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A Protocol for the Global Sensitivity Analysis of Impact Assessment Models in Life Cycle Assessment

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The life cycle assessment (LCA) framework has established itself as the leading tool for the assessment of the environmental impact of products. Several works have established the need of integrating the LCA and risk analysis methodologies, due to the several common aspects. One of the ways to reach such integration is through guaranteeing that uncertainties in LCA modeling are carefully treated. 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 and (ii) the importance of uncertain model inputs and the interaction among them.

KEY WORDS: Global sensitivity analysis; LCIA; life cycle assessment; risk analysis; uncertainty importance

1. INTRODUCTION

This work presents a protocol for performing global sensitivity analysis (SA) within the life cycle impact assessment (LCIA) phase of LCA.[1] The work plays a bridging role between LCA and risk analysis and contributes to strengthening their integration. Such integration has been suggested in the literature since the early 1990s[2–4] (see the detailed literature review in Section 2.1). On the one hand, authors have underlined the several common conceptual aspects between the two disciplines and the fact that the frequent links and exchanges would be ripe for mutual benefits. Both risk analysts and LCA practitioners make use of quantitative models in applications that range, respectively, from the evaluation of environmental and climate change policies[5–7] to the sustainability assessment of products and services.[8] Scott-Matthews and co-authors[9] state that *risk analysts should seek LCA guidance in translating a risk analysis into policy conclusions or even advice to those at risk*. Once the health risks from the exposure to a certain stressor have been characterized and quantified, in fact, it is necessary to go a step further

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in order to determine the policy implications of such exposure, and in order to avoid simplifications. The impact assessment phase of LCA, then, is fundamental to translate risks into policy actions and to guide decision making, and it is at this stage, in particular, that the synergies between risk analysis and LCA may be leveraged.

On the other hand, the literature in both fields evidences the conceptual issues that such integration poses and the fact that conceptual work is still needed for LCA analysts to fully benefit from the methodological advances in risk analysis and, on the other side, for risk analysts to be prepared for the new challenges that LCA poses to risk analysis. We address one of these challenges, namely, the need for proper global sensitivity analysis in LCA as a way to complement uncertainty quantification. However, while the conceptual premise demonstrated by previous studies is that the treatment of uncertainty in risk analysis applications can be transferred to LCA studies as well, one soon realizes that the complexity of LCA requires a deep understanding of the subject for such an extension to retain its full meaning. In this respect, the extension poses also a challenge to traditional risk analysis practice and its solution has the immediate result of making analysts more aware of the potential but also of the limitations of traditional global sensitivity analysis methods when these are confronted with new challenges.

The first step is to identify the common link. This is represented by the fact that, for the modeling of impacts of a certain stressor, LCA studies rely on characterization models. Characterization models are used to calculate science-based conversion 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).(10,11) 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 socioeconomic aspects.(12) LCA deals, in fact, with hundreds of potentially uncertain elementary flows and processes, and the impact assessment models used to characterize them (i.e., to quantify their relative impacts and make them comparable) have increased in complexity, since they now allow for the consideration of the spatial and temporal variability of emissions.(13,14) For these reasons, they are similar, in complexity, to integrated assessment models used by other decision-support tools in the environmental sciences (e.g., in climatic change studies). Moreover, this way of proceeding is similar to the *modus operandi* of quantitative risk assessment in the nuclear, space, and chemical sectors.(15–17) A first difficulty associated with LCA is the cross-comparison and validation of the results obtained. Even studies compliant with the ISO 14044 standard series on LCA(11) and dealing with identical systems showed large differences in the assessed impacts.(18) However, 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 utilize the appropriate sensitivity and uncertainty analysis tools.

In this respect, we need to observe that the importance of sensitivity analysis (SA) has been agreed upon since the beginnings of the development of LCA.(19) The ISO standard on LCA(11) recommends performing a sensitivity check on the data and methods as part of the evaluation of the information that is used in a study. However, the standard does not refer to a particular numerical technique, nor direct the user to a particular approach or way the data should be perturbed, so that, in the field of LCA there seems to be an overlapping of concepts falling under the label of SA. Conversely, in the risk analysis literature, the issue of a proper and consistent representation of uncertainty has been a central topic since the seminal work of Kaplan and Garrick(20) (see also Refs. 21 and 22 for a broad exposition). Refs. 12 and 23 to 32 are a few representatives of a series of studies in which methodological advances are obtained and applied in areas ranging from waste disposal,(27) to hurricane losses,(32) to climate change studies.(12)

