Representing Complex Adaptive Spatial Systems

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1. Introduction

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 20th 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 feedback mechanisms, non-linear dynamics, path dependency, adaptation, cross-scale interaction, self-organization, emergent behavior, and dissipative processes. Agent-based models (ABM) have been highly touted as appropriate tools for the study of complex adaptive spatial systems (CASS). Significant challenges exist, however, in the representation, validation, and interpretation of ABM of CASS.

Over the past five years the authors have investigated the utility of ABM in the representation of intelligent, mobile, spatially-aware, and adaptive decision-makers. More specifically, this research has 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 actions 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. In this paper we discuss these challenges, lay out a framework for the representation of ABM for CASS, and present a prototypical system for the interpretation of model results.

2. 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; 3) navigate through risky terrain; and 4) maximize utility. Learning safe routes through a landscape, for example, may require 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. Context given heterogeneous agents with bounded knowledge about complex spatial systems must, therefore, be agent-specific and derived from a spatio-temporal representation.

3. 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. The verification and validation of ABM of CASS is challenging (Figure 1). 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; the problem of multifinality. 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). Given equifinality and multifinality how do we prove that the emergent behavior produced by the system is, in fact, generative evidence of real complex behavior?

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, multifinality, 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. 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.

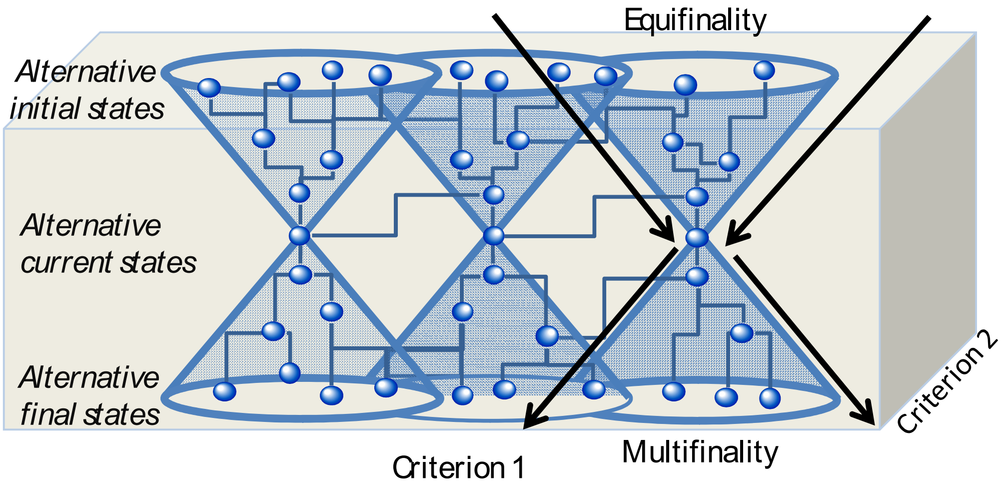

Figure 1. Interaction, self organization, equifinality, multifinality and bifurcation are all important in ABM of CASS, but significantly complicate issues of representation, interpretation, and validation.

