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Original Article

Meta-study of sensitivity analysis in solar renewable energy application

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Abstract

Sensitivity analysis reveals the relative weights of the assumptions and input parameters used in the model. It differs from uncertainty analysis, which deals with the issue of how uncertain the forecast is. Both sensitivity and uncertainty analyses must map on a model behaves when certain input assumptions and parameters are allowed to fluctuate within the range of possible values. While going down one-dimensional corridors, various uncertainties and sensitivity studies continue investigating the input space, leaving room for the most undiscovered input elements. Numerous highly cited publications fall short of the fundamental criteria to thoroughly investigate the space of the input components, according to a thorough systematic examination of the literature. Despite being discipline-specific, the findings show a concerning absence of good practices and accepted norms. The conclusion listed a few potential causes for this issue and offered suggestions for how the approaches should be applied correctly.

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1 Introduction

Mathematical models have risen to prominence as a tool for decision-making in a wide range of applications [1]. Models have grown increasingly complicated, trying to integrate more processes at an ever-higher resolution, driven by rising computational power combined with the wealth of data accessible. However, because of the increasing complexity, which is unknown, significantly more data must be supplied as model inputs [2]. Because of this, it is crucial to comprehend how these uncertainties affect the model output if the model is to be utilized effectively and responsibly in any decision-making process. Two essential methods are sensitivity analysis (SA) and uncertainty analysis (UA) to investigate the uncertainty of such models.

One definition of sensitivity analysis is “the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input” [3]. As a result, it is closely connected to uncertainty analysis (UA). However, it differs because it measures model prediction uncertainty without pinpointing the underlying assumptions. Ghanem et al. [4] suggested that a wide range of applications linked to uncertainty might be included in uncertainty analysis. Ideally, an uncertainty analysis precedes sensitivity: it needs to be estimated before uncertainty can be apportioned. This is not always the case, though, and applications that include model calibration or optimization may not require the measurement of uncertainty.

The specific terms need to be defined first before continuing. The type, structure, parameters, resolution, and calibration data of a model, as shown in Fig. 1, must all be described before one can begin to create it. Each of these is based on an assumption and has a corresponding uncertainty. A qualitative uncertainty analysis may investigate only a portion of these presumptions (varierated). The items altered in a SA or UA, model parameters, and any other sorts of assumptions that will be varied are all included in this subset, which we refer to as the input factors. It is essential to remember that any uncertainty and sensitivity analysis will not investigate the uncertainty in assumptions made outside of the input set. The model output refers to the model's conclusions for input factor values.

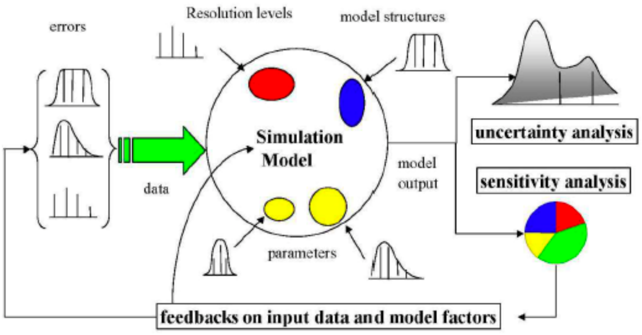


Fig. 1 Idealized uncertainty and sensitivity analysis.

In the UA, summary statistics from this distribution, including the mean, median, and variance, may be extracted. The mean may also be given confidence boundaries. At the same time, SA is used to quantify the contributions of model inputs, or sub-groups of inputs, to the uncertainty in the model output [5]. Saltelli [3] also stated that in this uncertainty setting, typical objectives are to identify which input factors contribute the most to model uncertainty ("factor prioritization") so that further information might be collected about these parameters to reduce model uncertainty or to identify factors which contribute minimally and can potentially be fixed ("factor fixing"). As a quality assurance tool, sensitivity analysis can also be used to understand better the processes within models and, in turn, the natural systems on which they are based [6]. For example, an unexpectedly strong dependence of the output upon an input may either shed light on an unexpected system feature or reveal a conceptual or coding error.

1.1 Common pitfalls of sensitivity analysis

The use of SA is fraught with several methodological and practical issues. Two widespread difficulties need to be addressed.