Indeed, several studies in LCA apply one factor at a time (OFAT) methods for SA. These methods have been widely criticized in the literature for two reasons.(33) First, OFAT approaches provide a very limited inspection of the model input space and deliver no indication about the presence of interactions. Second, and most important, OFAT methods do not account for uncertainty. These methods rest on an intrinsically deterministic frame that is inconsistent with the analysts' degree of belief in the presence of uncertainty. This way of proceeding is not in line with the recent LCA literature that underlines that, for the credibility of LCA, an important aspect is that results are accompanied by adequate uncertainty quantification,(34) so to best inform the decision process.(35) Reap *et al.*(36,37) claim that sensitivity and uncertainty analysis tools would improve the representativeness of the whole framework. 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 impact assessment phase is available to date.[38]

To construct a protocol on how to regularly conduct a SA in the impact assessment modeling phase of LCA while accounting for the relevant uncertainties, we proceed as follows. We cast global SA techniques in the context of LCA characterization models. We clarify the conceptual differences between SA tools, relating them to the tools that are used in current LCA practice. We introduce SA settings[28] in the LCA context. We then define a multistep 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 decisionmaker'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 noise.[39,40] Even though noise is related to sound emissions that are nontoxic and matter-less, noise may have serious health risks. These include an increased risk of cardiovascular diseases,[41–43] annoyance,[44] sleep disturbance,[45] and other public health implications.[46–48] Noise is the most lamented source of public complaints both in the industrialized and industrializing world[49] and high on the agenda of policymakers across the world.[49,50] Two alternative configurations of the same model, at a different level of complexity, are analyzed 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 article is organized as follows. Section 2 provides an overview of the available SA techniques and gives some insight into 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 analyzed 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

This literature review is divided into two main parts. At first, we review the literature that establishes the link and integration between LCA and risk analysis. We then explore sensitivity analysis methods, with their state of the art in the two disciplines.

2.1. LCA and Risk Analysis

After a series of autonomous applications in the late 1960s and the un-concerted development in the 1970s and 1980s, especially following the energy crises, in the last three decades LCA has definitely established itself as the central methodology for the determination of the environmental impact of products, thanks also to the availability of standard practices[11] and handbooks.[51–53] In the late 1990s, several research works identified the need for the integration of LCA and risk analysis as a necessary path to improve the support given by LCA to policy making.

The integration is bidirectional. In particular, Owens[54] proposes a conceptual framework "where risk assessment, LCA, and other procedures are managed to provide concerted information."[54, p. 364] This intuition is brought forward in several subsequent works. Matthews *et al.*[9] advocate such integration, proposing the use of risk analysis and LCA in combination. LCA helps, in fact, to support policymakers about the selection of alternatives to lower a certain risk and allows estimating the impacts of a certain product system without shifting the related risks elsewhere in a life cycle. The results of LCA studies allow a decisionmaker to consider the environmental risks associated with alternative product systems, highlighting environmental hotspots and providing a complementary perspective.[55,56] Harwich *et al.*[57,58] propose for the field of LCA to use uncertainty analysis techniques already in use in the field of risk analysis. Cowell and co-authors[59] discuss a common research agenda. As underlined in their introduction to the special issue on life cycle and risk analysis, Evans *et al.*[60] suggest that both disciplines would benefit from this integration. A systematic approach for risk analysis in support to decision making in environmental decisions supported by LCA is offered in Ref. 4. Roes[61] describes an integration of LCA and risk analysis in the evaluation of the environmental impact of the production of organic chemicals by petrochemical processes. The approach of Ref. 61 "combines classical risk assessment methods (largely based on toxicology), as developed by the LCA community, with statistics on technological disasters, accidents, and work-related illnesses."[61, p. 1311] Recent applications have focused on the need to use LCA and risk analysis in combination in order to fully capture the potential environmental and social impacts of emerging technologies.[62–67]

In this work, we move along these lines, and anew integrate the modeling phase of LCA with methods developed in risk analysis for the global sensitivity analysis of quantitative models.

2.2. 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 (**x**):

$$y = g\left(\mathbf{x}\right), \quad g : \Omega_{\mathbf{X}} \to \mathbb{R}, \tag{1}$$

where $\Omega_{\mathbf{X}} \subseteq \mathbb{R}^k$, with k denoting the number of model inputs (i.e., the size of **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 behavior of y given the values of the model inputs **x**.

