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Incorporating deep uncertainty into the elementary effects method for robust global sensitivity analysis

Lei Gao*, Brett A. Bryan

CSIRO Waite Campus, Urrbrae 5064, SA, Australia

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A B S T R A C T

Internally-consistent scenarios are increasingly used in social–ecological systems modelling to explore how a complex system might be influenced by deeply uncertain future conditions such as climate, population, and demand and supply of resources and energy. The presence of deep uncertainty requires model diagnostic techniques such as global sensitivity analysis to provide reliable diagnostic insights that are robust to highly uncertain future conditions. We extended the elementary effects method of Morris, which is widely used to screen important model input factors at low computational cost, by incorporating deep uncertainty via the use of scenarios, and evaluated its potential as a robust global sensitivity analysis approach. We applied this robust elementary effects (rEE) method to the highly-parameterised Australian continental Land Use Trade-Offs (LUTO) model—a complex, non-linear model with strong interactions between parameters. We compared rEE sensitivity indicators with robust global sensitivity analysis (RGSA) indicators based on the variance-based eFAST method that imposes relatively high computational demand. We found that the rEE method provided a good approximation of the main effects and was effective in screening the most influential model parameters under deep uncertainty at a greatly reduced computational cost. However, the rEE method was not able to match the accuracy of the eFAST-based method in identifying the most influential parameters in the complex LUTO model based on their total effects. We conclude that the rEE method is well-suited for screening complex models, and possibly for efficient RGSA of models with weak interaction effects, but not for RGSA of complex models. Despite its limitations, rEE is a valuable addition to the robust global sensitivity analysis toolbox, helping to provide insights into model performance under deep uncertainty.

1. Introduction

To provide a scientific basis for decision-making, social–ecological modelling is used more than ever to provide future projections of natural resource use, economic activities, environmental impacts, and their interplay at local to global scales (Wise et al., 2009; Nelson et al., 2010; Bateman et al., 2013; Liu et al., 2015). However, modelling and model diagnostics techniques, such as global sensitivity analyses (GSA), are challenged by the presence of deep uncertainty, where probabilities of the occurrence of future events are unknown, the uncertainty is uncontrollable, and predictions based on past data are unreliable (Knight, 1921; Wintle et al., 2010; Cox, 2012; McInerney et al., 2012). A common and effective way of coping with deep uncertainty is to characterise a range of scenarios, each of which is a structured account of a plausible future (Peterson et al., 2003; Wilkinson and Kupers, 2013; Kirby et al., 2014; Hatfield-Dodds et al., 2015; Kirby et al., 2015). Recent influential examples include the Representative Concentration Pathways (Moss et al., 2010; van Vuuren et al., 2011) and the Millennium Ecosystem Assessment (2005). A key characteristic of scenarios is *internal consistency*. In essence, parameter settings for each scenario are logical when taken together and varying individual parameters risks illogical or impossible parameter combinations. Scenarios should not include contradicting assumptions and must be regarded as plausible stories of the future by experts (van Vuuren et al., 2011).

In modelling complex social–ecological systems, GSA is seen as an increasingly important component which provides insights about the mapping of model inputs to model outputs, and major parametric uncertainty sources (Saltelli et al., 2000). It enables the quantification of the influence of uncertainty in model input parameters on the variability of model outputs (Saltelli et al., 2008). Information provided by GSA enables modellers to verify models and identify errors, to understand the structure of complex models, to prioritize influential parameters for data collection and refinement to improve the model accuracy and reduce uncertainty, and

* *Corresponding author.* Tel.: +61 8 8273 8109; fax: +61 8 8303 8750.
E-mail address: lei.gao@csiro.au (L. Gao).

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to identify benign parameters which can be safely ignored. GSA has been applied to a wide range of ecological and environmental models including hydrology (e.g., Nossent et al., 2011; Shin et al., 2013; Gan et al., 2014; Peeters et al., 2014), land use (e.g., Gao et al., 2015), forestry (e.g., Song et al., 2012, 2013), agriculture (e.g., DeJonge et al., 2012; Zhao et al., 2014), and population dynamics (e.g., Fieberg and Jenkins, 2005). Several methods for GSA have been proposed including screening (e.g., Morris, 1991), non-parametric (e.g., Saltelli and Marivoet, 1990), variance-based (e.g., Sobol', 1993; Saltelli et al., 2010), density-based (e.g., Liu and Homma, 2009), and expected-value-of-information-based methods (e.g., Oakley et al., 2010). Two key outputs from GSA are the main or *first-order* effects (variance contribution of an individual parameter to the total model variance) and the total effects (variance contribution resulting from the first-order effect of an individual parameter and all its interactions with other parameters). The extended Fourier Amplitude Sensitivity Test (eFAST) method (Saltelli et al., 1999) is a state-of-the-art GSA approach which can efficiently calculate both the main and total effects (Zhao et al., 2014). However, eFAST remains relatively computationally-intensive compared to the elementary effects (EE) method (Morris, 1991) which can approximate the total effects with greatly reduced computational demand (Campolongo et al., 2007; Herman et al., 2013). It has proven to be among the most efficient parameter screening methods and has been widely applied (e.g., Song et al., 2012; Herman et al., 2013; Zhan et al., 2013).

