Issues of Representation and Interpretation for Agent-based Models of Complex Adaptive Spatial Systems

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What we know of the world around us is, in large measure, the product of reductionist science. The basic tenets of this approach tell us that truth can be found through an understanding of individual system components; a system is the sum of its parts. While this approach served us well through much of the 20^{th} century, many scientists now believe that a reductionist approach alone is insufficient for the study of natural and social systems. These scientists promote a new approach based on complexity theory and complex adaptive systems (CAS) that is focused as much on the linkages among system components as the components themselves; a science where the underlying assumption is that a system can be more than the some of its parts. Traditional scientific methods, however, are often ill-suited to the study of complex systems characterized by feedbacks and non-linear dynamics, path dependency, adaptation, cross-scale interaction, self-organization, emergent behavior, and dissipative processes. Agent-based modeling (ABM) has been highly touted as an appropriate technique for the study of complex adaptive spatial systems (CASS).

My interests in ABM for CASS lie primarily in the representation of intelligent, mobile, spatially-aware, and adaptive decision-makers. More specifically, my research has been focused on how individuals make decisions about: 1) land use, land cover, and associated management strategies; 2) how to navigate across uncertain and risky landscapes (elk in this situation); and 3) how to organize to effect change in policies that, in turn, effect changes in the production of ecosystem services. Linking all three of these projects are underlying questions about how landscape structure emerges from individual and localized action and how feedback mechanisms link multiple social or spatial scales. Gaining an understanding of landscape-scale processes through the use of ABM presents significant challenges for the representation of spatially-aware cognitive agents and in the interpretation of model results. These challenges must, in my opinion, be addressed before ABM will meet our high expectations for the study of CASS. In the following discussion I lay out some of these challenges in greater detail.

Representational challenges

Two related and significant challenges for the development of ABM for CASS are the representation of cognition and context. Complexity is often discussed in terms of self-organization and emergent behavior; behavior driven, in part, by adaptive processes. For humans (and presumably other higher order animals), short-term adaptation requires cognition. Research is needed on how to represent and implement cognitive processes (learning, reasoning, and memory) in ABM for CASS. For example, spatial decision-making is often a collaborative, multi-objective, and semi-structured process supported by limited and uncertain knowledge. Agents built to support the simulation of CASS might, therefore, be required to learn to: 1) manage spatial resources under uncertainty; 2) organize, compromise, and collaborate to reach individual or societal objectives; and 3) minimize risk and maximize opportunity. “Hard-coding” these behaviors into a system is likely to lead to what Holland (1986) has referred to as “brittleness” and a failure to capture complex behavior. Unique to the simulation of spatial systems is the need to represent spatial cognition. Learning safe routes through a landscape may require, for example, the digital equivalent of cognitive maps that agents learn, store, reference, and adapt to changing risk surfaces. While there has been a significant amount of work done in machine learning for more simplified environments (e.g., robotics), little of this kind of work has found its way into models of complex adaptive spatial systems.

Cognitive behavior is, generally speaking, derived from a history of contextualized experiences. Spatially-aware, intelligent agents must, therefore, connect external stimuli (e.g., resources and threats), internal states (e.g., wealth, nutrition, social connections), and the states and behaviors of other agents (neighbors, colleagues, competitors) to successful behavior and generalize this knowledge to similar situations. Furthermore, an appropriate spatial response might depend on a particular sequence of events.

Context given heterogeneous agents with bounded knowledge about complex spatial systems must, therefore, be agent-specific and derived from a spatio-temporal representation.

Interpretational challenges
When we use simulation we need to know that the model accurately reflects the real-world processes of interest and that this model was accurately translated into software. The goal of complex system models is often to explore system-level behavior as it is produced by a large number of interacting and heterogeneous agents. ABM are often large and complicated, which makes model verification and validation challenging. Much has been written about the verification and validation of ABM and, while it remains a significant challenge, I will make just two quick comments here. The first comment (an admittedly obvious one) is that the identification and resolution of verification and validation problems becomes even more difficult given a virtual system expected to produce complex non-linear, stochastic, path dependent, and emergent behavior. If we accept, for example, an explanation based on complexity then we must also accept that an existing spatial pattern is just one realization of many possible alternative states. A model that fails to reproduce the existing state is not, therefore, necessarily in error. Similarly, the concept of equifinality suggests that a model that does mimic real-world patterns is not necessarily valid (Brown et al. 2006). Second, the use of ABM in CASS makes most sense when one is studying how the actions and interactions of individuals lead to system-level behavior. Relations among individuals or between individual and their environment at a single analytical scale can often be studied more directly using other techniques (e.g., a statistical approach). However, models of adaptive, contextually aware agents are complicated and the output difficult to interpret. How do we prove, for example, that the emergent behavior (ignoring for now how this is defined and measured) produced by the system is, in fact, generative evidence of real complex behavior, and not an unintended artifact of some simplifying assumption encoded into agent behavior?

This brings me to the final issue that I wish to address in this position paper. If a generative scientific approach, like ABM, is to be applied to CASS it must be transparent. We might expect system dynamics to be transparent simply because agent behavior is explicitly encoded, but issues of adaptation, equifinality, bifurcation, and divergence, the very behaviors we expect the system to capture, can quickly render the modeling process opaque. It makes sense to build into complex system models the same kinds of explanatory tools typically associated with expert systems, but tracking cause and effect for a CASS will be considerably more complicated. Can we determine *a priori* what an important event in an ABM simulation looks like? When, for example, is the variation in the state of some modeled component unimportant noise and when does it signal a bifurcation point? Building into ABM the ability to trace back through model output to gain an understanding of how a system got to where it did is likely to prove challenging, but it seems imperative that we do so if we are to make strong claims about our interpretations of model results. The first step toward such a capability might be the construction of the kinds of cognitive and spatio-temporal data representations discussed above.

Final thoughts
Given the challenges associated with cognition, context, and model interpretation, what conclusions can be drawn from ABM about complex spatial systems? A goal of statistically valid models of real world processes seems a ways off and, perhaps, even misguided. Perhaps the greatest value of agent-based models for complex adaptive spatial systems lies in the questions that they require us to ask about system behavior, the way that they require us to conceptualize system structure, and the opportunities that they provide for us to explore plausible outcomes and search for robust decisions.

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