2.3. Local Sensitivity Methods

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.[68] The perturbations of the model inputs can be finite in Tornado diagrams[69] and finite change sensitivity indices[16,70] or infinitesimal, in differentiation-based methods.[71–73] 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:

$$S_i = \left.\frac{\partial g\left(\mathbf{x}\right)}{\partial x}\right| . \tag{2}$$

In Helton,[74] partial derivatives are normalized by the nominal value of the factor or by its standard deviation. For instance, if one writes:

$$S_i = \frac{\partial y}{\partial x_i} = \frac{\partial y}{\partial x_i}\frac{x_i^0}{y^0}, \tag{3}$$

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 Ref. 75 for details).

Differentiation-based approaches compute a value for the sensitivity index S around a fixed nominal point $x^0 = (x_1^0, x_2^0, \ldots, x_k^0)$.[76] 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.[12,77] 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.

2.4. 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.[12] Global SA methods allow the analysts to consider the behavior 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 $\Omega_{\mathbf{X}}$ with the probability space $\Omega_{\mathbf{X}}$, $B(\Omega_{\mathbf{X}})$, $P_{\mathbf{X}}$, where the capital X denotes that the model inputs are now random variables, P_{X} denotes the probability distribution that characterizes the analyst's state of knowledge about the model inputs, and $B(\Omega_{\mathbf{X}})$ is a Borel σ-algebra.

Global SA methods have become the gold standard of sensitivity analysis under uncertainty.[77] 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 Refs. 29, 78, and 79. For details on screening methods, we refer to Refs. 80 and 81, on nonparametric methods to Refs. 82–84, and on expected value of information-based methods to Refs. 85–87. 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 Equation (1) is an integrable function on $(\Omega_{\mathbf{X}}, B(\Omega_{\mathbf{X}}), P_{\mathbf{X}})$, and if $P_{\mathbf{X}}$ is a product measure, (i.e., we assume that the model inputs are independent), then the following expansion of g(x) holds:[88]

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

where

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

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 pairs of variables; etc.[77]

If, in addition, we assume that $g(\mathbf{x})$ is square integrable, by the orthogonality of the functions in Equation (5), we obtain the complete ANOVA decomposition of the variance of $g(\mathbf{x})$:[88]

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

where

$$V = \int^{g^2} (\boldsymbol{x})\, dx - {g_0}^2,$$

$$V_{i_1,\ldots,i_S} = \int_{i_1,\ldots,i_S}^{g^2} (x_{i_1}, x_{i_2}, \ldots, x_{i_s})\, dx_{i_1} \ldots dx_{i_s}. \quad (7)$$

Of particular interest are the first and total order sensitivity measures. The first-order indices are defined, independently in:[24,89,90]

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

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 nonadditive, 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 Equations (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.[5] If correlations are present, Bedford[91] 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[92] 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) $F_Y(y)$, which represents the degree of belief about Y, and

[5]The field of variance-based sensitivity measures under correlations is an ongoing active field of research, with several authors proposing alternative approaches.[134,135]

b) $F_{Y|X_i=x_i}(y)$, which represents the degree of belief about Y when we receive information that $X_i = x_i$. Then, one can consider the quantity:

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

where $d\{F_Y(y), F_{Y|X_i}(y)\}$ is a chosen separation measurement between the conditional and unconditional model output distribution. $d\{\cdot,\cdot\}$ determines the so-called inner statistic of the global sensitivity measure.[93]

Depending on the chosen separation measurement, $d\{\cdot,\cdot\}$, one obtains a specific sensitivity measure. For instance, for first-order variance-based sensitivity measures, the inner statistics is obtained setting:

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

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

Setting:

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

and averaging over the marginal distribution of X_i, we obtain the δ^B importance measure:[94]

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

By setting

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

and

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

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.[95] 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.[93]

2.5. Estimation and Global Sensitivity Analysis Settings

The computational cost for computing all $V_{i_1,\ldots,i_S}$ in the variance decomposition of Equation (6) strictly following their definition equals $N^2(2^k - 1)$, where N is the Monte Carlo (MC) sample size. This cost makes the calculation rapidly infeasible as N or k increase. However, it has been drastically reduced over the last years in a series of works.[96–99] The algorithm in Ref. 98 estimates all first and total order indices at a computational cost of $N(k + 2)$ model runs. Moreover, using the *given data* logic, [99,100] 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 data set and is not related to a specific design. In this work, we profit from this fact and use the same data set generated for estimating all first and total order to estimate from it distribution-based sensitivity measures.

Finally, we need to conclude this review of global SA with an important methodological concept for sensitivity analysis introduced in Refs. 28 and 101. 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.[28,101] 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.[12,77,102] In the literature, several SA settings have been defined: factor prioritization, factor fixing, model structure, and sign of change.[77,94] In this work, we discuss the meaningful settings in the context of LCA.

