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Guest editorial

Complexity science, complex systems, and land-use research

'Complexity' has emerged as an important topic across many disciplines. This includes the social spatial sciences with their concern for describing, understanding, and explaining linkages between space – time patterns and processes involving component interactions, nonlinearity, feedbacks, and multiple scales. The number and variety of scholarly organizations, specialty academic journals and publications, and popular press books that self-identify under the rubric of 'complexity' are testament to shifts towards complexity thinking. The intellectual roots of complexity stretch back at least to early work on cellular automata, cybernetics, and general systems theory (Manson, 2001; Thrift, 1999). Some observers, apparently annoyed by potentially overexuberant claims made during complexity's popularizing phase of the 1990s, have espoused a 'been there, done that' attitude as exemplified by Berry's (1999) response of déjà vu to Krugman's (1991; 1996) 'new economic geography' (see also Berry, 1994) or Murray's "So what's new about complexity" (2003). These works raise the question: is there nothing new under the sun when it comes to complexity? We concur with others in answering that most likely there is nothing *entirely* new; for it is extremely rare if not impossible for any developments in scientific thinking and practice to *not* be indebted to antecedent ideas (see also Manson 2001; O'Sullivan, 2004). The present state of complexity science is characterized by accepted complexity hallmarks such as heterogeneity, historical and spatial contingency, path dependence, and feedbacks of social production and reproduction.

However, within the spatial sciences and particularly during the 1990s, it is hard to deny that new complexity-oriented developments *were* indeed brewing. If one envisions a logistic curve of diffusion, complexity work issuing from the early 1990s arguably was situated near the inflection point and an upward trend continues to the present. Or, conversely, has complexity topped out as Horgan (1995) suggested a decade past? Either way, complexity has clearly moved beyond beachhead status within the spatial sciences, and we see a continuing maturation phase unfolding in the coming years.

It is in light of these developments that the idea of a theme issue of spatially oriented, complexity-based research arose. This issue had its genesis in multiple sessions on "Geographical Perspectives on Complexity Theory and Complex Systems" held at annual meetings of the Association of American Geographers in Los Angeles (2002) and New Orleans (2003). The Los Angeles meeting hosted the first dedicated complexity sessions at this venue and, in retrospect, included an eclectic set of papers. The New Orleans meeting divided papers into more theoretically oriented and more modelling-oriented sessions. Four papers from the latter were subjected to the journal's peer review process and included in this issue of *Environment and Planning B*. Papers from the theory sessions appear in a theme issue on 'Space, place, and complexity science' in *Environment and Planning A* (O'Sullivan et al, 2006).

The fact that the four papers of this theme issue all investigate aspects of land use was not the original intent, yet it provides a thematic focus given its inherently spatial nature and the complex coupling of human decisionmaking agents with the landscapes that they transform over space and time (Parker et al, 2003). Thrift's observation that complexity is "a body of theory that is preternaturally spatial" (1999, page 32) resonates strongly with spatial science sensibilities and is borne out by canonical models such as

Conway's Game of Life, Bak's sand pile, and a wide range of published investigations situated in explicitly spatial environments. O'Sullivan et al (2006) articulate the "close alliance between space and place-based research and complexity as based on multiple related themes: *relationships between people and environment, spatial variability, processes at multiple and interlocking scales, and combined spatial and temporal analysis of system*" (emphasis added).

Complex systems and complex simulation models

What is complex about complex systems, and what is the role of simulation in their investigation? We answer both of these questions below in order to understand better the contributions of the papers in this theme issue. 'System' is commonly taken to mean a group of interacting, interrelated, or interdependent elements forming a holistic functional whole. Notwithstanding ontological debates concerning how we define the existence and boundaries of a system, we take it as given that systems (for example, land-use systems or spatial economies) exist and merit investigation. Beyond this, however, confusion and imprecision can arise with different understandings of the 'complex' nature of systems.

