Time dependent variance-based sensitivity analysis of development aggregation generated by heterogeneous land use agents

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***Abstract*—Agent-based models have been recognized as computational laboratories furnishing spatial scientists with a plausible exploratory apparatus for learning about land use dynamics through an explicit representation of human behavior. At the same time research suggests that the utility of agent-based modeling has been hampered by a limited understanding of the decision processes involving a wide array of stakeholders with different perceptions and preferences. Therefore, it is critically important to offer new tools for a more comprehensive inspection of uncertainties related to the interrelationships between individual choices and land development patterns. In this paper, we propose a new approach to evaluating agent behavioral uncertainty using time dependent variance-based global sensitivity analysis. The method produces time series of first order sensitivity indices that allocate the variance of development patterning to two heterogeneous behavioral features: *risk perceptions*, quantified through attitude utility functions, and *land preferences*, in the form of weights assigned to different decision criteria. We experiment with three ABM scenarios that emphasize the various decision components. The scenarios utilize a fixed number of parameters with changing distributions reflecting the behavioral characteristic under consideration. Outcome maps for each time step are summarized using the aggregation index, which is further employed in sensitivity computation. The resulting sensitivity indices are plotted against time to track the impact of input conditions on land use compactness. The comparisons of the plots reveal varying sensitivity trajectories that depend on the modified decision rule.**

Keywords: sensitivity analysis; agent-based model; behavioral heterogeneity

I. INTRODUCTION

Dynamic land use systems (LUS) have been recognized as one of the major players in global environmental change (Liu et al., 2007). The complexity of LUS is often attributed to human decision making, which involves a wide array of stakeholders with different perceptions, experiences, and preferences. Recently, agent-based modeling (ABM) has been widely utilized as a tool to study the behavior of land use actors and the interactions between human decision making and landscape characteristics (Parker et al., 2003, Verburg, 2006).

One of the advantages of ABM for LUS exploration is the explicit incorporation of decision making heterogeneity in the form of varying preferences, decision rules, and risk perceptions. The flexibility of behavioral representations is both a benefit and a drawback of ABM, since it introduces multidimensional uncertainty into the model, leaving the modeler with lots of issues to resolve. Too often ABM exploration lacks indicators that clearly depict the dynamics of model uncertainty, summarize the relative influence of inputs on model outcomes, and allow for identification of critical regions in the input and output space. Global sensitivity analysis (GSA) has been proposed to address these challenges, as a method aiming at systematic exploration of the most important drivers that shape the dynamics of models of deeply uncertain systems (Lempert et al., 2003, Saltelli et al., 2000, Lilburne and Tarantola, 2009).

Complex LUS are nonlinear by nature and yet little attention has been given to the role a well-structured time-variant GSA can play in ABM corroboration. In this paper, we propose to calculate and plot a selected sensitivity index for multiple time steps of model execution, in order to assess the robustness of land use compactness over space as well as time. Specifically, our analysis aims at addressing the following research questions: *What is the impact of different intensities of risk perceptions and landscape preferences on ABM outcome compactness stability? Do the sensitivities of these decision factors vary during model execution, or are they time invariant?* We employ a specific method of sensitivity analysis called variance-based GSA, which is summarized in the next section.

II. VARIANCE-BASED GLOBAL SENSITIVITY ANALYSIS OF LAND USE CHANGE

Sensitivity analysis of an ABM involves sweeping the parameter space and executing multiple model simulations for different input samples (An et al., 2005, Lilburne and Tarantola, 2009). Unlike more traditional, one-at-a-time approaches, GSA assumes that the perturbations applied to the model involve simultaneous variation of all factors over the entire problem space (Saltelli et al., 2000). Various GSA approaches have been employed in spatially-explicit research. One method, called variance-based GSA, is especially promising to evaluate dynamic and nonlinear systems, since it is model independent, that is, it does not assume any particular structure of the examined model. Variance-based GSA decomposes the variance of model output, isolating the effects of changes in model inputs, which are represented individually and in combinations (Saltelli et al., 2008). As a result, we can compute first and total order sensitivity indices that quantify both the independent and the interactive fractional contribution of a given input parameter (i) to the variance of the outputs. In this paper, we utilize the first order sensitivity index (Si), to evaluate ABM stability under varying input values. Since the ABM output is time-dependent, we calculate normalized Si for each time step, and then plot the values over time, creating a time series of ABM sensitivities, which we refer to as time-GSA (Saltelli et al., 1999).

