Challenges to evaluating models of geographic complexity

Steven M. Manson

Department of Geography, 414 Social Sciences, 267 19th Avenue South, University of Minnesota, Minneapolis, MN 55455

Abstract: Geographic complexity—the explicit integration of complexity research with space and place-based research—faces interrelated methodological, conceptual, and policy challenges. The rubric of model evaluation is central to both understanding and meeting these challenges. These include methodological issues such as sensitivity and complex scaling; the conceptual challenges of conflating pattern and process and reconciling simplicity and complexity; and policy issues posed by the science-policy gap and post-normal science. The importance of these challenges and the centrality of model evaluation to meeting them are demonstrated through examples drawn from human-environment systems, with particular reference to global environmental change and land-use and land-cover change. Specific model evaluation strategies are also offered.

Keywords: complexity, geographic complexity, model evaluation, geographic information science

Citation: Manson, S. M. (2007). Challenges in evaluating models of geographic complexity. *Environment and Planning B* 34(2): 245-260.

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1 Introduction

Complexity theory is leading many disciplines to consider the importance of geographic[1] concepts, while researchers of place and space increasingly use complexity theory (Thrift 1999; O'Sullivan 2004). This integration is especially notable in geographic information science (GISc), an early adopter of complexity approaches such as agent-based modeling and cellular automata. Despite good prospects for continued growth, geographic complexity faces intertwined methodological, conceptual, and policy challenges that remain to be addressed in a comprehensive manner. Model evaluation—calibration, verification, and validation—provides a useful, and perhaps necessary, rubric with which to examine these challenges and develop strategies that meet them.

In Section 2, we define geographic complexity and explore how its epistemological underpinnings point to the primacy of modeling and model evaluation in understanding systems of geographic complexity. Section 3 considers methodological issues raised by sensitivity and scale in complex systems while section 4 examines conceptual challenges posed by questionable conflation of process and pattern and the tension between simplicity and complexity in complex systems. In section 5, we consider policy challenges posed by the science-policy gap and the related notion of post-normal science. Each of these sections ends with potential solutions to the challenges raised by these methodological, conceptual, and policy issues. Throughout we also note critical connections between these challenges and draw on examples of coupled human-

[1] The term ‘geographic’ is not conflated with the discipline of geography, but instead with the interdisciplinary engagement with notions of place and space. This distinction is developed below.

environment phenomena, particularly global environmental change and land-use and land-cover change.

2 Geographic complexity and model evaluation

2.1 Complexity concepts and models

The complexity sciences can be seen as being comprised of three major streams (Manson 2001), although there are a variety of other schemas available as well (e.g., Byrne 1998; Cilliers 1998; Lissack 2001; Reitsma 2002). First, algorithmic complexity is concerned with the perceived complexity of system structure. Second, deterministic complexity examines complexity with the precepts of nonlinear analysis, chaos theory and catastrophe theory. Third, aggregate complexity focuses on how individuals working in concert create complex systems such as economies or ecosystems. All three apply generalized templates to an array of phenomena in a way not seen since general systems theory (von Bertalanffy 1968). Self-organization or emergence, for example, are conceptual templates applied from stock market crashes to earthquakes while patterns such as fractals and power-law distributions are seen as universal hallmarks of complexity (Malanson 1999; Manson 2001)

Complexity conceptual templates have associated computational approaches, use of which is necessary because many complex phenomena are difficult model with methods that simplify systems through principles of superposition, equilibrium, and linearity (Arthur 1999). Algorithmic and deterministic models simplify complex systems through information measures, nonlinear equations, and system models. Aggregate complexity uses methods that include evolutionary techniques (e.g., genetic algorithms and artificial life), neural analogs (e.g., artificial neural nets), cellular models (e.g., cellular automata, random Markov fields), and agent-based models (termed multi-agent systems or individual-based models). Many complex concepts cannot be explored without using these methods, which leads to epistemological ramifications considered below.

2.2 Geographic complexity

Geographic complexity may be defined as research that combines complexity science with geographic concepts (space and place) and uses modeling as a key mode to examine systems spanning multiple spatial, temporal, and societal scales. Complexity research increasingly uses concepts of space and place (see Byrne 1998; Cilliers 1998; Lissack 2001; Manson 2001; Reitsma 2002; Urry 2003). We term these "geographic" without implying that they are the sole province of the discipline of geography, much as the journals *Economic Geography* and *Journal of Economic Geography* are associated with geography and economics respectively. In terms of geographic research, there is fruitful collaboration between GISc and complexity, although there is also crossover between qualitative and quantitative complexity research.

Geographic complexity spans a range of substantive areas, takes an explicitly interdisciplinary cast, and examines systems spanning multiple spatial, temporal, and societal scales. While complexity sprang from the union of computer science, physics, biology, and economics (Lewin 1992), it has quickly become interdisciplinary. Geographic concepts, and GISc in particular, is similarly embraced by a variety of disciplines interested in explicitly combining complexity to geographic concepts of place and space. These range from public health (Gatrell 2005) to ecology, environmental biology, and climatology (Rind 1999; Phillips 2003; Roy et al. 2003; Brose et al. 2004), through to anthropology, economics, regional science, and sociology (Arthur 1999; Dean et al. 2000; Batten 2001; Sampson et al. 2002). This interdisciplinary focus allows complexity and GISc to model complex spatiotemporal phenomena, such as those that exemplify global environmental change and land change, that exhibit characteristics such as nonlinearity, self-organization, deterministic chaos, and path dependence (Rind 1999; Parker et al. 2003).