One understanding is that complex systems integrate multiple thematic domains. This can be thought of as related to, but not necessarily equated with, interdisciplinarity. One track of the US National Science Foundation's Biocomplexity in the Environment program solicits research requiring "quantitative, interdisciplinary analyses of relevant human and natural system processes and the complex interactions among human and natural systems at diverse scales." Similarly, in a panel discussion on urban systems research, White justifies the need to model cities by claiming that a city is "an integrated whole made up of a number of physical, biological, and human subsystems ... [and] none of the subsystems can be fully understood if they are considered in isolation from the others" (1998, page 357). Of course, interdisciplinarity need not be limited to a bridging of the natural and human domains, and it is easy to think of many scenarios operating wholly within either the social or the natural sciences.

A second and narrower understanding of complex systems lies in the paradox of complexity arising from simplicity. This view sees the complex nature of systems as emerging from nonlinearities thanks to the large number of interactions involving feedbacks occurring at one or more lower levels within the system. Moreover, this understanding is taken further by positing that rules governing these interactions are in fact simple so that the complex emerges from the simple. Manson (2001) refers to this as 'aggregate complexity'. Cellular automata (CA) models driven by simple, local rules or agent-based models coupled with automata landscapes are examples of aggregate complexity applied to human – environment systems. Implicit in this understanding is the existence of scale hierarchies, in which space – time outcomes of complex systems might include fractals, power laws, rank-size distributions, multiple and/or punctuated equilibria, threshold-related bifurcations, and the emergence of novel and unexpected structures (Batten, 2001).

At first glance, this understanding of 'complexity emerging from simplicity' is driven by reductionist approaches that vastly simplify microlevel processes in order to probe outcomes or behaviours at the macrolevel—hence, complexity's claim for holism. Although the implied linking of (spatial) pattern to process can be viewed positively, the messiness of the real world makes it difficult to find a balance between model parsimony and real-world pattern outcomes. This challenge can clearly be seen in the dynamic between pattern and process. The spatial sciences, especially with the advent of GIS, are particularly adept at describing spatial configuration and composition and, increasingly, the temporal domain. Prime examples are found in early work on fractal characterization of urban morphologies and other signature-based work, which laid the ground for subsequent process-oriented models of evolutionary dynamics (Batty and Longley, 1994). A focus on pattern continues to be important to generating, for example, novel approaches to situating space–time dynamical patterns within existing or yet to be developed typologies along the lines of an ordered–complex–disordered continuum or entropy-based schemes.

A third understanding of 'complex system' extends the notion of 'complexity emerging from simplicity' by creating more refined representations of microlevel heterogeneity and interactive processes and factoring in top-down (perhaps emergent) structures that feed back to influence bottom-up phenomena. This refinement of the process side has benefited from developments in dynamical spatial simulation techniques that support spatially distributed, cellular and object-oriented frameworks involving representations of decisionmaking agents and landscapes upon which natural and human processes effect change (see Parker et al, 2003). These models come at the price of increased complication because of the presence of many heterogeneous components, particularly when interacting parts (agents, components, patches, pixels, etc) are imbued with behaviours involving interdependencies, feedbacks, thresholds, and nonlinearities.

Importantly, this final definition of complexity, which relies on extending basic notions of 'complex systems', typically involves simulation modelling, which has become the de facto methodology of much complexity research. The subsequent need for a range of modelling approaches has led to associated challenges. An obvious one is that all models are based on a set of assumptions or approximations about how a system works. This is especially true for complexity models, which tend towards mathematical and computational models that are necessarily simulation models in which the primary structural decision revolves around dynamism. Unfortunately, given that computers are not strictly capable of handling continuous dynamics, most operational complex systems models can be characterized as dynamic, discrete change, and stochastic.

Following from the definitions of complexity noted above, complex system simulations are typically based on the global consequences of local interactions of members of a population. The models usually consist of an environment or framework in which interactions occur among individuals defined in terms of their behaviours or procedural rules and characteristic parameters. Individual-based models operate when the characteristics of each individual are tracked through time (Reynolds, 2005). This is in contrast to modelling techniques in which the characteristics of the population are averaged together, and the model attempts to simulate changes in these averaged characteristics for the whole population. Individual-based models are also known as entity models and are a subset of agent-based models.

