Philosophical and practical limits of Agent Based Models as viable systems for discovering and verifying new geographical knowledge

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New analysis and modeling approaches often call for reconsideration of methodological and philosophical stances if they are to be used appropriately. This is particularly true of Agent-Based Models (ABM), which can play a wide range of roles in scientific investigations, from characterizing emergent properties of data through prediction of future states, to positing explanations of possible causal mechanisms. In the biological simulation community, a similar recognition is summed up by Peck (2005) thus: "*Philosophers and practitioners of science are recognizing that simulation models are a new kind of tool that defies the categories, uses and restrictions found in the historical use of mathematical models*". Such models do not sit easily with the traditional view of models and their roles in geographical analysis (e.g. Chorley, 1964). While we do not agree that simulation is a 'new kind of science' we do believe that its application and interpretation, and legitimate roles and limitations, are not yet well understood. Equally, real-world experiments are not practical for many kinds of broad-scale, geographical inquiry, and simulation models allow exploration of alternative realities and responses to change. Thus, we must learn to use simulation technology in effective and defensible ways.

How do we validate such complex models? There is a danger that simulation models can become self-fulfilling prophesies because they often conflate different analysis activities that would ordinarily stand alone and be *independently* scrutinized. For example: data collection, model synthesis, numerical analysis, validation and presentation (e.g. Gahegan & Brodaric, 2002) are traditionally disjoint activities where uncertainties at each stage are accessible for independent investigation. In simulations, some (or all) of these activities may become intertwined. For example, data may be imputed, loaded into individual agents, which then interact via a (possibly evolving) set of rules to produce outcomes that appear realistic or useful. But mere plausibility is no guarantee that the explanations derived are true in the world. If the modeler expects certain outcomes, constructs rules and gathers data accordingly, then tests various models until their behavior matches expectations, then there is little independence and a lot of bias. Over-fitting will be rife and there is little chance for novel or unexpected outcomes to emerge.

How do we know what is going on 'inside' simulation models? Visualization in support of ABMs remains quite primitive, and typically unable to provide much insight into the complex interactions and states of many independent actors. Interactions become so complex that it is not possible to be sure exactly how the model is behaving. We may be confident in model outcomes as a realistic representation, but causal mechanisms (and explanations) may remain elusive. A related concern is that difficulty in observing what is going on 'inside' models often means that they are viewed in terms of (pre-selected) aggregate measures that reinforce the modeler biases.

Also, disparities between the scale at which models are developed (individual decision-making) and evaluated (aggregate outcomes) raise further questions about validation processes.

How geographical are ABMs, really? ABMs appear to be explicitly spatial, but that does not mean that they are inherently geographical. For the most part, ABMs represent only a very impoverished, grid-based geography, with poor handling of boundary conditions and without any inherent structure within the space (Gilbert & Bankes 2002). There are only a few exceptions, (e.g. O'Sullivan et al, 2003; Brown et al. 2005). That they are often considered as collections of actors within a geographical space does not mean that they magically resolve or avoid any of the classical statistical pitfalls that beset geographical analysis. In particular, it is unusual for models to reflect the multiple geographical (and social) scales at which decisions are made. ABMs are at their most convincing in contexts where constrained actors make decisions in 'reactive' ways, the prime example being various models of pedestrian behaviour (see e.g., Helbing et al. 2001), but such contexts represent a small percentage of cases where human activities make a difference.

How do we avoid merely reflecting our own biases? Arising from all of these questions, and as Bankes (2002) suggests there is a tendency to focus on those aspects for which straightforward behaviors can be constructed, or for which good data are available, but to ignore or play down other more problematic aspects. This leads to bias in the results (in terms of both explanation and prediction) and points to an important and elusive question: "*Did we really represent and explore the space of all <u>plausible</u> models?*" Currently, the search for a solution tends to stop when a useful model is produced (perhaps tested by goodness of fit to some desired outcome, or more informally because its behavior 'seems right'). This question does not apply to simpler forms of predictive modeling where the outcome can be validated straightforwardly (e.g. predicting stream discharge). But if the outcome is complex, the data uncertain, or the aim is to create an explanatory model (e.g. predicting a landcover change surface) it is very likely that a family of solutions exists, all of which would perform equally well—within the wide margins of confidence (*equifinality*). The internal differences exhibited by a family of models that produce similar outcomes could tell us much about the nature of the systems we analyze, including their stability and the confidence we should place on predicting future states. **Representing the hypothesis space of solutions and the regions within it that a simulation has (and has not) explored is a very difficult but important problem that needs to be addressed. Likewise highlighting and comparing the parameterization of solutions that produce similar outcomes. (See figure at end).**