2.3 Geographic complexity and model evaluation

Complexity research relies on modeling as its de facto epistemology (O'Sullivan 2004). Complexity has implicitly adopted the "semantic conception" of the relationship between theory, models, and reality (after Henrickson and McKelvey 2002). As per Figure 1, the classic view of science is termed the axiomatic conception of science, which holds that theory leads to testable models evaluated against reality. Less rigid and of broader applicability is the normal science conception (applied to organizational science by McKelvey (1999), where theory and reality are linked by human observers in addition to being understood through the use of models. Complexity science, however, has implicitly adopted the semantic conception of science, whereby models intermediate reality and theory. In other words, for complex systems, the linkage between reality and theory can be made only through computational modeling because this is the only means of capturing the complexity of both. While this tight theory-model-reality linkage exists for a variety of reasons (Henrickson and McKelvey 2002), most important for this discussion is the fact that we understand complex systems with models

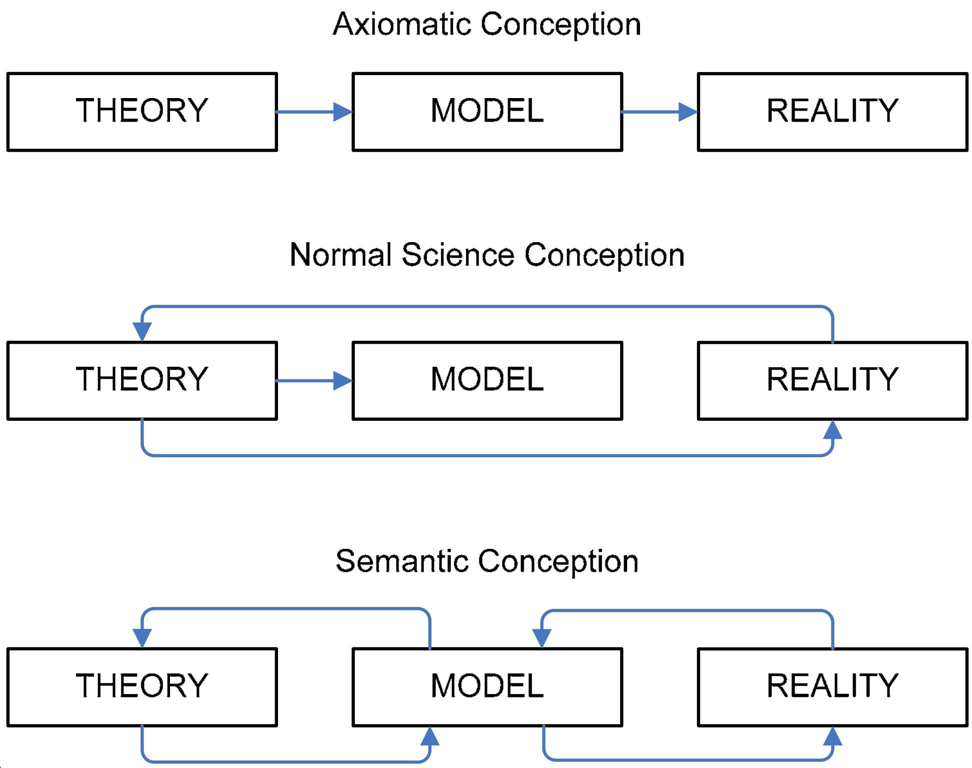

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Figure 2).

Model evaluation is a necessary focus for understanding and meeting the challenges faced in geographic complexity research. Evaluation is the means by which models test competing visions of the relationship between complex reality and complex theory. Evaluation is a general term for model calibration, verification, and validation, which involve, respectively: specifying or fitting a model; ensuring that it functions and is internally consistent; and comparing its structure and outcomes to information not used in its construction. In addition to research on model validation, there is a growing recognition that our ability to evaluate models of dynamic spatial systems is being outstripped by our capacity for building them (Gardner and Urban 2003; Manson 2003). Many complexity-based models of land use, for example, remain unevaluated, and those that are tend to be evaluated by extensions of standard statistical methods that are not oriented towards complexity as such (Verburg et al. 2005).

More importantly, while GISc is part of the broader effort of evaluating models of geographic complexity, it must also explicitly address the corollaries of complexity theory. GISc has very successfully concentrated on the mathematical and statistical evaluation of sensitivity and error propagation (Lanter and Veregin 1992; Heuvelink 1996); validation (Costanza 1989; Pontius 2000; Walker 2003); and conveying uncertainty to decision makers (Ehlschlaeger et al. 1997; MacEachren and Kraak 1997).