The first is a terminology issue; many scientists confuse what SA and UA signify. In a wide range of situations, such as economics, SA is seen as an examination of the accuracy of the forecast UA. This may result from an influential econometric work with the title "Sensitivity analysis might assist," which set out to ensure the robustness of a regression analysis regarding numerous modeling decisions, such as the choice of regressors. As a result, what we have defined here as uncertainty analysis is frequently referred to as "sensitivity analysis" in economics and finance. If the objectives are not met, it is evident that this might affect the effectiveness of an uncertainty and sensitivity analysis. Another issue, maybe because of their training and methodological propensity to think in terms of derivatives, is that modelers frequently modify components individually rather than all at once. Here, we dig deeper into this technical issue.

Many practitioners accept a taxonomy of SA based on distinguishing between local and global methods. Let f be a generic black-box representation of a model, which has input factors x = $\{x_1, x_2, \ldots, x_k\}$, and a scalar output y, such that y = f(x). A local method, in its simplest form, yields the partial derivative of the model concerning one of its input factors, i.e., $\delta y/\delta x_i$. Two notable deficiencies of this definition of sensitivity are that first, if f is nonlinear concerning x_i, then its partial derivative will change depending on where in the range of x_i, that choose to measure. Second, and more generally, if there are interactions between model inputs, then $\delta y/\delta x_i$, will also change depending on the values of the remaining input factors. In short, first partial derivatives are only a valid measure of sensitivity when the model is linear, in which case $\delta y/\delta x_i$, will remain constant for any x.

A common variation of the first partial derivative is usually called the *one-at-a-time* (OAT) approach. Let x_1^* , be the nominal value of the ith input factor. Now define $x_1^{max} = f(x_1^*, x_2^*, \ldots, x_i^{max}, \ldots, x_k^*)$ as the model output where all input factors are at nominal values except the ith, which is set to its maximum. An OAT sensitivity measure is e.g. $\Delta_i = (y_i^{max} - y_i^{min}) / (x_i^{max} - x_i^{min})$ where y_i^{min}, follows a similar definition. The OAT approach and partial derivatives (a type of OAT approach) keep all other input factors fixed except one being perturbed.

A global sensitivity analysis method at the other extreme could be an analysis of variance (ANOVA) as usually taught in experimental design, which informs the analyst about factors' global influence in terms of their contribution to the variance in the model output, including the effect of interactions among factors. Perhaps the most prevalent example of a global measure is the *first-order sensitivity index*,

$$s_i = \frac{v_{xi}\left(E_{x\sim i}\left(y|x_i\right)\right)}{V\left(y\right)} \tag{1}$$

where $V(y)$ is the unconditional variance of y, obtained when all factors x_i are allowed to vary, and $E_{x\sim i}(y|x_i)$ is the mean of y when one factor is fixed. Incidentally, this measure was initially proposed by Karl Pearson to measure nonlinear dependence between random variables. The first-order sensitivity index is a part of a class of sensitivity measures called 'variance-based.' Its meaning (under the assumption of independence between input factors) can be expressed in plain and could be fixed. S_i= 1 implies that all of the variances of y are driven by x_i, and hence that fixing it also uniquely determines y. Other global approaches to sensitivity analysis include *the elementary effect approach*, *global derivative-based measures*, *moment-independent methods*, *variogram-based approach*, and many others. Saltelli et al. [7] and Ghanem et al. [4] derive in detail the sensitivity indices.

Global approaches are requisite for accurate sensitivity analysis when models feature nonlinearities and interactions. It is helpful to think of the set of all possible combinations of input factors as an "input space." For example, with two model inputs, any combination of values could be marked as a point on a two-dimensional plane, with a range of factor 1 on one axis and the range of a factor of 2 on the other, in the case of three input factors, the input space would be a cube, and for higher numbers, a hypercube. Fig. 2 (left) illustrates an OAT design with two input factors and a corresponding global design (right) that might be used to estimate the global measures.

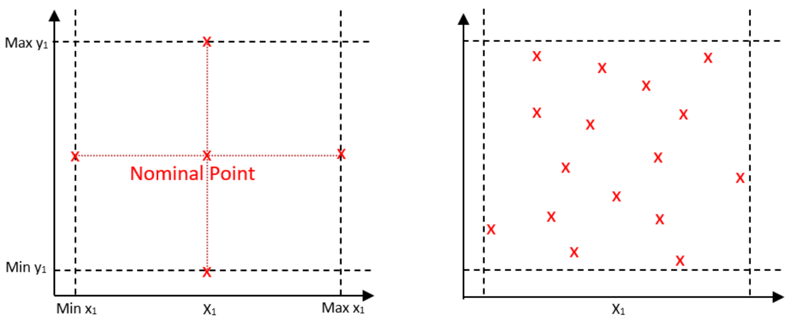


Fig. 2 OAT design (left) contrasted against global design (right).