Not all spatially explicit individual-based or agent-based models exhibit mobility, in which the individuals can move around their environment. Spatially explicit models may use either an approximated continuous or a discrete space. An autonomous agent can exist in isolation, or it can be situated in a world shared by other entities, in which case it might be reactive or deliberative (Moreno and Etxeberria, 2005). An autonomous agent may function exclusively with abstract information or it may be embodied in a physical manifestation. Combinations of situated, reactive, and embodied define several distinct classes of autonomous agents (Reynolds, 2000). In the two papers presented in this theme issue that employ simulation techniques, all agents are situated, embodied, reactive, virtual agents. Underlying the translation of complex system to simulation model is the premise that any agent in the system must be definable as a discrete entity (for example, see Chen, 1976) *and* function via a unique algorithm.

Any 'agent' that does not meet these two criteria is not an agent. Some authors confuse the environment with the agents acting upon those environments.

An agent-based model is any computational system whose design is fundamentally a collection of interacting parts. In the hierarchy of complex system models, the broadest definition is the agent-based model. Individual (agent)-based models are a subset of multiagent systems. Individual-based models are distinguished by the fact that each 'agent' corresponds to an autonomous individual in the simulated environment. Frequently, individual-based models with multiple individuals are referred to, incorrectly, as multiagent systems. Multiagency requires multiple algorithms, not, merely, multiple copies of the same individual. CA models are a subset of individual-based models, composed of spatially explicit, grid-based, immobile individual-based models.

Typically, traditional CA models are homogeneous with all cells identical and fully occupying space. Conversely, a grid-based individual-based model might occupy only a few cells and more than one distinct manifestation of that individual type might live on the same grid. Of course, a CA can have cells in various states, and so represent concepts such as 'empty' or 'occupied'. Although the distinction is mitigated by parallel-processing hardware, one difference is whether the simulation's inner loop proceeds cell by cell, or individual by individual. Further, reversibility is a significant difference between CA and other models; CA models are not reversible, all other agent-based models are. This matters because CA pattern trajectories from almost all initial states tend to merge with time into concentrated 'attractor' states. These attractor states, by definition, include only a very small fraction of the total list of all possible states. This process of irreversible evolution is the self-organization often referred to but 'unexplained' in the literature.

By searching for repeating patterns in multiple spatial and temporal scales, or hierarchical patterns, it becomes possible to characterize, at least in limited terms, the physical nature of a system (Wolfram, 1983; 1984). Some systems contain multiple variables with apparent complexity; however, a system based on multiple variables does not in itself guarantee complexity. In essence, multiple interactions impossible to characterize using traditional mathematical forms give the appearance of complexity while actually being more precisely defined as complicated (Messina, 2004). Frequently, modelling environments found in the literature confuse the two. This distinction is fundamental in any modelling endeavour purporting to be based on complex systems. The self-organizing nature of the driving (or pulling) attractor states determines the form and extent of the final, emergent patterns. In Wolfram class 4 CA models, the class typically associated with 'complexity', a particular final pattern may evolve from many different initial conditions (Wolfram, 1983; 1984). These types of systems require computational or algorithmic complexity equal to the explicit simulation in place (Manson, 2001). These systems are, in effect, unpredictable in a purely deterministic sense and must be resolved by explicit simulation.

In this issue

The four papers in this issue explore aspects of complex land-use systems and speak to issues raised by simulation modelling either directly or indirectly. Two of the papers present dynamic spatial simulation models—one via agent-based modelling and the other via CA. The remaining two papers complement a focus on simulation by focusing, in one case, on the representation of agent heterogeneity, and for the other, on identifying characteristic signatures of landscape complexity.

Fernandez et al tackle the problem of how best to represent agent heterogeneity for agent-based modelling of residential land-use dynamics in Michigan, USA. Agents in this case are individual householders who have a set of locational preferences with regard to exurban land-use decisions. One conclusion specific to this study is that agent heterogeneity is best represented stochastically by using means and standard deviations from empirically defined clusters (that is, agent classes) to populate agent-based models. The broader message is the need to inform microlevel representations with empirically grounded data. Their use of relatively traditional and mixed (though quantitative) methods is somewhat reminiscent of Byrne's (1998) critical realist interpretation of complexity science and is a reminder that much of the effort in complex systems research ought to occur before the first line of simulation code is written.