However, geographic complexity faces broader methodological, conceptual, and policy challenges

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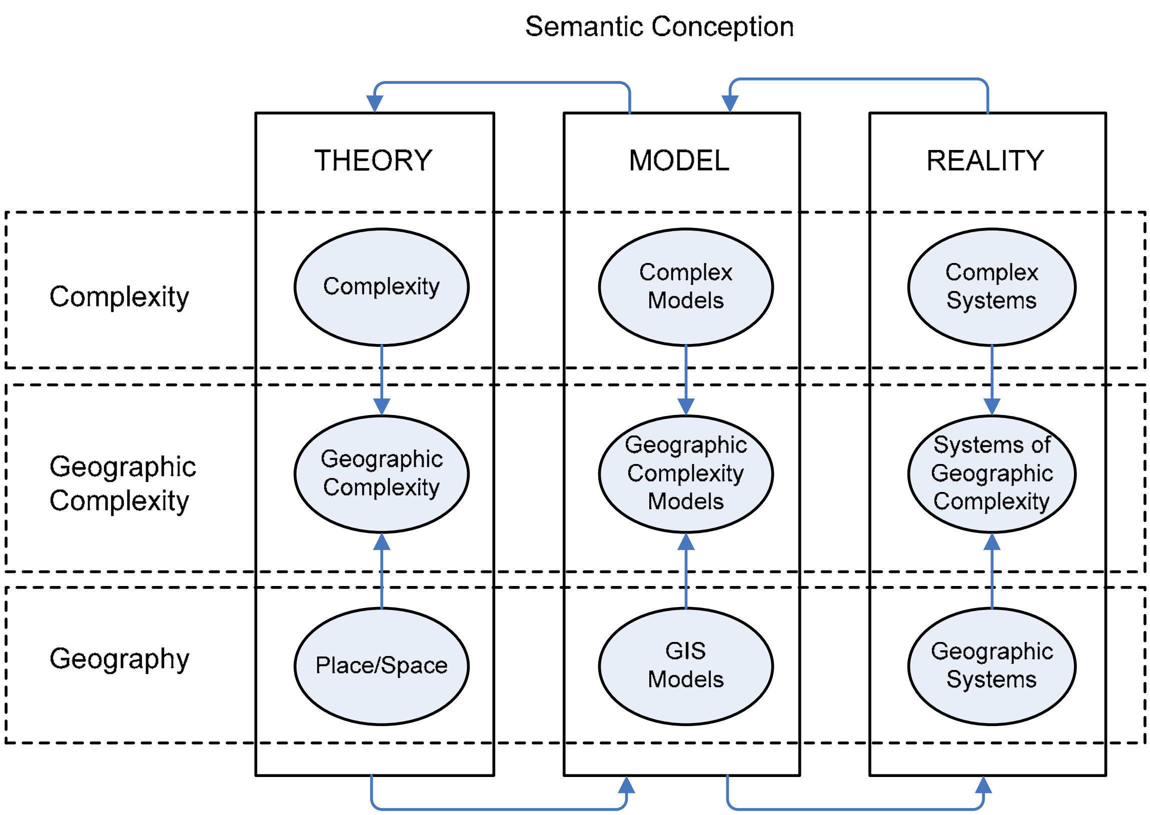
Semantic Conception
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GIS Models
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Figure 3). We highlight six distinct challenges in this paper: methodological issues of sensitivity and scale; conceptual challenges of conflating pattern and process and reconciling simplicity and complexity; and policy issues of the science-policy gap and post-normal science. There are many other challenges besides these, and within each, we only examine a few critical aspects. Similarly, we examine key linkages between these challenges while acknowledging that there are others beyond the scope of this piece.