OAT designs cannot effectively explore a multidimensional space. It can be further illustrated with a simple example from Saltelli and Annoni [7]. Imagine that the input space is a three-dimensional cube of side one. Moving one factor at a time by a distance of ½ away from the center of the cube generates points on the faces of the cube. Do not on its corners. All these points are on the surface of a sphere internal and tangent to the cube. It is shown in Fig. 3. The sphere's volume divided by the cube's volume is about ½. If we increase the number of dimensions, this ratio goes toward zero very quickly. In ten dimensions, the hypersphere's volume divided by the hypercube's volume is 0.0025, one-fourth of one percent. In practice, it is even more restrictive because the OAT design does not even explore inside the hypersphere and is limited to a "hyper cross." In other words, moving factors OAT in ten dimensions leaves over 99.75% of the input space unexplored. This under-exploration of the input space directly translates into secondary sensitivity analysis and is but one of the many incarnations of the so-called "curse of dimensionally" and the reason why OAT is perfunctory unless the model is proven to be linear.

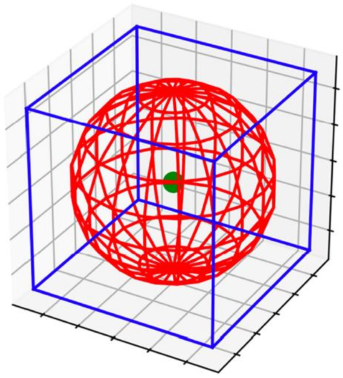


Fig. 3 A sphere is included in a cube (three-dimensional case) and tangent to its faces. The volume of the sphere divided by that of the cube is roughly ½. If the dimension were ten instead of three, the same ratio would be 0.0025.

Statisticians are well acquainted with this problem. In experimental design theory, factors are moved in groups rather than OAT to optimize the exploration of the space of the factors. In SA, global designs are either based on random, quasi-random, or space-filling designs; or on OAT designs that are repeated in multiple locations of the input space-the latter are used for global derivative-based measures, Monte Carlo estimation of variance-based sensitivity indices and elementary effects, among others.

2 Methodology

A thorough literature evaluation (a meta-study) was conducted to comprehend the prevalence and type of sensitivity analysis across various domains and the scope of the problems covered in the preceding section. Highly referenced works concentrating on sensitivity analysis served as the foundation for the evaluation. The idea was that the most frequently referenced publications should reflect "common practice" in that subject. As a result, by studying these publications, we should be able to draw the logical conclusion that the degree of rigor used in sensitivity analysis in a specific subject is on par with or lower than that of its most highly cited papers.

2.1 Selection Procedure

The Scopus database was used for the literature search. The following search parameters were used to find pertinent documents. First, the title, abstract, or keywords must contain the phrases "sensitivity analysis," "model/modeling," and "uncertainty." This ensures that the publication emphasizes sensitivity analysis concerning uncertainty and mathematical models. The publications were limited to the years 2012 through 2022 to present a sampling of recent research.

2.2 Review criteria

The following straightforward criteria were used to evaluate each paper.

1. Was uncertainty analysis conducted? If so, was a global or local approach employed?
2. Was sensitivity analysis conducted? If so, was a global or local approach employed?
3. Was the paper primarily focused on the sensitivity analysis method or the model (application)?
4. Was the model used linear or nonlinear, or was it unclear?

2.3 OAT/global uncertainty and sensitivity analysis

The focus of this work is the identification of OAT and global sensitivity analysis. We evaluated each publication and indicated if a sensitivity analysis, an uncertainty analysis, or both had been conducted. We investigated whether global or OAT methodologies had been used to derive the results for both the uncertainty and sensitivity assessments.

OAT methods are defined as all procedures where factors are moved only one at a time, even when derivatives are computed efficiently, such as when using the adjoint method. Furthermore, some methods, such as in or in, are based on derivatives but are classified as global methods because they sample partial derivatives or incremental ratios at multiple locations in the input space.

Global approaches are any movement of factors, such as in the Design of Experiment (DoE). A Monte Carlo analysis followed by an analysis of the scatterplots of y versus the various input factors x_i is also classified as global (albeit qualitative), as well as approaches based on regression coefficients of y versus x_i, the use of Sobol's sensitivity indices – independently of how these are computed, screening methods such as the method of Morris, Monte Carlo filtering, and the additional online material for the methods met in the papers reviewed [8]. Furthermore, [9] are the recent valuable reviews.

