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Sensitivity analysis of a sensitivity analysis: We are likely overlooking the impact of distributional assumptions

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ABSTRACT

Although uncertainty in input factor distributions is known to affect sensitivity analysis (SA) results, a standard procedure to quantify its impact is not available. We addressed this problem by performing a SA (generating sample of parameter distributions) of a SA (generating samples of parameter values for each generated distribution) of the WARM rice model using the Sobol' method. The sample of distributions was generated using distributions of jackknife statistics calculated on literature values. This allowed mimicking the differences in distributions that could derive from different selection of literature sources. Despite the very low plasticity of WARM, the ranks of the two most relevant parameters was overturned in 22% of the cases and, in general, differed from what achieved in earlier SAs performed on the same model under similar conditions. SA results were mainly affected by uncertainty in distribution of parameters involved in non-linear effects or interacting with others. The procedure identified parameters whose uncertainty in distribution can alter SA results, i.e., parameters whose distributions could need to be refined.

1. Introduction

Sensitivity analysis (SA) is increasingly used to develop, understand, improve and use environmental simulation models through the analysis of the impact of uncertain input factors on the variability in model outputs (Tarantola and Saltelli, 2003; Jakeman et al., 2006; Confalonieri et al., 2010a; Pianosi et al., 2016). Among the main purpose of SA, indeed, a key role is played by the identification of parameters to calibrate (Asseng et al., 2002), the improvement of models through reduction or simplification processes (Ratto et al., 2001), the support to model development (Jakeman et al., 2006), and the evaluation of models (Confalonieri et al., 2012). Under the assumption of relationships between model parameters and plant traits, SA was recently used also in ideotyping studies to identify plant traits on which breeders should focus on to increase quantitative and qualitative aspects of productions (Martre et al., 2015; Casadebaig et al., 2016).

A variety of SA techniques were proposed, each characterized by pros and cons that make them suitable for specific purposes or conditions. Among the most popular, the method of Morris (1991) is often used to screen parameters in case of models with many parameters or demanding in terms of computational time (Campolongo et al., 2007). The variance-based method of Sobol' (Sobol', 1993) is instead considered as a reference technique for its capability of decomposing the output variance into terms of increasing dimension, representing the contribution to output uncertainty of each input factor and of pairs, triplets, etc. However, it is very expensive in terms of model executions and – to reduce the computational time – it is often used to estimate the total sensitivity index (Homma and Saltelli, 1996), i.e., the overall contribution of each input factor, considering all possible interactions with others. Even in this case, the computational cost of Sobol' led to propose other methods based on the Fourier series expansion of the model output to reduce the number of model executions in the approximation of variance-based indices, like Fourier Amplitude Sensitivity Test (FAST; Cukier et al., 1973) and extended FAST (E-FAST; Saltelli et al., 1999). Extensive reviews of SA methods were recently proposed by different authors (e.g., Saltelli et al., 2005; Pianosi et al., 2016). In these reviews, the authors proposed effective criteria to select the SA method according to model assumptions, complexity and computational time per run, and they outlined ongoing development and research priorities.

Like many powerful tools, SA techniques need to be applied by carefully considering all the aspects that can affect their functioning. Results of SA are influenced by the conditions explored (Confalonieri et al., 2010b; Martre et al., 2015; Casadebaig et al.,