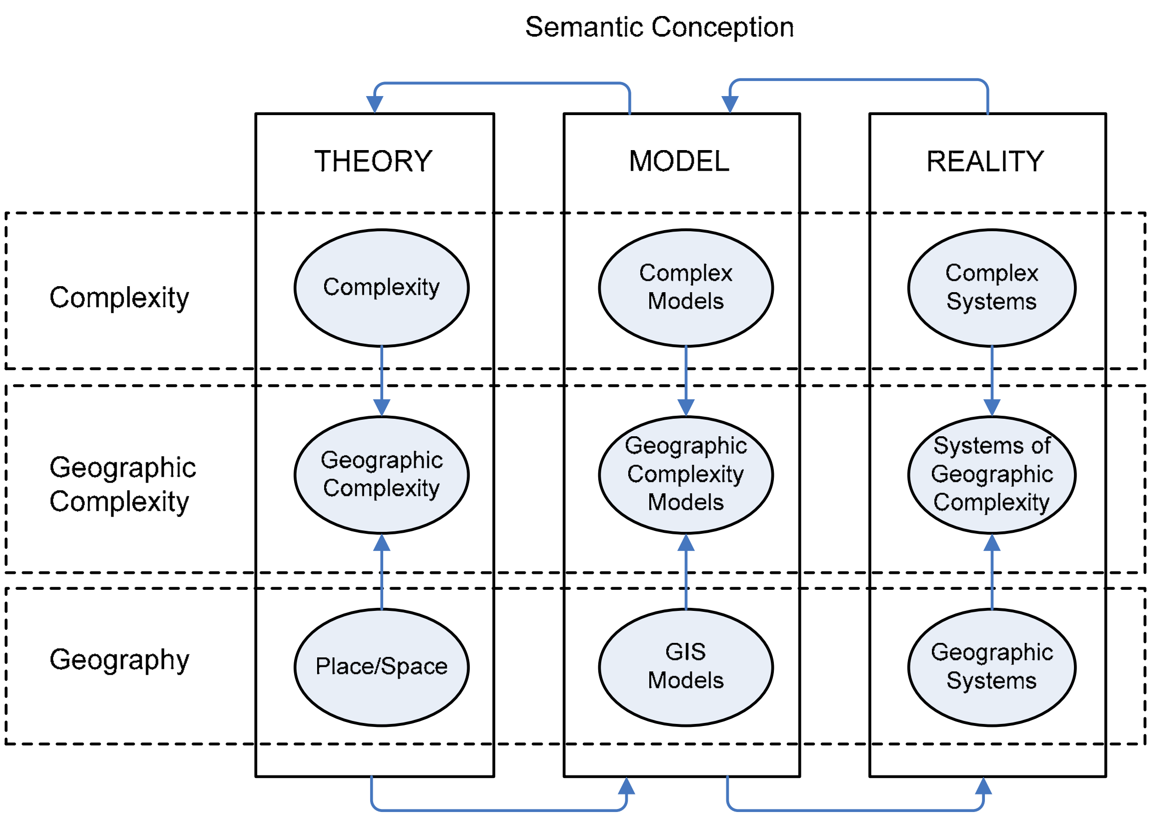

Figure 3 traces relationships between challenges that can be understood as propagating through second and third order relationships (e.g., sensitivity is linked to scale and in turn to pattern vs. process and post-normal science).

3 Methodological challenges

3.1 Complex sensitivity

While modeling dynamic systems is difficult for reasons ranging from implementation details to theoretical issues surrounding time, modeling complex systems entails dealing with how systems strike a balance between change and stability. Complex systems can exhibit sensitivity in that large and sudden shifts in system behavior can occur in response to relatively small perturbations in inputs. This attribute of complex systems complicates model use and evaluation because sensitivity is generally assessed by determining how incremental changes in input propagate through model structure to produce varying outcomes. A model with smoothly varying relationships can be examined by parameter sweeping but more complicated models can require sophisticated test designs that identify tipping points and fine thresholds (Crosetto and Tarantola 2001).

Sensitivity in complex systems is complicated further, in a broad sense by nonlinearity, where system outputs are not proportional to at least some portion of inputs. As Philips (2003) notes, nonlinearity often contributes to sensitivity in complex systems, but not all complex systems are nonlinear nor are all nonlinear systems complex. This contingency is seen in early models of deterministic complexity, such as the meteorological system described by Lorenz (1963) or population boom-bust cycles (May 1976). The overall state of these systems is sensitive to incremental changes in inputs, which necessitates sensitivity testing sufficiently sophisticated to identify them. Similarly, linked human-environment systems can possess distinct thresholds that define their resilience (capacity to absorb perturbations without affecting system structure), adaptability (ability to manage resilience), and transformability (capacity to create a new structure in the face of perturbations not accommodated by system resilience) (Walker et al. 2004). Complex systems can also exhibit sensitivity to initial conditions, or relatedly termed independence of initial conditions (Phillips 2003). Large shifts in system behavior can result from microscale perturbations, giving rise to multiple varying attractors (values of system state or phase variables towards which the system tends) across small shifts in inputs. Seemingly random behavior can be understood through systems of equations and strange attractors, or attractors towards which the system tends but never quite reaches (Mainzer 1996).

Complex systems can also be path dependent, where future states are highly dependent on and sensitive to previous states to the point of lock-in, where the system's path becomes fixed or constrained due to positive feedback. One of the key barriers to the introduction of new energy systems, for example, is lock-in of the current fuel distribution system (Grubb 1997). Similarly, Brown and others (2005) found that agent-based models can be used to confirm our understanding of how land use is path dependent.

3.2 Complex scale

Complexity offers new ways to think about scale as both a framework for analysis and a subject of inquiry, giving new interpretations to scalar concepts such as hierarchies, cross-scale interaction, self-similarity, or micro-macro linkages. Of particular importance to model evaluation is emergence: complex systems have qualities that are not analytically tractable from the attributes or states of their internal components, but instead result from synergistic interactions among these components (Holland 1998). Self organization in large systems such as the coupled economic-climate system leads to a variety of emergent phenomena important to global environmental change (Gibson et al. 2000; Easterling and Kok 2002).

Emergence is difficult to define, however, and so the less restrictive concept of supervenience may be more useful. It posits that a system's higher-level states, or macrostates, are dependent on the states of lower-level constituent elements, or microstates, such that macrostate changes cannot occur without causative changes in the underlying microcomponents. Importantly, "wildly disjunctive" or very different combinations of microstates can produce seemingly identical macrostates (Sawyer 2002: 542). More broadly, supervenience creates scalar hierarchies that complicate use of scale-sensitive metrics in model evaluation. Ecology's Hierarchy Theory similarly posits that scale levels in a complex system may have no a priori definition and can change over time (cf. O'Neill 1988; cf. Easterling and Kok 2002). The capacity for emergence to dynamically define scale levels bears on the use of statistical measures in model evaluation because most are subject to the ecological fallacy, the modifiable areal unit problem, and simultaneous change in resolution and extent (Bian 1997). While remedies for these effects exist, they rely on defining scale levels and these in turn are influenced by the capacity for scale levels to shift due to emergence and supervenience.

