Complications of complexity in agent-based models

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I have been working on both computational aspects of complex systems and agent-based models. My background is primarily in simulating vegetation dynamics using individual-based models (ibm) and cellular automata. This work includes analysis of the computational issues that arise when attempting to use evolutionary algorithms to simulate spatial systems that may exhibit self-organization and the difficulties of simulating agent decision making with too little data or not the right data to specify the decision. I am also involved in agent based modeling of land use decisions both directly and indirectly in ongoing funded research.

My perspective is that systems in which feedbacks occur between the spatial patterns and the drivers creating them are thus nonlinear, and varied spatial patterns can be produced by simple nonlinear processes. These “emergent” patterns that develop are at a scale (spatial, temporal or phenomenological) larger than the processes can be trivial unless they can be interpreted. Meaningful interpretation will depend on first better quantification of the dynamics of pattern and second, necessarily, on the development of an explanatory narrative. However, most systems of interest are both nonlinear and complicated. A real challenge is to determine to what degree the evolution of patterns is determined by the complications or the nonlinearity.

Models of agents are one way in which complexity and complication can be studied and perhaps differentiated, but they run the risk of confounding the two. Additionally, for the study of real places and people, models based on econometrics will be limited and the challenge is to bring narrative information into agent simulations. As well-known in ecological ibm, the initial locations of individuals strongly affects the outcome, and many agent models are not good at assigning calibrated agents to the right place (in some applications privacy issues will actually prevent this). The outcomes of agent models may then display results, especially “emergence,” that are at scales that are too coarse and/or general to help understand real places – although they may allow comparison with other dynamical systems and identify system constraints, which could be useful.

Key insights that I can bring to the table include (references cited are on my bio pages):

In self-organizing systems, evolutionary computation has the potential to help understand the broad form of the functions describing system behavior, but self-organization limits or perhaps prohibits the determination of a narrow range of function specifications (Malanson & Zeng 2004).

Local, nonlinear pattern-process feedback can extend to broader scale linear correlations between pattern and process This type of interaction indicates self-organized complexity, but the form is yet to be determined (Zeng & Malanson 2006).

The introduction of exogenous drivers of pattern formation into a self-organzing system produce a threshold response where the size of the patterns exceeds the spatial extent of the self-organizing feedback (Zeng, Malanson, Butler, in review).

GIScience and landscape ecology can develop synergies by building on this area of geocomputation and complexity theory, as in analysis of attractors in state spaces of spatial metrics from spatially explicit simulations and representing their uncertainty; visualization is insufficient (Malanson et al. 2006a).

Power-law distributions and/ or alternative approaches in self-organized complexity, including self-organized percolation and the inverse cascade model, and highly optimized tolerance, based on their common ancestry in percolation theory, might provide insights into spatial pattern development (Malanson et al. 2006b).