2.6. 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 formalized 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:[103]

- uncertainty or error propagation[104,105] or uncertainty analysis,[106] defined as the systematic study of the propagation of uncertainty from input uncertainties to output uncertainties;
- perturbation analysis,[106,107] or marginal analysis,[104,108] oriented at analyzing how much small marginal perturbation of the model inputs propagate as smaller or larger deviations of the resulting output;
- key-issues analysis[19] or uncertainty importance,[13,103] defined as the identification of the most influential input that determines 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 (Sections 2.3 and 2.4), 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[109] 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.[34,110] Following the OFAT approach, it is up to the practitioner to decide which model input to change and by which amount,[13] which may, in turn, lead to misleading results if the scope of the analysis is to assign a measure of importance to the model inputs.

Imbeault-Tétreault and colleagues[111] analyze the output of the LCIA phases, considering log-normally distributed model inputs from the ecoinvent database.[112] 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.*[113] use a set of sensitivity intervals and weights stemming from the use of multicriteria decision analysis and the fuzzy outranking technique to conduct SA. In Ref. 114, changes in input data of ±1% and ±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,[115] who 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[116] 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 Ref. 117, which presents as SA the change in impact scores from the variation of single model inputs in four main phases of the life cycle 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.*[118] uses 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.*,[38] we find the first available study that uses global SA 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

At different stages of an LCA study, uncertainty may be analyzed 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 that 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 Ref. 103, 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 analyzing 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 characterization models, it is recommendable to use global SA techniques, which allow fully evaluating the complex nonlinear, nonmonotonic models that are used in LCA.

The characterization models and resulting characterization factors are often a major source of uncertainty for LCA studies.[119] 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 characterization 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 modeled.[120] 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. Global Sensitivity Analysis Settings for Characterization Models

In this section, we demonstrate the use of global SA to develop and study a characterization model in LCIA. The protocol here proposed is applicable to all other parts of the LCA framework that require the use of complex nonlinear integrated assessment models, as well as to other models 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 characterization model ϑ, represented in Fig. 1, as part of the impact assessment phase of LCA.[11]

The characterization model is a function of a series of model inputs (e.g., effect factor, fate factor, damage factor; see Ref. 121), which are, in turn, dependent on the stressor-specific components that characterize a certain impact category (e.g., temperature, deposition, concentration).

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

$$Q_{cs} = \vartheta_c(\boldsymbol{x}), \tag{17}$$

where ϑ_c represents the nonlinear function representing the characterization model for impact category c, per stressor s, and Q_{cs} is the characterization 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 characterization model, of which one wants to understand the behavior and study the structure, without any *a priori* physical assumption[122] 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 characterization model in LCIA (see Fig. 2).

The protocol in Fig. 2 nests model development with uncertainty analysis and global SA. In the model