Emergence also makes it difficult to elucidate causal relationships among system elements because there is no one-to-one relationship between the microstates and macrostates in a given system. Emergent patterns are not obvious outcomes of given microstates nor, therefore, are modeling artifacts therefore easily distinguished from legitimate results (Holland 1992). Spatial ordering of transition rules in cellular automata, for example, can create model results that are artifacts of path-dependency and sensitivity to initial conditions (Ruxton and Saravia 1998). This problem is more acute with models of geographic complexity than with linear regression, for example, because the effect of model structure on outcome is ill defined. Evaluation metrics of outcomes alone therefore do not assess structure because of the potential for wild disjunction. This is considered in detail below with respect to the challenges of linking pattern and process.

3.3 Discussion

The nature of sensitivity and scalar behavior in complex systems suggests several model evaluation strategies. It is necessary to identify when assumptions about linearity and tractability in evaluation are at odds with sensitivity effects, such as sensitivity to initial conditions, or processes that dramatically change the system end state, such as path dependence, lock-in, and attractors. It is possible to assume that system dynamics are linear, for example, but this does not allow for complex behavior outside of model assumptions. It may be necessary to use specialized methods that actively poll sets of interacting parameters in order to identify nonlinear relationships among system components (Miller 1998) or tease out how differences in model outcomes are due to random noise versus path dependence (Brown et al. 2005).

There is a balance between sensitivity and metastability in complex systems that suggests lower and upper bounds for evaluating models of complex systems. The lower bounds are defined by how small perturbations in a complex system can be amplified into large and long-lasting effects (Cartwright 1991), including perturbations introduced through normal sources such as noise in data collection or errors in prosaic tools such as pseudorandom number generators (Van Niel and Laffan 2003). Upper bounds exist in how models of geographic complexity exhibit metastability through strange attractors, path dependence, and lock-in for socioeconomic (Byrne 1998; Elliott and Kiel 1999) and physical systems (Sivakumar 2000; Phillips 2003). The key implication for model evaluation of the interplay between sensitivity and metastability is that caution is warranted when using evaluation methods that assume linearity for extrapolation purposes or that seek applicability across scale levels.

Finally, model evaluation highlights, and to some extent drives, a move to better communication. Few publishing venues outside of manuscripts with digital media can provide model source code for evaluation, although venues such as online journals increasingly invite multimedia submissions (e.g., *Ecology and Society* or *Journal of Artificial Societies and Social Simulation*). Models of geographic complexity can also require a great deal of explication, which results in papers that are laden with figures, graphs, and technical appendices—all of which give the reader a complete picture at the cost of drowning him or her in detail. Scale and sensitivity merit evaluation tools that go beyond histograms, residual plots, and summary statistics and towards those that support iterative exploration of inputs and outputs (Frey and Patil 2002). Adoption of common modeling frameworks is beginning to allow external evaluation of models, as seen with SWARM or REPAST for agent-based models (Tobias and Hofmann 2004) or SLEUTH for cellular automata (Clarke 2004).

4 Conceptual challenges

4.1 Conflating pattern and process

Perhaps the most important issue in evaluating models of geographic complexity is the subtle relationship between pattern and process. Geographic complexity research can too easily focus on patterns of complexity instead of complex processes, whereby a system is considered complex if it merely exhibits certain hallmark patterns of complexity. These run the gamut from algorithmic complexity metrics to deterministic complexity concepts like strange attractors and aggregate complexity notions such as scale invariance. Conflation of pattern and process is one of the most exciting aspects of geographic complexity because hallmark patterns of complexity may lend insight into complex processes. A variety of scalar distributions—fractal variants, power-law, Pareto, Zipf—are associated with emergence, self-organized criticality, complex adaptive systems, and scale-free networks (Bak 1996; Barabási and Bonabeau 2003). GISc and geographic complexity have similarly examined links between the complex pattern and causative processes (Batty and Longley 1994; Goodchild and Quattrochi 1997).

While complex patterns arise from complex processes, they also result from non-complex processes or, more troubling, complex processes antithetical to one another. Taken to an extreme, the conflation of pattern and process is less about the plausibility of complex mechanisms and more about generating complex patterns. A prime example is given by *A New Kind of Science* (ANKOS, Wolfram 2002), which rearticulates the twin concepts that the physical universe can be seen as being represented by discrete computer programs and that complex systems beyond a certain level of apparent complexity are computationally equivalent. This leads to the compelling notion that most complex systems at their heart are essentially similar because they can be modeled as discrete complex computational processes. By way of illustration, ANKOS uses cellular automata to create patterns, in the form of computer images, which mimic those found in reality (e.g., animal pigmentation or air turbulence).

This work exemplifies two drawbacks of conflating complex pattern with process. First, complexity is meant almost exclusively in terms of a narrowly defined pattern that does not begin to approach the many different kinds of complex patterning possible (Mitchell 2002). Second, presence of complex patterns alone cannot be taken as an indicator of complexity. Many processes can create a single pattern (termed equifinality) and many patterns can arise from a single process (Beven 2002). Importantly, a system with complex patterns may have underlying processes that are not complex or they may be modeled as being complex in a way that is not consistent with real processes. While the patterns in ANKOS may be caused by cellular automata-like processes in reality, for example, there is no guarantee that they are (Giles 2002). Finally, emergence and supervenience, explored above, only add to the fragility of linkages assumed to exist between microcomponent processes and macrostate patterns.