In broad terms, GSA works by varying individual model inputs within a specified range of uncertainty in a structured way, running the model under each parameter combination, and quantifying the sensitivity of outputs to variation in inputs. However, under deep uncertainty, varying the attributes of scenarios independently may invalidate their internal consistency, risking implausible or impossible parameter combinations. Gao et al. (2015) found statistically significant differences between scenarios in the influential and non-influential parameters identified, and in parameter influence, both in terms of their ranking and in the magnitude of their total effects. Gao et al. (2015) proposed a robust global sensitivity analysis (RGSA) approach by employing four decision criteria in determining a set of sensitivity indicators that are robust to deeply uncertain futures represented as scenarios. Each criterion was used to calculate a robust sensitivity indicator based on the sensitivity indices from the eFAST method under different scenarios. However, the computational load of the eFAST method limited the utility of eFAST as a robust GSA as Gao et al. (2015) had to run the model at a coarse resolution, even using high-performance computing and parallel programming techniques (Bryan, 2013). For analysing the sensitivity of large models there is a need to incorporate robustness into a more computationally-efficient GSA method such as the EE method.

In this paper, we modified the EE method to perform a robust elementary effects (rEE) global sensitivity analysis of the Australian continental Land Use Trade-Offs (LUTO) model (Bryan et al., 2014; Connor et al., 2015) across four global scenarios. The EE method overcomes the limitations of derivative-based methods (Saltelli et al., 2008) and measures global sensitivity by sampling throughout p-level parameter space (p is the number of levels to which each dimension of the parameter space is divided). We incorporated internally-consistent scenarios into the p-level sampling space and evaluated its capability for RGSA. The effectiveness of the rEE method was assessed by statistically comparing its robust sensitivity effects with the estimates of Gao et al. (2015) obtained by applying four decision criteria based on their eFAST-calculated measures of first-order and total effects. We discuss the advantages and limitations of rEE as a method for performing global sensitivity analysis that is robust to deep uncertainty.

2. The LUTO model

2.1. Brief overview of model and scenarios

The LUTO model provides a comprehensive assessment of Australia's future land use and ecosystem services (e.g. food, carbon, energy, biodiversity, and water) under external drivers of global change and domestic policy. The details of the LUTO model are presented by Bryan et al. (2014) and Connor et al. (2015) and are summarised here. The LUTO model estimates the potential extent and impacts of land use change at a spatial resolution of ~1.1 km grid cells across the 85.3 million hectares of Australia's non-contiguous intensive agricultural land. The LUTO model incorporates traditional market dynamics into land use change decision-making and quantifies the impact of global change on ecosystem services. The model generates spatio-temporal outcomes at annual time step for the period from 2013 to 2050. Exogenous parameters are updated with each time step, including global prices for carbon and energy, and global demand for crops and livestock. Then an optimiser embedded in the model allocates land in each spatial cell to one of five categories of alternative land use: agriculture, carbon plantings, environmental plantings, biofuels, and bioenergy.

Four global scenarios or *global outlooks* denoted L1, M3, M2, and H3, were defined within CSIRO's Australian National Outlook initiative as different combinations of global economic, population, greenhouse gas emissions, and climate settings. The outlooks can be broadly described as combinations of low (L), medium (M), and high (H) emissions, and low (1), medium (2), high (3) global population projections (Supplementary Material Table A1). The outlooks were created via integrated assessment using the Global Integrated Assessment Model (Newth et al., 2015) and are internally-consistent pathways to the Representative Concentration Pathways 2.6 (L1), 4.5 (M2, M3), and 8.5 (H3) (Moss et al., 2010; van Vuuren et al., 2011). We refer the reader to Hatfield-Dodds et al. (2015) and Newth et al. (2015) for detailed scenario specifications.

2.2. Input factors and output variables

We performed GSA on 50 parameters (excluding fixed ones) of the LUTO model. The parameters were classified into 9 groups: scenario, agriculture profit function, reforestation inputs, reforestation costs, biofuel inputs, biofuel costs, climate impacts, water, and other (Supplementary material Table B1). Each global outlook was represented by a time series of each scenario parameter during the period 2013 to 2050. For parameters with no information available to determine their ranges, 30% either side of the reference value was used as the bounds. The ±30% variation was uniformly applied to all spatial parameters but ignoring the variation characteristics that may change non-uniformly over space. Some recent progress has been made in investigating the effect of spatial parameters on sensitivity (Dong et al., 2015) but more effort is required. A uniform distribution was assigned to each parameter due to limited information on parameter distributions. 24 output variables were selected and evaluated (Supplementary material Table B2), representing the major ecosystem services (agricultural production, carbon emissions abatement, biodiversity services, biofuel and bioenergy production, and water resources) and the area of each land use.

3. Robust sensitivity analysis methods

The four external scenario inputs were incorporated into the rEE method to provide a robust global sensitivity analysis, giving a comprehensive assessment of the influence of each input parameter