In this paper we take a first step toward building such a tracking system. We begin with the assumption that the dynamics of ABM of CASS will be explored using Monte Carlo simulation. Each simulation (i.e., each realization in the Monte Carlo simulation) leaves a "trace" in state space (Figure 2). These state traces can be evaluated at multiple scales. Furthermore, the state space into which simulations runs are mapped can be objective, geographical, or policy spaces (Bennett et al. 2004). For example, the changing state of individual agents can be traced through time and compared to the trace of the same agent in other simulation runs. State can be measured by fitness (e.g., wealth or health— measures in objective space), decisions made (measures in policy space), or routes taken (measures in geographic space). System-level state changes can, in like fashion, be evaluated as a function aggregate indices of fitness (objective space) or landscape structure (geographical space). The "entity" being tracked can be an individual agent or the system itself (in this sense the system is treated as if it is an agent).
Measures of similarity must be devised to implement the proposed tracking system. In the work presented here we build on measures suggested by Bennett et al. (2004) and Xiao and Armstrong (2005). Random perturbations and changing context will produce differences in system and individual state among the alternative Monte Carlo realizations; some of these changes will be significant, others are best treated as noise. A mechanism is needed to group like entities and highlight significant changes if we are to make sense out of maze of data produced by multiple realizations of the same complex system. Aggregating a set of traces differentiated by minor variations is, essentially, a process of generalization. In this work, we "band" together traces with similar state at specified time intervals using cluster techniques; a cluster represents a generalized version of single entity through time. When a trace deviates sufficiently from earlier traces it can be considered to be a new entity and, thus, should be stored for subsequent analysis. In the prototype system a bifurcation node is created to capture the temporal topological link between the old and new entity. This tracking structure produces a graph that can be queried to better understand system dynamics. Of particular interest here are the conditions that lead to significant changes in state (e.g., what happens at a bifurcation point). To help answer such

questions the trace graph stores the spatio-temporal representation of objects (see above); thus facilitating comparisons among objects before and after bifurcation nodes.

Clearly, different levels of generalization will lead to different graphs. Furthermore, lags may exist between precipitating events and changes in individual or system state. The implications of generalization and temporal lags on the interpretation of system dynamics will be explored during the summer of 2007. One solution that will be investigated is the implementation of this tracking system as a fuzzy graph and the representation of bifurcation zones.

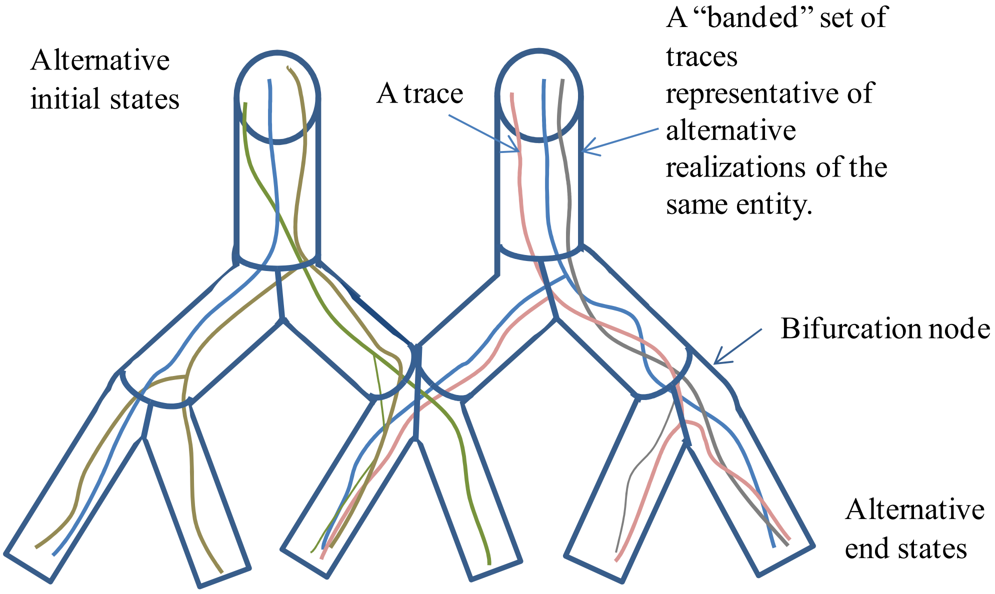

Figure 2. A tracking system for the interpretation of ABM of CASS. Note that above is representative of a divergent system, convergent systems, and systems possessing both divergent and convergent patterns are also possible.

4. Caveats

Please note that an earlier version of this paper was presented at the Agent-based Models of Complex Spatial Systems (Santa Barbara 2007). Here we extend this discussion by more fully describing our agent-based framework and the tracking system that we designed to better understand and interpret ABM of complex spatial systems. This system is a work in progress with results expected by mid to late summer.

5. References

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