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Sensitivity analysis: A discipline coming of age

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ABSTRACT

Sensitivity analysis (SA) as a 'formal' and 'standard' component of scientific development and policy support is relatively young. Many researchers and practitioners from a wide range of disciplines have contributed to SA over the last three decades, and the SAMO (sensitivity analysis of model output) conferences, since 1995, have been the primary driver of breeding a community culture in this heterogeneous population. Now, SA is evolving into a mature and independent field of science, indeed a discipline with emerging applications extending well into new areas such as data science and machine learning. At this growth stage, the present editorial leads a special issue consisting of one Position Paper on "*The future of sensitivity analysis*" and 11 research papers on "*Sensitivity analysis for environmental modelling*" published in Environmental Modelling & Software in 2020–21.

1. The topic

Sensitivity analysis (SA) is the tool to gauge how the inference originating from a model is dependent upon the assumptions and parameters feeding into it. SA tackles the trade-off between model completeness and model interpretability, i.e. when the complexity of a model is justified by the quality of the data feeding into it, and for many other applications linked to the quality of models. Sensitivity analysis could thus be seen as the hermeneutics of mathematical modelling, to discern the meaning carried by the model under its mathematical and algorithmic formalism.

SA has been historically, but informally, a fundamental underpinning of scientific discovery and human decision making. Consider for example the classic laws of sliding friction, whose discovery is commonly attributed to the experiments by Leonardo da Vinci in the 15th century (Hutchings, 2016). These laws state that the friction force acting between two sliding surfaces is proportional (i.e., linearly sensitive) to the load pressing the surfaces together, but is independent of (i.e., insensitive to) the apparent contact area between the two surfaces. These laws were discovered by a series of physical experiments designed informally based on basic principles of SA, changing one factor at a time in a system and assessing the impact of that change.

In the early 20th century, the need for the efficient design of physical and chemical experiments, to acquire representative information about the existence or strength of effects of one or multiple variables on another variable in a system, was the motivation for the development of a new paradigm called 'design of experiments' (DOE) (Fisher, 1953). DOE was a first step towards formalization of sensitivity analysis. Later in the century, the birth and growth of computational models of real-world systems demanded newer paradigms to enable answering SA-type questions in the context of complex and high-dimensional, but cheap-to-run, computer experiments. In response to this demand, in the 1980s and 90s, SA as a formal way of thinking started to materialize (Sobol', 1993).

In the last few years, the SA community has gained visibility and assertiveness, thanks to the efforts of the community, and to the journal Environmental Modelling & Software (EMS) which has seen SA as an essential discipline and set of tools for studying environmental system models. Of particular note is a manifesto for good modelling practices published by Nature (Saltelli et al., 2020) that also acknowledged the fundamental role of sensitivity analysis. Another recent recognition of SA's service role is a paper on major challenges in socio-environmental system modelling (Elsawah et al., 2020) appearing in the same period. The challenges coincide with several of the topics flagged by the SA community.

Now, SA has started finding applications beyond conventional

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computational models, in areas such as machine learning and data science. In the context of machine learning, different recently developed heuristics to facilitate feature and structure selection and to address issues around explainability and interpretability are rooted in principles of SA (see Bach et al., 2015; Galelli et al., 2014; Samek and Müller, 2019; Toms et al., 2020, or Razavi et al., 2020b for a review). Further formalization and standardization of SA approaches and tools in the field of machine learning can be instrumental in addressing the grand and emerging challenges that machine learning is facing in terms of explainability and interpretability and therefore falsifiability (Razavi, 2021; Rudin, 2019).

Finally, SA is now emerging as a paradigm that can directly deal with data, in the absence of any model describing the underlying system that the data is collected from (Pianosi and Wagener, 2018; Plischke et al., 2013; Sheikholeslami and , 2020). The 'given-data' SA can provide unprecedented opportunities for scientists and practitioners across a wide range of disciplines to interrogate available datasets of any size, small or large and on a range of in-situ and remotely-sensed variables, to learn about their correlational or possibly causal relationships.

2. The SAMO conferences

Started in 1995 in Belgirate, Italy, and held since then every three years, the SAMO (sensitivity analysis of model output) conference series has been instrumental in creating a community of practitioners in what was once an archipelago of teams and disciplines.[1] Unlike many other disciplines, the field of SA does not owe relevance to a specific discipline only, and many researchers, typically with vastly different research and educational backgrounds, have contributed to it over the years. SAMO has been central to bringing a 'community' feeling to this field. Because of all these efforts, SA is now beyond its original settings such as factor ranking or prioritization and its potential extends well into evidence based policy, data science and machine learning. In accord with the increasing prominence and relevance of SA, a web site is being constructed to link all conference pages.[2]

3. The special issue and contributions

The papers which make up this special issue for SA have been appearing in the journal of Environmental Modelling & Software (EMS) between 2020 and 2021. These two years bracket the 9th international SAMO conference, held at the Open University of Barcelona in October 2019 (Open University of Catalonia, 2019), and the next 10th conference to be held in March 2022 in the USA, at Florida State University (Florida State University, 2022).

