex Models: A Bayesian Approach." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 66:751–69. Retrieved (<http://doi.wiley.com/10.1111/j.1467-9868.2004.05304.x>).
- Owen, A. B. 1998. "Latin Supercube Sampling for Very High-Dimensional Simulations." *ACM Transactions on Modeling and Computer Simulation* 8(1):71–102.
- Owen, A. B. 2006. "Halton Sequences Avoid the Origin." *SIAM Review* 48(3):487–503.
- Padey, Pierryves, Robin Girard, Denis le Boulch, and Isabelle Blanc. 2013. "From LCAs to Simplified Models: A Generic Methodology Applied to Wind Power Electricity." *Environmental science & technology* 47(3):1231–38. Retrieved (<http://www.ncbi.nlm.nih.gov/pubmed/23259663>).
- Patil, S. R., and H. Frey. 2004. "Comparison of Sensitivity Analysis Methods Based on Applications to a Food Safety Risk Assessment Model." *Risk Analysis* 24(3):573–85.
- Plischke, Elmar, Emanuele Borgonovo, and Curtis L. Smith. 2013. "Global Sensitivity Measures from given Data." *European Journal of Operational Research* 226(3):536–50.
- RABITZ, H. 1989. "Systems Analysis at the Molecular Scale." *Science* 246(4927):221–26.

Rabitz, Herschel, and Ömer F. Aliş. 1999. "General Foundations of High-dimensional Model Representations." *Journal of Mathematical Chemistry* 25(2-3):197–233. Retrieved (<http://link.springer.com/article/10.1023/A:1019188517934>).

Reap, John, Felipe Roman, Scott Duncan, and Bert Bras. 2008a. "A Survey of Unresolved Problems in Life Cycle Assessment." *The International Journal of Life Cycle Assessment* 13(5):374–88. Retrieved (<http://www.springerlink.com/index/10.1007/s11367-008-0009-9>).

Reap, John, Felipe Roman, Scott Duncan, and Bert Bras. 2008b. "A Survey of Unresolved Problems in Life Cycle Assessment: Part 2: Impact Assessment and Interpretation." *The International Journal of Life Cycle Assessment* 13(5):374–88. Retrieved (<http://www.springerlink.com/content/u52158r5q2502v4r/abstract/nhttp://www.springerlink.com/content/u52158r5q2502v4r/fulltext.pdf>).

Robert, Christian P., and George Casella. 2010. *Introducing Monte Carlo Methods with R*.

Rosenbaum, Ralph K., Manuele Margni, and Olivier Jolliet. 2007. "A Flexible Matrix Algebra Framework for the Multimedia Multipathway Modeling of Emission to Impacts." *Environment International* 33(5):624–34.

Sakai, Shinsuke, and Koji Yokoyama. 2002. "Formulation of Sensitivity Analysis in Life Cycle Assessment Using a Perturbation Method." *Clean technologies and environmental policy* 4(2):72–78.

Saltelli, A. 2002. "Making Best Use of Model Evaluations to Compute Sensitivity Indices." 145:280–97.

Saltelli, A. et al. 2008. *Global Sensitivity Analysis -- The Primer*. Chichester.

Saltelli, A., M. Ratto, S. Tarantola, and F. Campolongo. 2005. "Sensitivity Analysis for Chemical Models." *Chemical Reviews* 105:2811–28.

Saltelli, A., M. Ratto, S. Tarantola, and F. Campolongo. 2012. "Update 1 of: Sensitivity Analysis for Chemical Models." *Chemical Reviews* 112(5):1–21.

Saltelli, A., and S. Tarantola. 2002. "On the Relative Importance of Input Factors in Mathematical Models: Safety Assessment for Nuclear Waste Disposal." *Journal of the American Statistical Association* 97(459):702–9. Retrieved (<Go to ISI>://000178018500005).

Saltelli, a., S. Tarantola, and F. Campolongo. 2000. "Sensitivity Analysis as an Ingredient of Modeling." *Statistical Science* 15(4):377–95.

Saltelli, A., S. Tarantola, and K. Chan. 1999. "A Quantitative, Model Independent Method for Global Sensitivity Analysis of Model Output." *Technometrics* 41:39–56.

Saltelli, Andrea. 2002. "Sensitivity Analysis for Importance Assessment." *Risk Analysis* 22(3):579–90.

Saltelli, Andrea et al. 2010. "Variance Based Sensitivity Analysis of Model Output. {D}esign and Estimator for the Total Sensitivity Index." 181(2):259–70.

Sobol, I. M. 1998. "On Quasi-Monte Carlo Integrations." *Mathematics and Computers in Simulation* 47(2-5):103–12.

Sobol, I. M. 2001. "Global Sensitivity Indices for Nonlinear Mathematical Models and Their Monte Carlo Estimates." *Mathematics and Computers in Simulation* 55(1-3):271–80.

Sobol', I. M. 1993. "Sensitivity Analysis for Non-Linear Mathematical Models." *Mathematical Modelling and Computational Experiment* 1:407–14.

Sobol', I. M., and S. Kucherenko. 2009. "Derivative Based Global Sensitivity Measures and Their Links with Global Sensitivity Indices." *Mathematics and Computers in Simulation* 79:3009–17.

Sobol', I. M., V. I. Turchaninov, Yu. L. Levitan, and B. V. Shukhman. 1992. *Quasirandom Sequence Generators*. Moscow.

Storlie, Curtis B., Laura P. Swiler, Jon C. Helton, and Cedric J. Sallaberry. 2009. "Implementation and Evaluation of Nonparametric Regression Procedures for Sensitivity Analysis of Computationally Demanding Models." *Reliability Engineering & System Safety* 94(11):1735–63.

Strong, M., and J. E. Oakley. 2013. "An Efficient Method for Computing Partial Expected Value of Perfect Information for Correlated Inputs." *Medical Decision-Making* 33:755–66.

US - EPA, CREM. 2009. "Guidance on the Development, Evaluation, and Application of Environmental Models." *Environmental Protection EPA/100/K-(March):99*. Retrieved (<http://www.epa.gov/crem/>).

Verones, Francesca, Stephan Pfister, and Stefanie Hellweg. 2013. "Quantifying Area Changes of Internationally Important Wetlands due to Water Consumption in LCA." *Environmental science & technology* 47(17):9799–9807. Retrieved (<http://www.ncbi.nlm.nih.gov/pubmed/23930946>).

Wagner, H. M. 1995. "Global Sensitivity Analysis." *Operations Research* 43,6:948–69.

Zhou, Xiaoying, and Julie M. Schoenung. 2007. "An Integrated Impact Assessment and Weighting Methodology: Evaluation of the Environmental Consequences of Computer Display Technology Substitution." *Journal of Environmental Management* 83(1):1–24.