More broadly, it is important to appreciate how models from the natural sciences are inappropriately exported to other contexts. This work often relies on deduction by analogy by matching patterns in a system to those in another and positing that their underlying processes are similar. Phenomena ranging from earthquakes to species extinction, for example, have been examined for hallmarks of complexity, such as scalar distributions and emergence, that are seen as indicative of underlying processes such as self-organized criticality (Bak 1996). Deduction by analogy, however, can lead to superficial notions of causality (Plotnick and Sepkoski 2001). In many biogeophysical settings "self-organization has been ascribed to phenomena that exhibit scaling features with little attention to the processes of organization" (Malanson 1999: 751). Even more problematic is use of natural science complexity concepts to model social systems in a manner that may be considered superficial because many aspects of human experience may lie beyond the ability of complexity modeling given its focus on simple causative processes giving rise to complex patterns (cf. Stewart 2001; Urry 2003).

4.2 Simplicity and complexity

Related to conflation of pattern and process is the difficulty of reconciling the simplicity of complexity concepts with messy reality. Complexity is considered a "generative science" (Epstein 1999: 41) that sees system regularities emerging from local interactions of autonomous entities—in essence, simple interactions lead to complex outcomes. Parallel to this is how algorithmic complexity and deterministic complexity identify the simple mechanisms that underlie seemingly complex systems. Interpreting complexity concepts to accommodate empirical observations and extant theories may lead, however, to models that stray from the wellspring of complexity research—that complexity arises from simplicity.

Cellular automata or agent-based models, for example, are used to replicate real-world patterns of land change but they must arguably use realistic generating processes to do so. These models are attractive because they can capture complex dynamics through local spatial rules applied to cells or simple interactions among agents (Parker et al. 2003). As these models become more complex, however, they can jeopardize the simplicity that makes them attractive in the first place or as a means of finding common ground with other complexity research (Torrens and O'Sullivan 2001). Classic cellular automata rules do not adequately reproduce real patterns of land use and urban growth, so from relatively early on they have been supplemented by global factors that modify rules or by local factors that modify rules for specific neighborhoods (White et al. 1997). An explicit goal of geographic complexity—simplicity—is balanced against the need for more complicated models of reality.

Another wrinkle is introduced when models of geographic complexity are inductively calibrated. With agent-based and cellular automata models of land use, there are many examples of researchers linking theory to models (usually locational theory to global parameters or pertinent data layers) and the models to reality by calibrating them against empirical observations through full parameter enumeration or best-fit optimization (Verburg et al. 2005). The potential drawback of calibrating models in this manner is the assumption of stationarity in rules over time. Even when transition rules are chosen to represent processes, when they are calibrated with inductive techniques against empirical patterns, the model therefore may not apply to situations beyond those found during the inductive calibration stage (Hodges and Dewar 1992). The equifinality problem also resonates here because model processes may not match those in reality, only the patterns. As a result, Torrens and O'Sullivan argue that much research in "urban [cellular automata] modeling is just that: research in modeling, and not research on urban dynamics and theory" (2001: 166).

This situation is even more important with methods such as artificial neural networks. While they can be evaluated with respect to outcomes, they generally cannot by evaluated with respect to structure or process because network configurations map poorly onto real processes (Intrator and Intrator 2001). The inability to evaluate structure is not critical when these models are used to assess the relative contributions of inputs to outcomes, in which case sensitivity testing and validation of model outcomes suffices (e.g., Shellito and Pijanowski 2003). Otherwise, not representing a process beyond a black box, however, renders the model less able to reflect changes and nonstationarity in the underlying system.

4.3 Discussion

Geographic complexity researchers are creating models that navigate the perils posed by conflation of pattern with process and the tension between simplicity and complexity by examining a variety of real settings (Malanson 1999; Parker et al. 2003; Phillips 2003). Through the rubric of model evaluation, geographic complexity moves beyond the superficial conflation of pattern and process by grounding models in the real world through empirical research and relating models back to theory. As Clarke (2004) notes, there must be a move in geospatial modeling towards determining the minimum scientifically acceptable level of calibration as a function of real world measurements.

Another strength of geographic complexity is its openness to interdisciplinary perspectives. Interdisciplinarity is challenging for reasons including a paucity of common metrics and language, imbalance in power and prestige between disciplines, inconsistent peer-review mechanisms, and issues of transparency and reproducibility (Risbey et al. 1996). Nonetheless, there is increasing recognition that large complex systems must be understood through interdisciplinary approaches. It is possible to identify emergent land-change phenomena, for example, by bridging the qualitative–quantitative divide through combining geospatial technologies such as remotely sensed imagery and global positioning system data with qualitative in-depth interviews (e.g., D'Aquino et al. 2003). Explicitly incorporating qualitative data is critical because data for validation must be held apart from that for calibration, and studies of land change, for example, have only recently been able to acquire data for more than one or two periods (Goldstein et al. 2004). While combining qualitative and quantitative research is difficult given their fundamentally different and sometimes openly antagonistic worldviews, geographic complexity is accepted by researchers that range from realist to constructivist in their ontological orientation (Manson and O'Sullivan 2005). In many ways, this work is an extension of approaches such as Qualitative Comparative Analysis or Fuzzy-Set Social Science, which bridges the divide (particularly in the social sciences) between seeking generalities and focusing on the complexity of specifics by balancing case-based research and larger variable-centered research (Ragin 2000). The importance of modeling to geographic complexity may prove to be an asset here because model creation helps to negotiate consensus views of research domains (Nicolson et al. 2002). Interdisciplinary research, either explicitly through large team-based research projects or implicitly through cross-fertilization of ideas, can attenuate the propensity for conflating pattern and process and help reconcile simplicity and complexity.