One might wonder what an OAT uncertainty analysis looks like. Some papers quantify uncertainty by observing y_i^{max} and y_i^{min} , for each input factor during an OAT experiment, and assign the range of uncertainty on y as [y_i^{min}, y_i^{max}], where $y_i^{min} = min(y_i^{min})$, and similarly for y_i^{max}. This ignores the additional uncertainty in y when more than one factor at a time is set to its maximum or minimum values.

2.4 Method/model

It is helpful to distinguish between model-focused and method-focused papers.

Model-focused papers are defined as those which focus on a model and use sensitivity analysis as a tool to investigate uncertainty or other aspects of the model. These papers will often significantly impact the application (ultimately the outcome of concern), for example, in assessing the uncertainty/sensitivity of climate models or the other models used in decision-making. The primary conclusions of the paper are therefore related to the model.

Method-focused papers introduce sensitivity analysis methodology and use a model as a case study to demonstrate a new approach. Conclusions are therefore focused on the method's performance, and results relating to the model are of secondary interest. Typically, the authors are familiar with sensitivity analysis techniques, which allows them to propose new approaches. These papers are more likely to feature high-quality sensitivity analysis techniques.

2.5 Model linearity

Finally, each publication was evaluated to see whether or not the application model was linear because OAT techniques are only viable in the event of a linear model. Although this was not always evident, it was highlighted where linearity could be determined.

3 Results

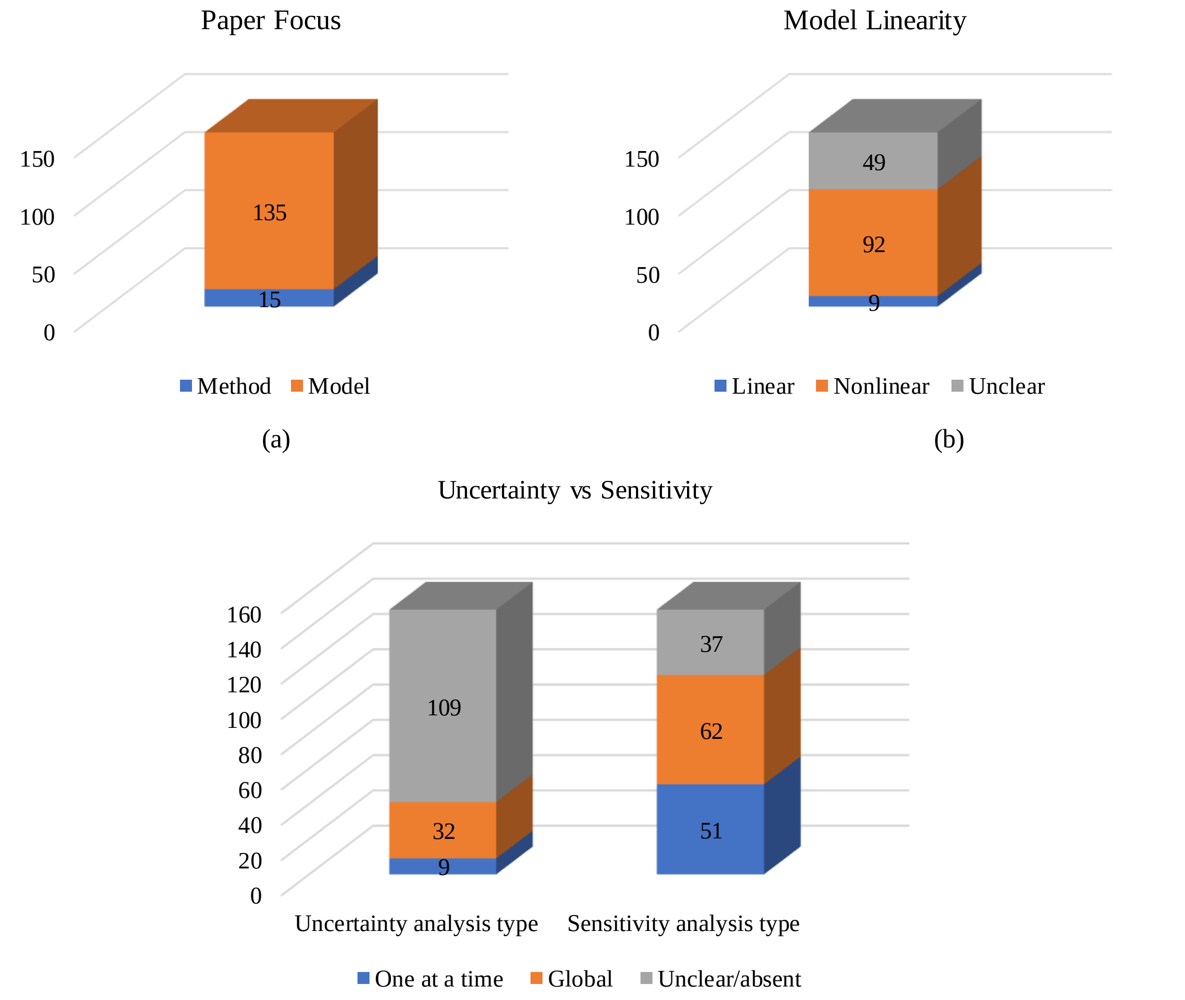
This section discusses the results from the meta-study done on all the related papers. The following sub-section discusses the reasons for bad practices and recommendations for best practices.