Sengupta et al utilize a survey of agricultural producers from Southern Illinois to identify three possible categories of agents that behave differently in response to a common policy scenario, the Conservation Reserve Program. In developing the agents, the authors highlight the complex nature of the response to policy that is observed in the real world. In particular, the interplay of demographic characteristics with biophysical drivers is identified as one of the most significant determinants that generate different outcomes. The incorporation of spatial contagion due to social networks or neighbourhood effects is mentioned as a future research direction.

In Messina and Walsh, classically 'complicated' population/environment data are explicitly modelled in a complex systems framework. In the only paper in this theme issue that is unabashedly about CA, the authors develop and present a custom software implementation. The authors discuss the modellers' quandary of balancing simplification and generalizability. If one goal of complex systems modelling is generalizability then modellers must conform to the broader scientific concerns about model construction. Combining social and biophysical data is often an explicitly stated goal of complex systems modelling. In practice, this combination is much harder to accomplish, and the authors detail these issues and propose solutions.

Crawford's contribution explores how the concept of self-organized criticality (SOC) might be used to describe and ultimately model landscape dynamics in Rondônia, Brazil. Self-organization, and SOC in particular, is one of the stronger claims made by complexity science that has garnered relatively little attention in the social sciences compared with the volume of natural science publications (although see Portugali, 2000). Here, Fourier-based methods of pattern analysis are applied in the spatial domain to identify signatures of SOC. Crawford views colonist households as dissipative agents that collectively imprint a complex order on landscape pattern via the injection of energy. Unlike other work in this area, he is careful to avoid promoting SOC as a totalizing framework because of the implausibility of pure self-organization in empirical, social environments containing agent heterogeneity, especially where it is problematic to exclude broader systemic influences that run counter to the concept of self-organization. SOC, more than most other theories of complexity, exemplifies a 'complexity from simplicity' understanding of complex systems. The potential for future research to take advantage of SOC depends on striking a balance between the messiness of real-world land-use behaviours and the simplicity of SOC's energetics-based approach.

Concluding thoughts

As models become increasingly sophisticated, it is obvious that they are indeed more complicated even as they aspire to represent system complexity better. Although Occam's razor may inform decisions about which parts and behaviours to include (and exclude) and how to represent heterogeneity, these decisions are influenced differentially according to individual or collective research scopes and goals, commitments to theoretical 'first principles', capabilities for empirical data, and technical proficiencies.

Because any model is by definition a simplification, more refined models have the potential to fit within an understanding of 'complexity emerging from simplicity'. To return to the theme of paradox, distinctions among the growing array of complex systems models might best be framed around degrees of simplicity which would seem to revolve around some combination of purpose, taste, and technical know how. Speaking more broadly of complexity theory (or theories), Manson (2001) cautions that the value of complexity exists in the eye of the beholder. A similar sentiment likely exists with regard to the nature of the 'complex' in complex systems, and the same can be said for the nature of the 'simple' which curiously has received little attention.

As a parting thought, it is important to note that up to this point we have been guilty of imposing two potentially misleading binary constructs: complex – simple and pattern – process. With regard to the latter, we by no means wish to suggest that one must be privileged over the other, but it is fairly evident that pattern (structure), however it may look, is created over time via any process. Something always takes shape, changes shape, and comes out the other end in either real or virtual worlds. As the modus operandi of much complex systems research, simulation risks being critically flawed if plausible representations of processes with linkages to empirical patterns are untenable.

Our hope is that the contributions to this theme issue will help to move complexity science and complex systems research forward. Although the current pace of simulation modelling research will continue if not increase, difficult issues surrounding ontological notions such as self-organization and emergence have received less attention than other aspects of complexity, which suggests the need for redoubled effort in this area. Finally, we thank Michael Batty for allowing us the space to discuss and present empirical examples of complexity science, complex systems, and land-use research.

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