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Multi-scale spatial sensitivity analysis of a model for economic appraisal of flood risk management policies

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A B S T R A C T

We demonstrate the use of sensitivity analysis to rank sources of uncertainty in models for economic appraisal of flood risk management policies, taking into account spatial scale issues. A methodology of multi-scale variance-based global sensitivity analysis is developed, and illustrated on the NOE model on the Orb River, France. The variability of the amount of expected annual flood avoided damages, and the associated sensitivity indices, are estimated over different spatial supports, ranging from small cells to the entire floodplain. Both uncertainty maps and sensitivity maps are produced to identify the key input variables in the NOE model at different spatial scales. Our results show that on small spatial supports, variance of the output indicator is mainly due to the water depth maps and the assets map (spatially distributed model inputs), while on large spatial supports, it is mainly due to the flood frequencies and depth–damage curves (non spatial inputs).

Software availability

Name of software: NOE
Description: The NOE model computes expected annual flood damages at the scale of individual flood-exposed assets, from a given situation, i.e. from a land use map, a set of water depth maps, and a set of depth–damage curves. It also computes expected annual avoided damages at the same scale, when comparing one situation with another.
Developers: N. Saint-Geours, T. Langer, F. Grelot and J.-S. Bailly
Source language: Python (arcpy library) and R
Software required: ArcGIS©
Availability: Contact the developers

1. Introduction

Among the numerical models which are used to investigate environmental issues, many rely on spatially distributed data, such as Digital Terrain Models (DTM), soil maps, land use maps, etc. These spatially distributed models, or simply *spatial models*, allow for an explicit description of the spatial structures, spatial interdependencies, and spatial dynamics involved in the physical, biological, or anthropogenic processes under study. However, it is now well known that all numerical models—including spatially distributed ones—are fraught with uncertainties, which may stem from a lack of knowledge about the phenomena under study, from the natural variability of the quantities of interest, from measurement errors, model assumptions, or numerical approximations (Walker et al., 2003). Hence, when a spatial model is used as a support tool for decision-making, one must remember that *"anyone using uncertain information—meaning the overwhelming majority of mapped data users—should consider carefully the possible sources of uncertainty and how to deal with them"* (Fisher et al., 2005).

To address this issue, a number of uncertainty analysis (UA) and sensitivity analysis (SA) methods, both qualitative and quantitative,

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have been developed over the last decade (Saltelli et al., 2008). They study how model outputs react when input variables are uncertain. UA focuses on the propagation of uncertainties throughout the model and aims to quantify the resulting variability of the model output. SA seeks to study how the uncertainty in a model output can be apportioned to the uncertainties in each of the model inputs. It allows input variables to be ranked according to their contribution to the output variability. SA thus helps to identify the key input variables, those that determine the final decision of the model end-user, and on which further research should be carried out. UA and SA methods have been gradually adopted by modellers in different disciplinary fields, especially in environmental research (Ascough et al., 2008; Cariboni et al., 2007; Tarantola et al., 2002), and today are widely recognized as essential steps in model building (CREM, 2009; European Commission, 2009). One of the most common SA approach is variance-based global sensitivity analysis (VB-GSA), which widely explores the space of input uncertainties (global method), and does not require any preliminary hypothesis (linearity, regularity) regarding the model under study (Saltelli et al., 2008).

However, partly because of the curse of dimensionality, SA methods have seldom been applied to environmental models with both spatially distributed inputs and outputs. A few recent works have tried to tackle this issue (Lilburne and Tarantola, 2009, for a review). Both Ruffo et al. (2006) and Saint-Geours et al. (2013) used geostatistics to simulate the uncertainty on spatially distributed model inputs and incorporate them into a VB-GSA approach. Moreau et al. (2013) investigated the sensitivity of the agro-hydrological TNT2 model to five different soil-map patterns, making use of a fractional factorial design to carry out an analysis of variance, while Chen et al. (2013) recently discussed sensitivity analysis for spatial multi-criteria decision making models. In addition, other authors developed new procedures to compute sensitivity indices for a spatial model output, either with respect to its spatial average (Lilburne and Tarantola, 2009) or with respect to the values of the model output at each point of a study area (Heuvelink et al., 2010; Marrel et al., 2011). A number of recent papers also deal with the issue of CPU time expensive environmental models, for which standard sensitivity analysis techniques cannot be applied; in this case, the construction of a cheap meta-model (emulator) is often necessary, see (Petropoulos et al., 2013) for a recent illustration on the SimSphere soil–vegetation–atmosphere-transfer model. The design of such meta-models for expensive computer codes with spatially distributed inputs and outputs is still an open research question (Marrel et al., 2011).