3.1 Uncertainty analysis

Although uncertainty analysis and sensitivity analysis are separate (but related) sciences, the phrase "sensitivity analysis" is occasionally used in the literature to refer to both terms. Consequently, several studies that dealt with pure UA were included in the list of papers examined. 37 of the 150 publications examined did not include any sensitivity analysis at all and only addressed uncertainty analysis; this is a clear case of sensitivity and uncertainty analysis being confused.

The frequency of UA identified in the literature review is reported in Fig. 4. About 3/4 of the studies either did not have any UA or did not adequately state their approach. It is not unexpected that many studies pay little attention to the UA section, given that our search query primarily targeted sensitivity analysis papers. However, most of the UAs that were seen were global in character. This is likely because an "OAT uncertainty analysis" is perhaps less prominent than a Monte Carlo analysis, which involves randomly selecting from input distributions.

The hypothesize that either the writers involved were ignorant of the opportunity to rank the factors by relevance using simple scatterplots of the outcome vs. the input, or they did not believe this type of analysis to be relevant or valuable. Once a specific practice gains traction in a field (i.e., it appears in highly cited articles), it establishes a solid precedent that is hard to overturn. Researchers and reviewers (not unreasonable) presume that an approach is valid if it appears in influential journals.



(c)

Fig. 4 Reviewed papers based on focus (a), model linearity (b), uncertainty, and (c) sensitivity analysis paper.

3.2 Global versus local SA

Now that the sensitivity analysis has been discussed, Fig. 4 demonstrates that 41% of sensitivity studies employ global techniques, 34% use OAT methods, and 25% have unclear method types or no sensitivity analysis. This is encouraging because over half of the research uses global methods. Still, according to our search criteria, at least one-third of highly cited publications employ subpar OAT techniques.

According to Ferretti et al. [10], a global SA method is adopted in even a tiny percentage of studies that include sensitivity analysis. The variations in the results can be attributed to at least three factors. First, as has been proven here, “sensitivity analysis” is frequently used to denote uncertainty analysis. As a result, the top curve in Fig. 5 displays a mixture of UA and SA and a necessary proportion of articles that do not include mathematical modeling. Second, the number of global SA studies is probably underestimated since papers may employ basic global methods, like scatterplot-based analysis, without necessarily citing the mentioned articles or methodologies. Finally, in the manual literature review, we only include highly cited papers—which, in theory, should be of a better standard than the norm in a particular field.

3.3 Method and model focus

Fig. 4 demonstrates that, unexpectedly, the application—that is, the model at hand—rather than the methodology is the main emphasis of most studies. Out of the 150 publications, 41 were methodological, for example, focused on SA/UA approaches. Thirty-two of these support the use of global methods. On the other hand, this is good since it demonstrates the promotion of international approaches. On the other hand, a few methodological articles continue to recommend OAT techniques that are statistically inaccurate.

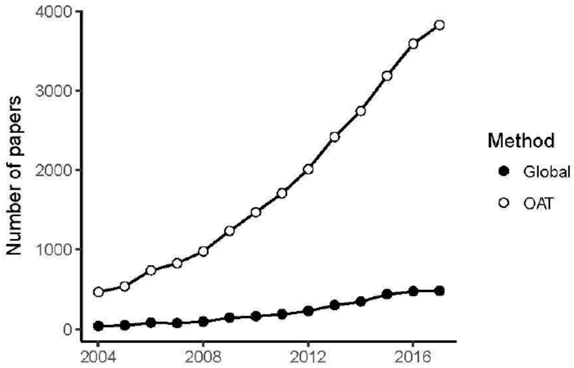


Fig. 5 Results from Ferretti *et al.* [10].