A. Experimental Procedure

To explore the sensitivity of the LUS ABM presented below, the following steps are performed for every land development computational experiment (Lilburne and Tarantola, 2009):

- Randomly generate n Monte Carlo input samples based on predefined probability functions using a quasi-random Sobol' experimental design
- Execute the model n times for t time steps
- Calculate the aggregation index (AI) of output land use patterns with FRAGSTATS (McGarigal and Marks, 1995)
- Use the AI together with the input samples to calculate time series of Si for every input i

III. Agent-Based Model Formulation

The ABM is composed of five heterogeneous developer agents and 5041 developable land cells that form a grid of 71 rows x 71 columns. A location on the lattice can be either undeveloped or developed. Agents make decisions based on two spatial decision criteria: land value (LV) and scenic beauty (SB) (Fig.1, where darker locations are more preferred). Each agent is equipped with three attributes: preferences (weights) for LV and SB, and perception of risk.

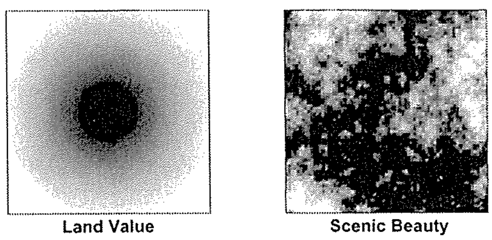

Figure 1. Input spatial criteria used in agent decision making

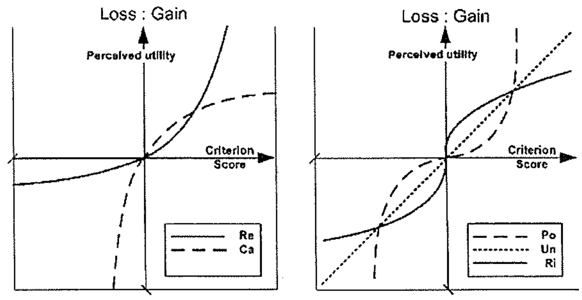

Figure 2. Attitude Utility Functions used in the ABM experiments (Left – Experiment 1 and 3, right – Experiment 2): Re – reckless, Ca – cautious, Po – poor, Un – unbiased, Ri – rich.

Based on the previous work by Ligmann-Zielinska (2009), this research utilizes a simplified approach to representing the perception of risk in the form of attitude utility functions (AUFs, Fig.2). These nonlinear AUFs reflect the perception of risky decision-making that spans over a bipolar continuum from risk seeking (reckless), through risk-bearing (rich), risk impartial (unbiased), risk-avoiding (poor), to risk-averse (cautious). Through these functions, the decision criteria scores are reevaluated and expressed as positive and negative deviations (gains and losses) from the neutral linear criterion-option utility relationship. These modified criteria values are then weighed (W_{sb} for SB and W_{lv} for LV, respectively) and aggregated into a composite site score using an extended Ideal Point decision rule.

Simulations (n=1280) are executed for 70 time steps with every agent developing 3 cells per step (1050 cells or ~21% of land developed at the end of the simulation). For every time step, an agent samples 10% of developable sites and evaluates them based on an ordered choice of location utilities. The agent picks the sites that score highest in the resultant ranking. Such an investment plan is then checked for potential conflicts among all developers in the model. If a competition for a given site arises, a bidding mechanism is employed. The agent with the highest rank for a particular location wins the site over its competitors, who revisit other developable locations in quest for potential investment opportunities.

During the model execution, every new buildup impacts the immediate surroundings of the developed cell (Ligmann-Zielinska and Sun, 2010). Two feedback parameters are introduced: increase in land value (I_{lv}) and decrease in scenic beauty (D_{sb}). In particular, new development has a positive impact on land value and a negative impact on scenic beauty. The explicit feedbacks are represented as a ratio of change in the nearest 3x3 neighborhood of every developed cell. Therefore, with every time step passed, every neighbor of a newly developed cell increases its LV by a fraction I_{lv} and decreases its SB score by a fraction D_{sb}.