Nevertheless, to date, none of these studies has reported on a key question: the link between UA/SA and spatial scale issues. Indeed, in many environmental models, the end users are interested in the aggregated value of some spatially distributed model output over a given spatial unit v. In most cases, the aggregated value is just the linear average or the sum of model output over v (e.g., the average porosity of a block, the total evapotranspiration over a plot of land, etc.). But Heuvelink (1998) observed that under a change of spatial support v, the relative contribution of uncertain model inputs to the variability of the aggregated model output may change. Hence, in a spatial model, the results of UA/SA depend on the spatial scale of the problem. Unfortunately, the notion of spatial scale—made up of the scale triplet (Blöschl and Sivapalan, 1995): spatial extent, support, spacing—is mostly ignored in the mathematical frameworks of SA methods. Among scale issues, the so-called *change of support problem* has long been discussed in the field of geostatistics: we know that the variance of an uncertain spatially distributed quantity depends on the spatial support v over which it is aggregated. Up to our knowledge, only Saint-Geours et al. (2012) tried to translate this problem into the context of variance-based GSA. On a simple model, they showed how the sensitivity indices of model inputs depend on the spatial support v over which the model output is aggregated; denoting with $\pi(v)$ the ratio of sensitivity indices of spatially distributed model inputs vs non-spatial inputs, they found a relation of the form $\pi(v) = v_c/|v|$, with $|v|$ the surface area of v and v_c some critical value. When the model output is aggregated on a spatial support of area $|v|$ smaller than v_c, the ratio $\pi(v)$ is larger than 1, which means that the sensitivity indices of spatially distributed inputs are larger than those of non-spatial inputs, and thus that spatially distributed inputs contribute more to the variance of model output than non-spatial inputs. On the contrary, if $|v|$ is larger than v_c, then $\pi(v) \leq 1$, and the non-spatial inputs are key contributors to model output variability. However, their work was mainly theoretical, and their results only valid under restrictive assumptions of inputs stationarity and model additivity. In particular, they did not examine if their conclusions would hold on a real, complex test case.

The aim of this paper is thus to investigate, on an applied case study, how the results of an uncertainty and sensitivity analysis interact with a change of spatial support of the model output. We discuss this question through a complete case study on a model for economic assessment of flood risk management policies, named NOE (Saint-Geours et al., 2013). The NOE model has both spatially distributed inputs (topography, map of water heights, land use map, etc.), and spatially distributed outputs (avoided flood damage indicators). A number of recent studies already performed UA/SA of flood damage assessment models, in whole or in parts (Apel et al., 2008). Most of these studies are limited to the forward propagation of uncertainty (UA), the perimeter of which can vary from a single module of the complete model—e.g., land use (Te Linde et al., 2011), hydraulic simulation (Bales and Wagner, 2009), estimation of damages (Koivumäki et al., 2010)—up to the entire modelling chain (de Kort and Booij, 2007; Qi and Altinakar, 2011). Fewer publications address the issue of ranking the various sources of uncertainty with SA (de Moel et al., 2012). In particular, Saint-Geours et al. (2013) already carried out VB-GSA on the NOE model over the Orb Delta, France. However, in this study, they disregarded spatial scale issues: sensitivity indices were only computed with respect to the aggregated value of model output over the entire floodplain, without examining model behaviour at finer spatial scales. There are at least two motivations for an in-depth study of this issue. First, it would bring a better understanding of the behaviour of the NOE model, by identifying the key input variables *at different spatial scales*. Next, analysing the uncertainty and sensitivity of NOE model outputs at different spatial scales would provide the model end-users (i.e., local water managers) with a more complete information and may help them in their decision making.

In order to demonstrate how UA/SA can bring a new insight into scaling issues in spatial modelling, we perform a *multi-scale VB-GSA* of the NOE model. Our idea is to compute variance-based sensitivity indices with respect to the NOE outputs aggregated over different spatial supports v. We will try to answer the following questions: what is the uncertainty of the NOE output, at different spatial scales? What are the key input variables that explain the largest fraction of the variance of the NOE output, at different spatial scales? How does the uncertainty of the NOE output, and the related sensitivity indices, vary in space, at a fixed spatial scale?

The next section (Section 2) starts with some relevant background information on the selected study site (the Orb Delta), and presents the NOE model. Next, we display a brief introduction to the concepts of VB-GSA, and portray into details how we simulated the uncertainty sources in the NOE model, propagated them with Monte-Carlo simulations, and how we computed multi-scale variance-based sensitivity indices (Section 3). The results consist of