3.4 Model linearity

An OAT or derivative-based technique is suitable if a model is linear, as was previously mentioned. However, at least, based on the publications, it is rarely straightforward if the model is linear or nonlinear. The proportions of linear and nonlinear models are displayed in Fig. 4. We could only determine the model's linearity in 6% of the cases; in contrast, over 50% of the articles had nonlinear models, with the other cases being uncertain. This proves the first point: researchers frequently use nonlinear models. Global approaches are typically required in seconds to undertake a methodologically good sensitivity analysis.

3.5 Discussion

This subsection discusses reasons for bad practice, a brief about isolated communities, and parallels with the p-value plus recommendations for best practice which could be a basic guideline for future practitioners or researchers.

3.5.1 Reasons for bad practice

The findings of this investigation unequivocally demonstrate that highly cited articles frequently have significant methodological issues. Why does this happen so frequently? We hypothesize that there are at least five of them, which we list here.

- First, modeling, which is not a cohesive field in and of itself, is integrally linked to sensitivity analysis. Every discipline approaches modeling following local disciplinary norms and procedures [8] since modeling often needs skills acquired through experience and incorporates parts of both craft and science [11]. It is generally isolated because sensitivity analysis practice is scattered throughout each modeling field. This fragmentation prevents the topic from developing and good practices from spreading while also allowing misconduct to go largely unchecked.
- Second, the meanings of sensitivity analysis and uncertainty analysis are frequently confused among scientists. It is not unexpected that the quality of sensitivity analysis is occasionally inadequate if the meaning of sensitivity analysis is not even comprehended.
- Third, a solid statistical foundation is necessary to perform and evaluate the findings of a global sensitivity analysis. In general, it is possible that scientists are not even aware that global sensitivity analysis methods exist. The time and money needed to acquire and comprehend the essential procedures may be prohibitive for researchers because they lack the relevant statistical expertise and training. Researchers frequently fall back on the more straightforward OAT strategy in these situations. It also makes interpretation simpler since the change in the model's output must solely be the result when one input factor is changed. Global techniques may also

be disappointing since the model's likelihood of malfunctioning or crashing increases as more factors are adjusted. It is essential to highlight that this is why a global SA is a helpful tool for model verification: it is uncommon to conduct a global sensitivity analysis without finding model flaws. Modelers refer to this jokingly as Lubarsky's Law of Cybernetic Entomology, which states that "there is always one more bug."

- Fourth, although there have been mature global sensitivity analysis methodologies for more than 25 years, it may not have been enough time for established good practices to spread throughout the many study domains where modeling is applied. This may be partly because there are not enough comparable examples from other disciplines. In addition, researchers frequently adopt the techniques found in highly cited articles (assuming that they represent best practices), even though these techniques are frequently methodologically flawed, as this study has shown.
- Finally, these tactics' candor may make people reluctant to use them [12]. A suitable approach may provide an unfavorably broad distribution of the desired outcome by honestly propagating all the input uncertainty. For instance, a cost-benefit analysis that presents a distribution that includes potential high losses and potentially large rewards may not be what the problem's owner would prefer to hear. This is equivalent to saying that the inadequacy of the evidence is disclosed together with the inference's instability. This circumstance could lead modelers to "massage" the input factor uncertainty to have the result fall within a more desired range [12]. It may be appropriate to use sensitivity auditing, an extension of sensitivity analysis beyond parametric analysis to include an assessment of the full knowledge- and model-generating process for policy-related cases, to assess the credibility of the degree of uncertainty attributed to each input factor [13]. Ensure that the uncertainty has not been inflated nor deflated significantly in cases with significant asymmetry between model developers and users. Regulatory debates, for example, frequently include inflation and deflation of uncertainty; usually, the "regulated" tend to inflate uncertainty to oppose regulation, while regulators have the opposite tendency.

3.5.2 Isolated communities

In a transversal topic like SA, which is used in various scientific and modeling disciplines, researchers from different professions find it challenging to interact with one another. Since modeling is a non-standardized subject, uncertainty and sensitivity analysis follow suit, making it challenging for good practices to gain traction. It is worth discussing the disorganized status of sensitivity analysis practice in more detail.

For instance, system ecologist Robert Rosen addresses the particulars of modeling in the scientific process in his book "Life Itself" [11]. Here, he suggests we should consider the role of causality while creating a model to describe a natural system. The claim is that material, efficient, and ultimate causality maintain the integrity of the natural system—Rosen uses the word "entailed"—keeping it in balance. Rosen utilizes the four Aristotelian causality categories—on which we will not expand here—to demonstrate that no causal arrow passes from the natural system to the formal one. In other words, the actions of encoding (Fig. 4) are motivated by the modeler's wants and skill rather than causality, which would fix the model definition. The implications are that various modeling teams can yield completely different models and inferences given the same data.