The issue includes a major effort from the SAMO community, an EMS Position Paper signed by as many as twenty six practitioners of the discipline (Razavi et al., 2021), entitled "The Future of Sensitivity Analysis: An essential discipline for systems modeling and policy support", and 11 research papers, many originating from SAMO 2019 (Open University of Catalonia, 2019). All papers can be reached via the journal's homepage (Razavi et al., 2020a). More papers from the same SAMO 2019 event are collected in a twin special issue in the journal Reliability Engineering and System Safety (RESS) (Iooss and Sudret, 2021).

The Position Paper maps the open challenges which need to be tackled to fully transform SA into a recognized discipline, from the need to identify best practice and the attendant teaching material to the tackling of applications in new domains (Fig. 1, from Razavi et al. (2021)).

The Position Paper also discusses how to engage more with modelling in the social sciences, which is one of the great challenges identified in Toms et al. (2020), and with the decision sciences. Incorporating input from the social sciences for the quality of models is also an important topic, as discussed in Bammer et al. (2020). Another theme discussed in the Position Paper is how to tackle 'Deep Uncertainty' problems, following the interesting discussion on the topic in relation to the present pandemic (Saltelli et al., 2020; Steinmann et al., 2020). A major challenge is also undertaking uncertainty analysis on models with high runtimes. Efficient sampling methods and model emulation techniques are required to address it, as well as discussing with modellers when these analysis are worth the effort and the prioritization of computational resources that they demand.

One field of potential development identified in the Position Paper is machine learning. Almost all approaches toward interpretability and explainability are 'informally' and sometimes 'formally' based on SA. The recent use of sensitivity analysis in the context of variable selection in regression (Becker et al., 2021), by practitioners acquainted with sensitivity analysis literature, confirms that similar developments are also possible for machine learning - likely to be a hot application for SA in the coming years. In addition, most often, emulators (cheap surrogate models developed from the full model representation), typically rooted in machine learning, are used to generate sensitivity measures such as Sobol'.

The other papers in the present special issue represent an interesting compilation of ongoing SA research topics: comparing the efficiency of existing SA methods (Puy et al., 2021a; Azzini et al., Rosati); SA for spatially and temporally distributed outputs (Roux et al., 2021); SA for problems with dependent variables (Il Idrissi et al., 2021); development of new software tools for SA (Kimet al., 2021); development of efficient visualization approaches to understand SA results (Şalap-Ayça et al., 2021); application of SA to statistical modelling problems such as propensity score matching (Woo et al., 2021); combining methods such as variance based and distribution based (Baroni and Francke, 2020); and new applications of SA to large models (Korgaonkar et al., 2020; Susini and Todd, 2021).

4. The road to SAMO 2022: conclusions and challenges ahead

Historically, various heuristics based on principles of SA (but not named so) have been the fundamental underpinnings of a variety of analyses in modelling and decision making.

Such a process has a long history of application, perhaps in all areas of science. Examples include: assessment of the effectiveness of a decision option in a policy-making problem; the impact of a problem constraint on the optimality of a cost or benefit function via shadow prices; or the role and function of a model parameter in generating a model output. Such analyses are generally referred to as 'Local Sensitivity Analysis'. Often, not having gone through the learning curve of the SAMO community, these applications leave scope for improvement in terms of multidimensional exploration of the input space via a specific design of experiment.

Now that SA is gradually being recognized as an independent discipline with its own community, an available handbook with different language versions (Douglas-Smith et al., 2020; Saltelli et al., 2008; Wu et al., 2018) and various software tools (Adams, 2020; Baudin et al., 2017; Herman and Usher, 2017; Iooss et al., 2018; Kucherenko and Zaccheus, 2018; Marelli and Sudret, 2014; Noacco et al., 2019; Puy et al., 2022; Razavi et al., 2019; Tong, 2015), SAMO's effort to disseminate what SAMO does best must be redoubled.

SAMO should also continue its tradition to go beyond an analysis of 'just' model parameter or structural uncertainty, opening up to normative or framing dimensions in the analysis of the quality of a model, as discussed in both the manifesto and the Position Paper (Saltelli et al., 2020; Razavi et al., 2021). SA is now well-positioned to guide the process of scenario generation about the possible future states of the world to address societal needs by identifying dominant controls of human–natural systems (Razavi et al., 2020c; Ghoreishi et al., 2021; Puy et al.,

[1] All SAMO proceedings 1995–2019 are stored at https://bit.ly/3zJPmCe.