5 Policy challenges

5.1 Science-policy gap

Exploration of complex systems through modeling makes geographic complexity disproportionately vulnerable to the science-policy gap, or the misunderstanding about scientific results and, more broadly, the scientific research process among scientific, policy, and public communities (Bradshaw and Borchers 2000). The science-policy gap exists in part because of the intrinsic nature of scientific knowledge. There is broad acceptance in the philosophy of science that scientists approximate knowledge by assessing the accumulated weight of evidence for a given position—truth resides in scientific consensus. This formulation is epistemologically neutral because consensus may be achieved through a realist focus on replication (such as hypothesis testing, independent trials, and confirmatory research) or constructivist channeling of knowledge (such as coercive power relations and discursive practices) (Jasanoff and Wynne 1998). Consensus is leavened with minority viewpoints and the potential for Popperian falsification and Kuhnian paradigm shifts.

The science-policy gap is due in part to general misunderstanding about the role of consensus and the potential for falsification in knowledge generation. This gap exists for complex phenomena such as global environmental change and land change because they exhibit confounding behavior (e.g., nonlinearity, sensitivity to initial conditions, or self-organization) and because they span multiple spatial and temporal scales marked by lags and cross-scale interaction. As a result, there is a disconnect between tempered, contingent scientific knowledge and the level of certainty often wanted by policy makers. This disconnect can occur in the most deliberative settings, as when judges or juries consider expert witness testimony in courtrooms (Abraham and Merrill 1986), and it certainly occurs in broader policy spheres, such as governmental legislation with respect to environmental systems (Breyer 1993).

Consider the role of the media in the divide between scientific and lay understanding of global environmental change. From the early 1990s, there has existed broad scientific consensus on the existence of anthropogenic global warming, but this view has always been accompanied by contrary ones (Oreskes 2004). The journalistic convention of ‘balanced’ reporting translates this broad scientific consensus—large majority vs. small minority—into a discourse of balanced views. It also conflates uncertainty about issues such as the validity of hundred-year temperature forecasts with uncertainty about issues over which there is very little disagreement (Boykoff and Boykoff 2004).

The science-policy gap will always exist to some extent because models of many systems cannot support full consensus. Oreskes and others (1994) argue that absolute validation and verification of models of natural systems is impossible because the models are simplifications of open systems (only a closed system can be fully validated) and this argument extends to human-environment and social systems because they are no less open-ended (Batty and Torrens 2005). Models therefore can only be evaluated subject to several kinds of uncertainty: theoretical, empirical, parametric, and temporal (Oreskes 1998), all of which apply to complex models. Theoretical uncertainty, which stems from either not understanding aspects of a system or encountering irreducible limits to knowledge (Couclelis 2003), is accentuated by the evolving nature of complexity theory in general and more specifically by the nature of systems to which it is applied. Empirical uncertainty, where system characteristics are not amenable to measurement, is a key challenge to complexity research given the need for large spatiotemporal data sets and difficulty of defining emergence or deterministic complexity (Zimmer 1999). Parametric uncertainty, driven by the need for well specified yet manageable model inputs and relationships, is potentially heightened in complex systems due to the need to accommodate a range of relationships among system components and evolving definitions of geographic complexity concepts and models (Parker et al. 2003). Finally, temporal uncertainty, or the extent to which the modeled system remains stable or knowable in time, is pronounced in the dynamic, feedback-laden behavior of complex systems, as seen above in the context of complex scale and sensitivity.

5.2 Normal and post-normal science

The science-policy gap is affected by the relationship between normal and post-normal science. The gap and associated issues of evaluation largely exist under the aegis of normal science, when scientists convey to policy makers knowledge that has a high degree of certainty or when scientists can clearly identify the steps necessary to achieve the level of knowledge necessary for policy formation. Normal science therefore can be characterized as hard science guiding soft policy making, or where the science for a given issue is quite clear at both a conceptual and technical level, and it only remains for the political process to act on the science. Normal science is still prone to the science-policy gap but the gap can be narrowed through research and communication.

Post-normal science, conversely, applies to situations characterized by some combination of deep uncertainty, large decision stakes, and disputed values (Funtowitcz and Ravetz 1994). It is characterized as where soft science informs hard decision making, or where the science is uncertain at either, or both, the conceptual and technical level, for issues that require difficult political decisions. As such, post-normal science deals with issues that are largely beyond the science-policy gap. Post-normal science is concerned with large, complex systems, particularly those that lie on the interface between environment and human systems, such as nuclear power generation or global environmental change (Ravetz 1999).