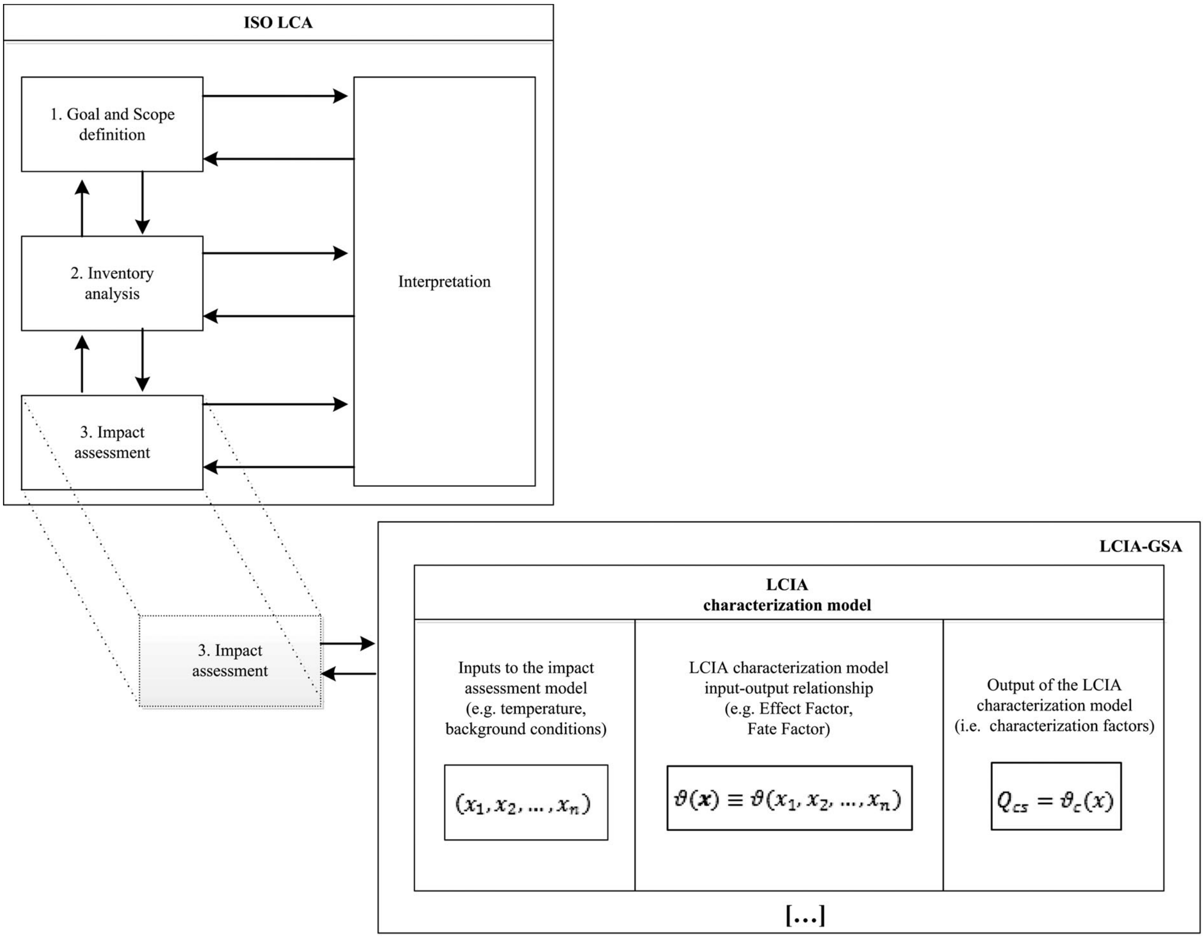

Fig. 1. Characterization model and LCIA global SA in the LCA framework.

development phase, the LCA analysis identifies the uncertain model inputs (step 1a in Fig. 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). In LCIA, 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 reader is referred to Refs. 26 and 123–125 for additional details). The following step (2c) consists of the evaluation of the model in correspondence with 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 data set generated by MC simulation is postprocessed 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.[126]

If the results are in accordance with intuition and confidence in the estimates allows, conclusions