Some issues we are interested in and on which we can most readily contribute:

1. Providing ways to better understand—by visualization—the detailed inner working of ABMs
2. Building ABMs that are more geographically explicit
3. Developing measures of confidence in the results obtained from ABMs, for example by representing the path that potential model solutions have taken through the hypothesis space.
4. Adding to the theoretical understanding, and creating associated guidelines on best practices for the use and evaluation of ABMs in geographical analysis.

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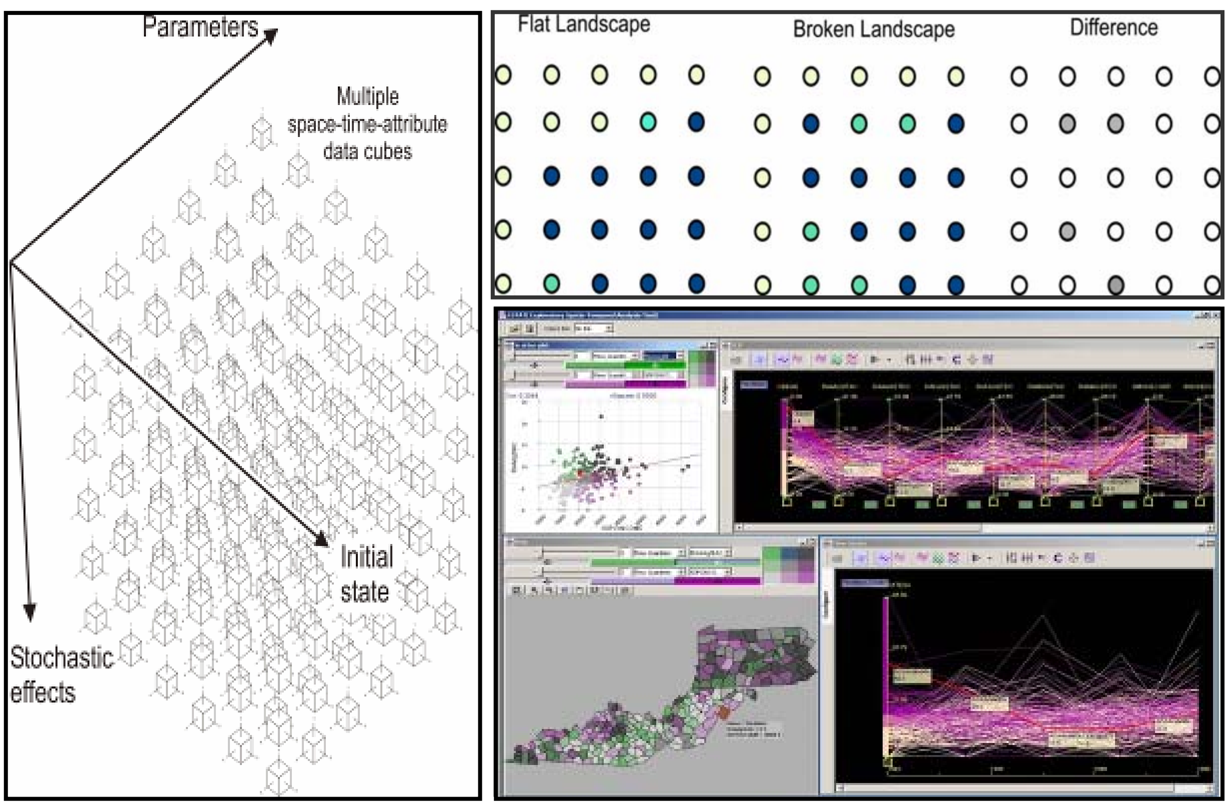

LEFT: Visualizing the space of *possible* models, with the aim of uncovering *plausible* models—then examining their similarities and differences. TOP RIGHT: Examining the effects of changing parameters on model outcomes (left & middle grid), explicitly representing where different outcomes occur (right grid). BOTTOM RIGHT: Visualizing the parameters and outcomes in sets of model runs.