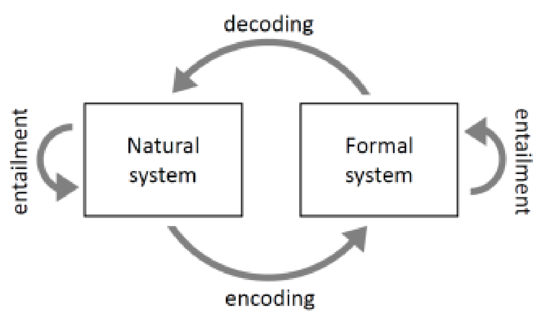


Fig. 6 The modeling relation following Rosen [11].

According to the proverb attributed to George Box, all models are erroneous. Some are helpful. Therefore, the success of the modeling operation is determined by its usability. Alternatively, lack thereof - of the insights made possible by the operation of decoding.

Thus, the modelers' work quality is vital to the model. This helps to explain why modeling was never established as a separate field, along with various modeling uses, goals, and limitations. In our opinion, this contributes to explaining why modeling is so discipline-specific [14]. One of the reasons methodologies that are ancillary to modelings, such as uncertainty and sensitivity analysis, are not part of a standardized syllabus being taught across all disciplines and are occasionally ignored even in communities proficient in modeling is the spread of modeling practices and cultures.

Despite the fragmentation of sensitivity and uncertainty analysis, some cross-disciplinary networks exist. One such community might be said to have formed around a series of SAMO conferences (for sensitivity analysis model output) since 1995, which is active in dissemination and training. In the United States, for instance, SA-related activities are under the heading of 'Verification, Validation, and Uncertainty Quantification (VVUQ), a journal of the American Society of Mechanical Engineers. Other sensitivity analysis-related gatherings include the *Conference on Uncertainty Quantification* organized by the Society for Industrial and Applied Mathematics, the *International Conference on Uncertainty Quantification in Computational Sciences and Engineering* organized by the European Community on Computational Methods in Applied Sciences, and sessions in thematic conferences such as the *Uncertainty in Structural Dynamics* conference organized by Departmental of Mechanical Engineering of the KU Leuven.

Despite these groups, most practitioners are dispersed in small, isolated areas, and sensitivity analysis is therefore not included in any recognized curricula. Who or what scientific body then has the authority to determine if a practice is beneficial or destructive? For example, who can authoritatively encourage modelers against interpreting too much into the outcomes of multi-model ensembles as if they were a sample drawn randomly from a distribution [12]? For the time being, no one has answered this question. This poor situation would be improved if statistics as a discipline took charge of statistical techniques for model validation and verification. This would significantly advance modeling practice without turning modeling into a discipline. Most, if not all, of the sensitivity analysis methods, are statistical.

3.5.3 Parallels with the p-value

The systemic issues in sensitivity analysis are comparable to the current p-value crisis in statistics. Many published study results are of poor quality, according to a 2005 article [15]. Media outlets picked up on the report, and in 2013 the magazine "The Economist" devoted its cover to the topic ("How science goes wrong," 2013), along with a detailed article outlining the complexities of the use and misuse of statistics in determining the relevance of scientific conclusions. The usage of the p-value, which is defined as "the likelihood under a certain statical model that a statistical summary of the data (for example, the sample mean the difference between two compared groups) would be equal to or more extreme than its actual value," was the specific area of concern [16]. Researchers use the p-value as a critical tool to determine if a particular finding is the product of chance alone or represents an impact that merits publication.

In 2016, the pressure on the statistical community was so intense that the American Statistical Association felt compelled to step in and issue a statement outlining the proper use of the test [17]. Attempts to replicate published results reveal that the generalized failure in using the p-value is caused by a complicated mix of factors, including improper incentives and poor training [18,19].

The problem is seen as a combination of confirmation bias - authors looking for the effect they presume will be there (confirmation bias), authors desperate to publish a positive result (publish or perish), or p-hacking - changing the setup of the study or the composition of the sample till an effect emerges, and HARKing, formulating the research Hypothesis After the Results are Known [20]. In the latter, comparison tests between various variable combinations are repeatedly performed until a "significant" result is obtained, which is against the P-criterion tests for the application.