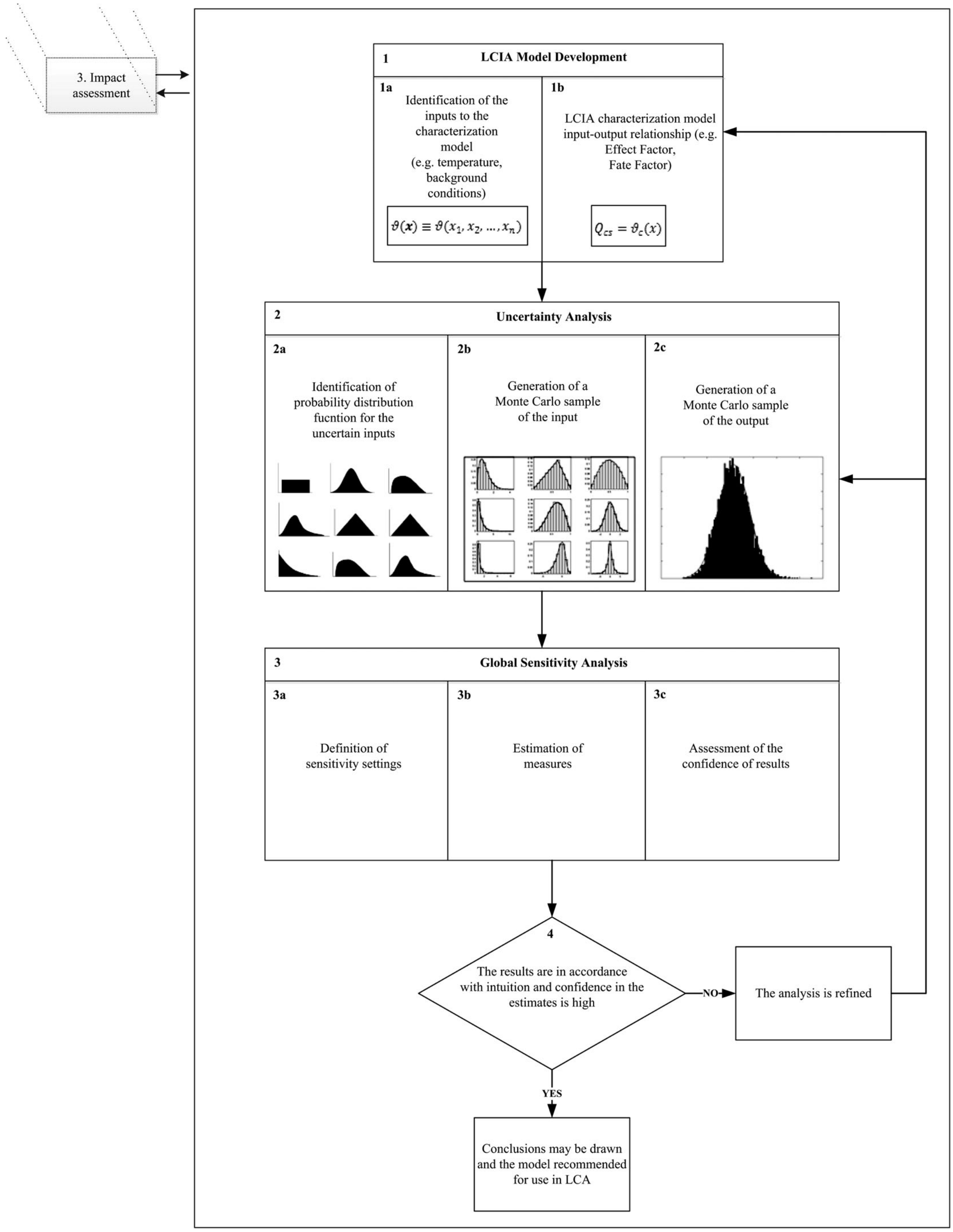

Fig. 2. Protocol for the analysis of an LCIA characterization model.

can be drawn and the model can be given to decisionmakers and used in LCA (step 4). If not, one needs to repeat the analysis. If the sensitivity analysis produced results not in accordance with intuition, then the analyst needs to establish whether counterintuitive results are representative of some combination of aspects that were not previously considered (and thus constitute new insights) or whether they are due to possible numerical inconsistencies present in the code or in the distribution assignment.

Then, one needs to intervene in the code or in 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.

3.3. Application of LCIA Global SA Protocol to the Noise Characterization Model

The protocol is here applied to a characterization model developed for the quantification of the impacts on humans from the exposure to noise emitted by a variety of sources in a life cycle (noise model, from now on[39,40]). The exposure to noise is of particular relevance for environmental risk assessment,[127] since it affects a considerable part of the population.[50] Therefore, the novel inclusion of noise impacts in LCA[40] provides a fitting test case for the integration of risk analysis and LCA. Cucurachi *et al.*[39] define a theoretical framework for the inclusion of the impacts of noise on humans in LCA studies. In Cucurachi and Heijungs,[40] the methodology has been operationalized and characterization factors are provided to be used in LCA studies. In the following, the protocol is applied to the two acceptations of the noise model.

3.3.1. Step 1: 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.[39] 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 characterization 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 attenuation 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, and β refers to a penalty added according to the time of the day the emission takes place. Furthermore, A_{att} may be expanded into:

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

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 characterization factors formulas the indexes used in LCA to define the compartments of emission and exposure and refer to Refs. 39 and 40 for more details on the model.

We may consider the complete formula for the calculation of the characterization 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 Equations (18) and (19) as the uncertain variables that will be analyzed (step 1a in Fig. 2). We considered two alternative configurations of the noise model:

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

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

- **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 I):

$$\begin{aligned} y_{EM} &= \vartheta_{EM}(\boldsymbol{x}) \\ &= f(W_{amb}, D,\ A_{att}[T, Prs, \mathrm{Rel}Hum, fm, \\ &\qquad d, G], Nf, \beta). \end{aligned} \quad (21)$$

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 I). In the simple model, the analysis is

Table I. 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)
fm	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)

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 are 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 Fig. 2).

3.3.2. *Step 2: Uncertainty Analysis*

In order to identify the most representative distributions for the model inputs (step 2a of the protocol; see Fig. 2), the data provided in Cucurachi and Heijungs[40] were confronted with data from the noise literature. In Table I, 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.

Given the low calculation time required by the running of the two configurations of the model a MC sample of $N = 120{,}000$ was selected. Sobol quasi-random sequences[128–130] were used to generate the sample for the uncertain inputs (step 2b). Data were stored and used for the calculation of the two outputs y_{SM} and y_{EM}, according to the defined computational model (step 2c).

3.3.3. *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 behavior 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

Table II. 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
fm	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.

unity (see Section 2.4). 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 2.4 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 2.4. As mentioned in Section 2.5, 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 *sobol2007* function of the package *sensitivity* of the software [R].[131] The function allows implementing MC estimations of both first and total order sensitivity indices simultaneously, at a computational cost of $N(k + 2)$.[98] 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 Equations (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 II, the results are reported for both configurations (step 6 of the protocol).