[2] See also https://www.gdr-mascotnum.fr/samo.html.

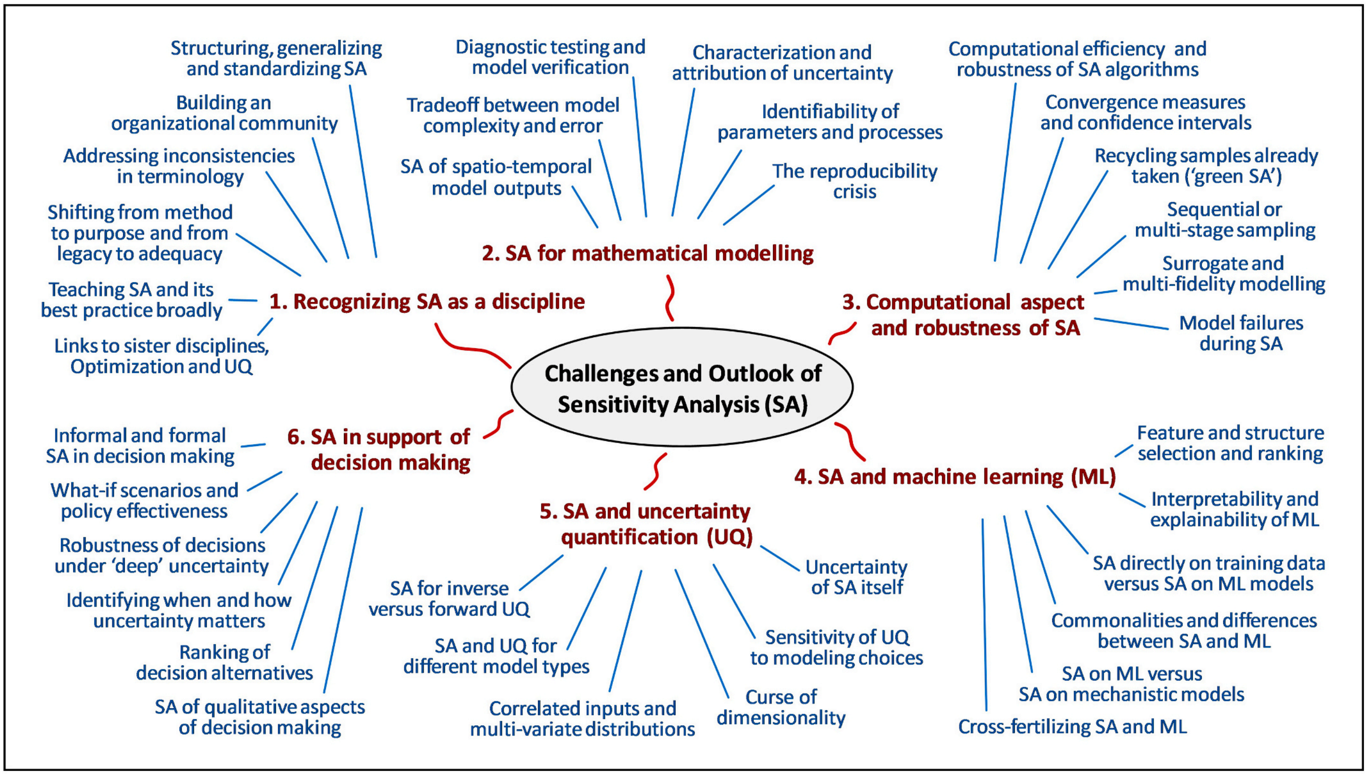

Fig. 1. From Razavi et al., 2021.
The six major themes of 'challenges and outlook' in the theory, methods and application of SA.

2021b), see also the growing literature around sensitivity auditing, an extension of SA to policy relevant modelling studies (Saltelli et al., 2013).

A challenge for the SAMO community is how to reach out to modellers in all disciplines to support not only good practices and ongoing method development for their problem contexts, but also to avoid rediscovery and relabeling of established SA methods in different applications. One area where there is likely scope for cooperation is between the SA community and modellers engaged in 'ensemble modelling', e.g. in climatic studies (Parker, 2013). The application of uncertainty and sensitivity analysis may lead to a reconsideration of the severity of environmental threats based on point estimates (Puy et al., 2020), and their use is hence to be advised in the making of ecological policies.

The "coming of age" mentioned in the title of our editorial will not be without devoted efforts and the occasional conflict. But the payoff in terms of societal acceptance of mathematical models justifies it.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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