IV. Experiments

We start from establishing a base case scenario, which represents a point of departure for two successive experiments E (Table 1). Note that, for all experiments, I_{lv} and D_{sb} are drawn uniformly from a range [0.02, 0.06].

TABLE I. PARAMETER DISTRUBUTIONS FOR ABM EXPERIMENTS. AUFS: RE RECKLESS, CA CAUTIOUS, PO POOR, UN UNBIASED, RI RICH; D: DISCRETE UNIFORM DISTRIBUTION OF ALL COMBINATIONS OF PARAMETER VALUES FOR FIVE AGENTS

Experiment	Agent Decision Making Parameters	
	AUFs	*Land Value Weight*
[1] Base	D(Re,Ca)	D(0.15,0.5,0.85)
[2] Balanced attitude	D(Po,Un,Ri)	D(0.15,0.5,0.85)
[3] Balanced preferences	D(Re,Ca)	D(0.4,0.5,0.6)

The objective of E1 is to assess how agents' AUFs, which are either extreme risk averse (cautious) or extreme risk taking (reckless), affect the resultant development compactness (Fig.1). The agents are not only extremely polarized in terms of risk perception, but they also differ considerably in the preferences assigned to the two decision criteria (for example, one agent uses a 85:15 ratio for the LV:SB weights, whereas another agent uses a ratio of 15:85).

Unlike E1 which employs behaviorally antagonistic agents, E2 and E3 focus on more balanced decision making, with moderate attitudes towards risk in E2, and less volatile preferences for SB and LV in E3. With these modifications of agent decision mechanisms, we want to address the question of whether heterogeneous yet balanced land use behaviors influence the outcome land use aggregation and its associated uncertainty (Brown and Robinson, 2006).

V. RESULTS AND DISCUSSION

We start from summarizing the patterns using AI calculated for every time step of every simulation run. Table 2 shows the results for t=70. Observe a considerable variation within scenarios (cv=0.38 for E1 and E2, cv=0.26 for E3). Moreover, E2 bears a substantial statistical similarity to E1. To further test the variability among scenarios, we conducted t-tests between E1 and E2 and E1 and E3, respectively. We used two tail p-values from the tests. In the E1 vs. E2 case, we recorded p=0.74 (α=0.05), indicating that there is no statistically significant difference between AI values of both scenarios. For the E1 vs. E3 test, we recorded p<0.00005 and we can conclude that there are statistically significant differences between outcome pattern aggregation of these two scenarios. Consequently, we can hypothesize that, with all other factors unchanged, less variable preferences have more impact on development aggregation than the less extreme attitudes to risk.

TABLE II. SUMMARY STATISTICS OF AGGREGATION INDEX CALCULATED AT THE END OF MODEL EXECUTION

Experiment	Mean	Std	Min	Max
[1] Base	35.1	13.4	7.9	96.2
[2] Balanced attitude	34.9	13.5	8.6	88.1
[3] Balanced preferences	39.5	10.5	18.1	86.8

A. *Development Probability Maps*

As the next step, we calculated for E1 and E3 the mean development per cell among all n simulations. Fig.3 renders the result maps for the last time step. Although there is an observable similarity between the scenarios (with the most probable locations developed around the center of the landscape) the maps confirm the conclusion derived based on the AI statistics (Table 2) stating that E1 results in more variable development allocation than E3. The visual analysis of the maps strengthens our hypothesis about a substantial influence of preferences on development aggregation, when measured relative to other input parameters.

B. *Time Dependent Global Sensitivity Analysis*

Using SimLab open source software for uncertainty and sensitivity analysis (http://simlab.jrc.ec.europa.eu/), we calculated the Si sensitivity measures outlined in section II. The results, plotted cumulatively, are depicted in Fig.4. Based on the first-order effect, which assumes that the input parameters are independent from each other, W_{lv} and D_{sb} have the largest fractional contribution to the variance of land use aggregation. Surprisingly, the least influential are the AUFs, which, when taken singly, contribute to output variance in at most 5% for the first 3 time steps of E1 and are nonexistent afterwards. For E3 AUFs have also a negligible influence on AI variance across time.