Table II shows that, in the simple model configuration, the highest contributor to the output variance is Nf, the population level, which contributes 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 II shows that the highest contributors are, respectively, D, β, and d. However, the total sum of the first-order indices adds less than 1%, thus suggesting that interactions strongly influence the model behavior.Thus, as far as this setting is concerned, we can conclude that the model is nonadditive, and interaction effects dominate over individual effects.

We then come to the analysis of the *key-uncertainty drivers.*

For the model at hand interaction effects strongly influence the model behavior, 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 II), 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 *Rel Hum* may again suggest a methodological issue in the estimation of a 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* [93, p. 3]; see also the multiplicative model in Ref. 93, for which estimation of variance based sensitivity measures results inaccurate.

We then used bootstrapping[126] 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. Fig. 3 displays the confidence intervals obtained using 500 bootstrap replicates.

Fig. 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 2.5, from the same data set 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 III (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 Fig. 4). 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.

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 previously estimated. 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.[39]

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 III suggest that, if more resources were to be available, a modeler 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.

3.3.4. Step 4: Results Evaluation

With these results in mind, following the final decision step 4 of the protocol presented in Fig. 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.[132] 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.[133] Such a technique emphasizes the agreement/disagreement for the most important variables and places reduced weight on agreement/disagreement for the variables of low

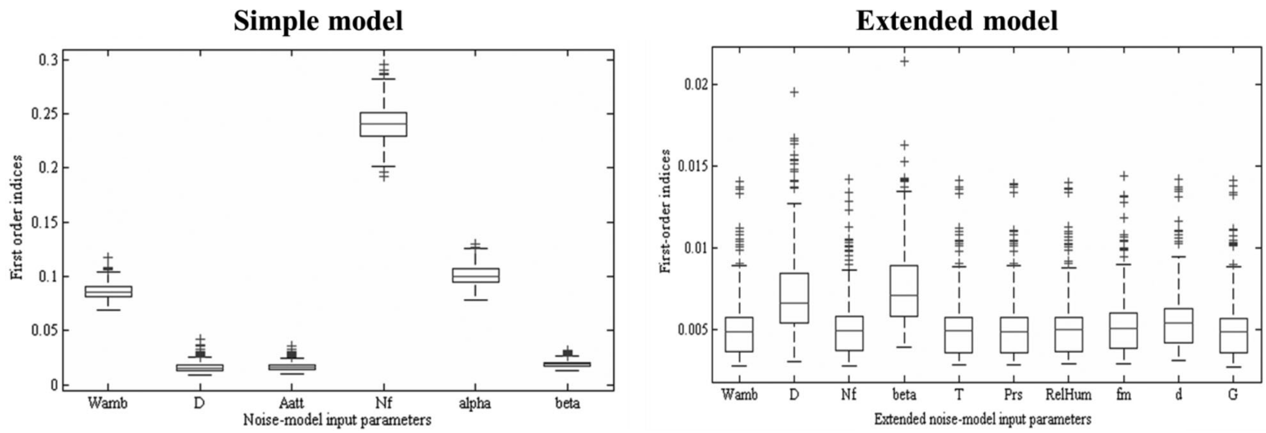

Fig. 3. Result of 500 bootstrap runs of the calculation of first-order indices for the simple and the extended model.

Table III. 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
fm	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

importance.[132, p. 166] Table IV displays the resulting correlations among Savage scores.

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.