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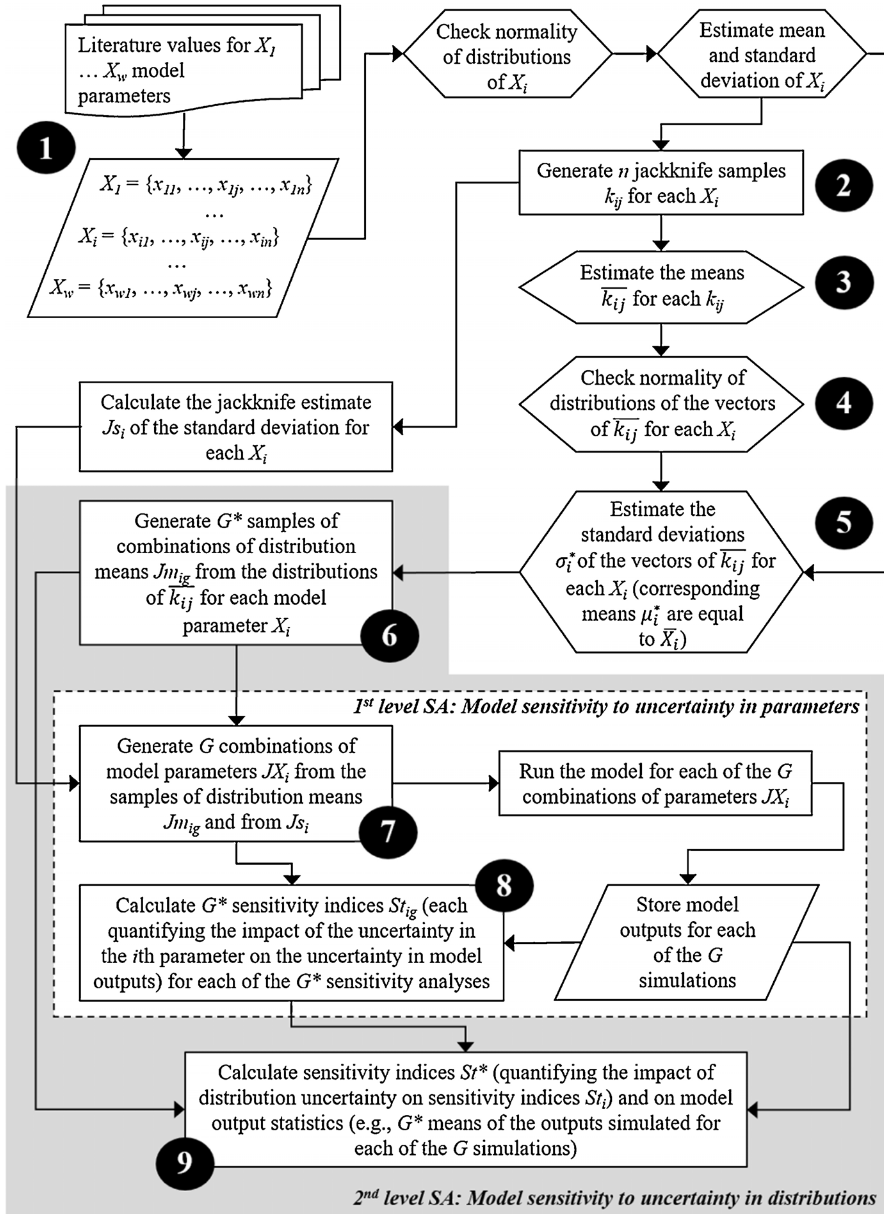

Fig. 1. Flowchart of the procedure proposed to analyze the impact of the uncertainty in parameters and parameter distributions on model behavior. Black circles with numbers indicate the key steps in the procedure (described in detail in the text).

2016; Cerasuolo et al., 2016), i.e., by the set of model inputs that are not investigated by the SA but define the simulation scenario. This pushed Stearns (1992) to the point of stating that model sensitivity is *situational*. The influence of the conditions explored on SA results can be large and its extent varies in accordance with the model plasticity, defined as the aptitude of a model to change the sensitivity to its parameters while changing the conditions explored (Confalonieri et al., 2012). The mathematical expression proposed for the quantification of plasticity is $L = TDCC \cdot e^{\sigma_{SAM}-1}$, where $TDCC$ is the top-down concordance coefficient (Iman and Conover, 1987) and σ_{SAM} is the standard deviation of a normalized agrometeorological indicator (Confalonieri et al., 2012). L ranges from 0 to about 1.51, with highest plasticity at 0. Despite their capability of quantifying the impact of uncertain input factors on model outputs, SA methods themselves can be affected by uncertainty in their own parameters. Indeed, all SA methods require some settings to be specified, at least the size of the sample of combinations of input factors (number of executions). Some methods need a seed for sample generation, e.g., Morris, FAST/E-FAST methods and some of the regression-based approaches (e.g., Latin hypercube sampling, random). The Morris method requires also the number of levels to define the parameter hyperspace. Confalonieri et al. (2010a) analyzed changes in SA results originated by changes in the parameters of the methods, and in many cases the variations they obtained were not negligible. Recent studies on the convergence of SA methods presented effective procedures to define optimum sample size according to the specific simulation exercise (Nossent et al., 2011; Wang et al., 2013; Sarrazin et al., 2016), thus partly reducing the uncertainty related with SA method parameterization.

One of the most critical steps in SA is to define ranges – and possibly distributions – for parameters (Pianosi et al., 2016), and this is particularly true for variance-based methods. Many authors, indeed, demonstrated how different definitions of parameter ranges/distributions can drastically alter SA results. Shin et al. (2013) altered the range of two parameters of two hydrological models by arbitrarily changing their original upper-bound values