The significance of weights and D_{sb} on AI variability can be explained as follows. Observe that the spatial distribution within the criteria layers drives the magnitude of compactness in the area (Fig.1). Moreover, the intensity of the D_{sb} either substantially strengthens or significantly diminishes the patchiness of SB, making the aggregation of the development very sensitive to this spatial criterion.

The sum of all Si tells us about the fraction of outcome variability explained independently by the inputs. Analyzing the complement of this sum to 1.0 allows us to recognize the fraction of outcome variability that cannot be explained by single factors but rather by their interactions (white background in the Si plots in Fig.4).

Observe that the variance of AI for E1 can be easily explained by factors treated individually. In other words, the behavior of the ABM is very linear when the E1 input configurations are employed. E3 exhibits a somewhat higher interactivity of factors, especially at the beginning of the simulation (t<5) and after the first quarter of model execution (t>25 and t <35).

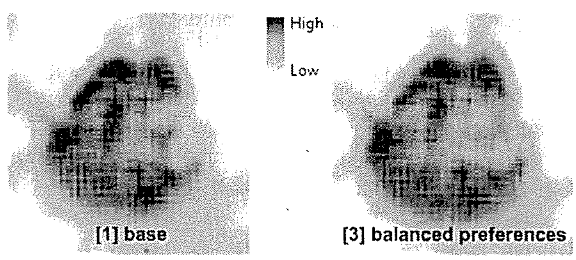

Figure 3. Mean land development for t=70 calculated among n=1280 model executions for experiment 1 and experiment 3

VI. Conclusions

Variance-based time-GSA offers an untapped so far potential for evaluation of spatial ABM robustness. Very few studies have been conducted to date to assess the temporal variability of outcome sensitivities of LUS ABMs. Such oversight may result in inadequate model evaluation. Provided that the sensitivity analysis is undertaken for the final results of ABM executions, we can potentially lose the dynamics of sensitivities throughout the whole simulation run. For example, E3 revealed that for $t<20$ D_{sb} is more influential than W_{lv}, whereas after $t=30$ the ABM becomes more sensitive to the uncertainty associated with W_{lv} (Fig.4).

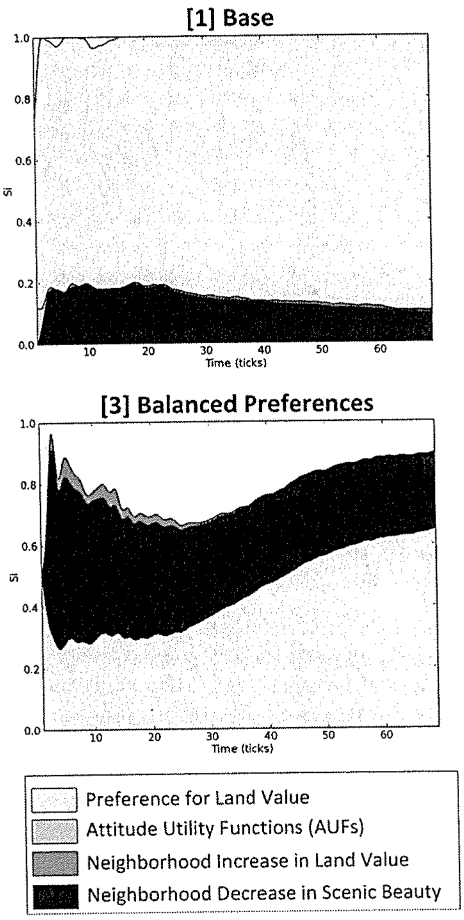

Figure 4. First order sensitivity index (Si) calculated for the aggregation index of land use ABM outcome maps for experiments 1 and 3

Based on the three scenarios, we can conclude that output development aggregation of the presented ABM is much more sensitive to agent heterogeneous preferences for landscape characteristics than to the disparate attitudes towards risk. Furthermore, reducing the amplitude of preferences (E3) increases input factor interactivity.

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