Overall, it is evident that poor statistics can have severe repercussions. In a similar vein, given the pervasiveness of models, it is not difficult to envision the effects of incorrect or absent uncertainty and sensitivity evaluations. This can result in neglecting hazardous situations for a facility in risk analysis, resulting in incorrect investment or decision analysis policies. Finally, a correct UA would demonstrate clearly that the uncertainties are too significant to conclude, but a missing uncertainty analysis would let bold risk or cost-benefit analyses be conducted on centennial periods.

3.5.4 Recommendations for best practice

This study does not call for providing a comprehensive manual on sensitivity analysis. Despite this, and sensitivity analysis utilization varies significantly between disciplines, adopting best practices would help all fields. The following recommendations are on our list of preferences, consistent with the methodological paper discussed in this study.

- Whether using an experimental design, Monte Carlo simulations, or other ad hoc designs, both uncertainty and sensitivity analysis should be based on a comprehensive examination of the space of input factors. The discussion in this paper has shown that local/OAT approaches fall short in their ability to capture nonlinear problems.
- With a few exceptions, conducting both sensitivity and uncertainty analysis is recommended. Knowing the source of volatility and uncertainty would seem reasonable once an analyst has conducted an uncertainty analysis and been advised of the inference's robustness. On the other hand, a sensitivity analysis without consideration of uncertainty is often irrational since the relevance of a factor's influence on a model's output depends on whether the result has a slight or high variance. However, there are instances where the analyst may be satisfied with a pure sensitivity analysis, such as studies to determine the output's dominant impacts for a future model reduction or calibration study.
- The theme of sensitivity and uncertainty analysis should be the primary concern. Most models include several outputs that may be utilized to address various inquiries. Each model's output and its input factors' connection (sensitivity) might change significantly. Concentrating the sensitivity analysis on the specific issue the model responds to rather than the model is crucial.
- Sensitivity analysis should enable the relative significance of input factors and combinations of factors to be evaluated, either numerically (regression coefficients, sensitivity measures, or other) or visually (scatterplots).
- Because there are many assumptions in estimating the uncertainty in input factors, sensitivity and uncertainty analyses are themselves questionable, and modelers should be transparent about how they arrive at the stated uncertainties. This should be considered, and attempts should be made to represent the uncertainty of input assumptions appropriately.
- "It is crucial to understand that what is being determined, not the sensitivity of the parameter in nature, is the sensitivity of the parameter in the equation. Even a seemingly faultless uncertainty and sensitivity analysis cannot guarantee accuracy. Finding a certain model parameter's sensitivity is pointless if the model is inaccurate or poorly represents reality."

Regarding the best approach to utilize, our preference is for experimental, model-independent methods that can capture interactions and address various issues. A meticulous uncertainty analysis, followed by a sensitivity analysis, is a crucial component of a model's quality assurance and a requirement for any model-based analysis or inference.

4 Conclusions

The key takeaway from this study is that a thoroughly conducted sensitivity analysis is a crucial component of a model's quality assurance and a prerequisite for any model-based analysis or inference. However, since these assessments are rare and frequently wrong, there is a pressing need to improve mathematical model quality control processes. Up to 65% of the examined (highly cited) studies are based on flawed methodologies (varying one input factor at a time). Notably, a massive percentage of the articles examined utilize sensitivity analysis methods that violate basic experimental design principles and improperly explore the space of the input factors, leading to an overestimation of uncertainty and incorrect estimation of sensitivity. Even in the most lenient interpretation, where all models with unknown linearity are presumed linear, more than 20% of publications still have improper techniques.

Additionally, many studies combine sensitivity and uncertainty analysis, likely worsening the challenge of sharing best practices. Two conclusions may be drawn from the fact that these values apply to highly cited publications. First, if we believe that highly cited papers reflect the highest methodological rigor in a particular subject, the overall situation may be considerably worse. Second, some of the articles in their field that receive the most significant attention are utilized as models for best practices. They may consequently encourage the use of flawed techniques going forward. In the case of sensitivity and uncertainty analysis, it is becoming more and more important to heed this advice. We believe that part of the sensitivity analysis issue stems from the fact that mathematical modeling is not a discipline unto itself and that each field of science and technology handles modeling according to its traditions and practices. Analyses of uncertainty and sensitivity are also without a disciplinary home. In data analysis, where abuse of the p-value has been identified as one of the causes of the current reproducibility problem affecting science, there are troubling parallels between the situation and what we have seen. This parallel is significant because it warns about the trustworthiness of research if such persistent methodological flaws are not corrected.

Declaration of Conflict of Interest

The authors declared that there is no conflict of interest with any other party on the publication of the current work.

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