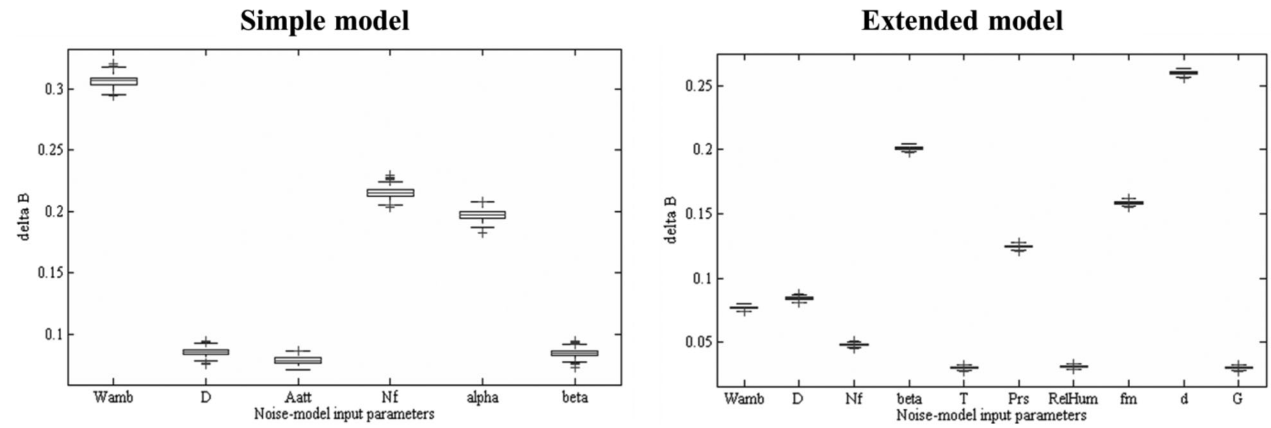

Fig. 4. Result of 500 bootstrap runs of the calculation of δ^B for the simple and the extended model.

Table IV. 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 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 IMPACT ASSESSMENT MODELS

The LCA community is recognizing the need for improving its methods for the sensitivity and uncertainty analyses of LCA codes. Our work has investigated this issue, unveiling several aspects. We have seen that global SA is applicable in portions of the LCA framework 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 be lost.

We have defined the settings for our sensitivity analysis in Section 2.9. Suppose that the analyst uses a one-way sensitivity approach in the context characterized so far. First, she would be ignoring uncertainty about the model inputs because, we recall, a one-way sensitivity analysis is deterministic. But, even if this is the case (i.e., ignoring uncertainty), how would the analyst assign the ranges of the model inputs? If these are arbitrarily assigned, then the results of the OFAT sensitivity have little value. However, suppose the analyst interprets these ranges as the 0.05 and 0.95 percentile of some plausible uncertainty distribution. What results would she obtain? Let us test this approach for the simple and the extended versions of the noise model analyzed in this article. For the simple model, the ranking of the most influential parameters identifies the penalty β as the most influential parameter, followed by the directivity component D. In the extended model, the OFAT approach identifies *fm* and D as the most influential parameters, with the rest of the parameters resulting as equally unimportant. Thus, the obtained ranking are quite far from the most rigorous ranking obtained using a global sensitivity analysis method. These results show once again the limitation of the OFAT procedure. Therefore, given that distributions are available to the analyst, the use of a deterministic method that ignores the distributions would only make sense for computational convenience, but is not conceptually justified.

The use of global techniques in the protocol allows overcoming the limitations of OFAT techniques, which have been almost exclusively used in the field of LCA. In particular, global techniques allow in the context of LCA supporting better decisions for policy-making purposes, thanks to a better understanding of the impact assessment models that are used to produce impact scores. More trustable results strengthen the capability of LCA to pinpoint environmental hotspots in complex value chains.(1)

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 inputs are used to calculate an output. The protocol and the *given data* strategy that are here proposed and applied to the study of complex impact assessment models may be also applied to analyze the results of complete LCA studies for which data from MC are often readily available to the analyst. 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.[6] MC simulation alone, however, does not allow the analyst to identify key drivers of uncertainty, or to understand the structure of the input-output model.(12) In this respect, an issue is represented by the need to define a joint distribution function that truly represents the decisionmaker's degree of belief about the model inputs. In the context of LCIA model development, modelers 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 judgment. 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.

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 are possible to fix in the remainder of the analysis. This is particularly relevant in the context of LCIA modeling, where it is common to use characterization 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 modeler in deciding which model inputs could be averaged without affecting the uncertainty of the model. Once the modeler 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 characterization 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 characterization factors that are specific to highly localized conditions. Those model inputs with the largest values of all measures should be prioritized and further analyzed and localized.

[6]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 modeling time. For the calculation of sensitivity measures in this article both [R] and Matlab®(136) 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 sustainability assessment and decision-support tool to guide policy decisions. The application of the proposed global SA techniques would increase the confidence of decisionmakers and users of existing LCIA models, and also of any future developments of novel impact assessment models and characterization factors. Relying on an ensemble of sensitivity measures, the protocol provides the LCA modeler with a series of powerful tools that increase the validity of the LCA framework, and particularly the transparency of the modeling phase of LCIA characterization models.

The protocol helps to set rules and a common shared procedure that puts the uncertainty and sensitivity analyses practice in the field of LCA in line with the practices that are already common for other decision-support tools in the environmental sciences, and also in the risk analysis community. The combined use of LCA and risk assessment techniques may further be fostered by such a platform. Read along the lines of the works of Refs. 2, 4, 55, and 66, our work also contributes in reinforcing the link between LCA and risk analysis.

Finally, 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.

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