The term science-policy gap also implies that science is insulated from society. This notion that has been abandoned in the philosophy of science, however, and replaced by considerable evidence that science and society are intertwined, especially for complex problems such as global environmental change that have political and cultural overtones. Actors support their viewpoints by characterizing, or mischaracterizing, model evaluation. Model uncertainty about some aspects of global environmental change, for example, have been purposely used by interests supporting global-warming policies like carbon taxes to make extravagant claims about unlikely scenarios in order to encourage action (Lomberg 2001) while those opposed to these policies parlay uncertainty into policy gridlock (Gelbspan 2004). While science as a whole is not bought and sold, it is embedded within a larger societal context in a way that is seldom fully appreciated by scientists or the public alike.

The potential for surprise in global environmental change further illustrates the nature of post-normal science and its ramifications for geographic complexity. Global environmental change has long spurred debate about the severity of change impacts and the opportunity costs of ameliorating them (Abelson 1990). These debates center around uncertainty, as when assessing the impact of carbon taxes on fossil fuel use, carbon emissions, and resultant anthropogenic climate impacts. Uncertainty here is constrained by roughly linear relationships, however, so models find that incremental carbon tax increases will generally have incremental effects on emissions (Dowlatabadi 1998). There are other parts of the global environmental system, however, that are prone to larger, abrupt shifts such as the sudden cessation of ocean circulation or emergence of fundamentally new energy technologies (Schneider 2004). These kinds of change can be usefully studied through geographic complexity but they still have aspects that are subject to post-normal science.

5.3 Discussion

Policy makers see models as arrayed along a continuum ranging from being 'truth machines' to merely offering one guess among many (Risbey et al. 1996). This divergence of views is legitimate for models of geographic complexity because they cannot be evaluated fully for reasons including incomplete scientific consensus, the complex nature and open-endedness of the systems modeled, and intractable uncertainty. While modelers conduct evaluation in accordance with their epistemic communities, the models are also used outside of these communities, and modelers are therefore partially responsible for how models are used. This is especially true given that there is no strict divide between science and it broader social milieu.

Meeting this responsibility requires us to swallow a bitter pill—in some respects better models of geographic complexity will not lead to better policy decisions. The underlying ethos of model evaluation is that decision makers can make better decisions if they are given understandable, trustworthy indicators of model validity. GISc and allied fields are constantly improving these methods, but they are limited by the science-policy gap and post-normal science for the case of geographic complexity. In some situations, the best case scenario is that policy makers can interactively plumb possible system scenarios through models as a form of "computer-assisted reasoning systems" (Bankes et al. 2002: 383).

Even if there was no science-policy gap for complex systems, they remain the province of post-normal science because they act over multiple spatial and temporal time scales that embody uncertainty and involve high stakes. Decision makers are therefore often left with just argument by analogy, such as looking to past climate change as an analog to current change (Glantz 1991), which can be susceptible to the problems of deduction by analogy found in conflating pattern and process. Offsetting these policy challenges requires inclusion of non-scientists in model evaluation. The public have knowledge and values about problems, such as global environmental change, that are complete, internally consistent, and ethically responsible, as when they take into account the welfare of future generations (Zehr 2000). GISc has a strong history of participatory modeling that is seeing renewed interest through public participation GIS (Leitner et al. 2000). Incorporating knowledge from a variety of sources leads to the construction of better models, broader model evaluation, and increased decision-maker understanding of models. This is seen in agent-based modeling efforts that incorporate local indigenous knowledge in understanding the effects of global environmental change (Nicolson et al. 2002) and in participatory modeling of land change for natural resources management (D'Aquino et al. 2003).

Explicit inclusion of non-scientists in model evaluation is also important to meeting the challenges of post-normal science (Funtowitcz and Ravetz 1994), which requires us to accept that some phenomena may be beyond modeling, or at least that some models remain beyond evaluation; our “thinking requires understanding that all models are wrong and humility about the limitations of our knowledge. Such humility is essential in creating an environment in which we can learn about the complex systems in which we are embedded" (Sterman 2002: 501). Models not amenable to evaluation are still useful as heuristic, bookkeeping, or training devices (Hodges and Dewar 1992).

Finally, geographic complexity researchers can consider how uncertainty and the potential for surprise in complex systems contributes to debate on the precautionary principle—when faced with deep uncertainty and high stakes, such as the potential for catastrophic climate change, how can we act in a manner that is reasonable given the scientific evidence, dictates of cost effectiveness, and the potential for inaction to lead to irreversible harm (O'Riordan and Cameron 1994)? By understanding the corollaries of the science-policy gap and post-normal science, we can identify situations under which society should pursue the precautionary principle in order to address surprising system behavior that can be understood through geographic complexity.

6 Conclusion

This is an exciting time to be doing geographic complexity research. Complexity methods and concepts are maturing while geographic research, particularly as incarnated in GISc, is rapidly expanding. While adopting and adapting complexity concepts and methodologies, complexity researchers that actively engage with concepts of place and space are sculpting the larger complexity research agenda. They are also beginning to offer unique insight into methodological issues such as sensitivity and complex scale; conceptual challenges of conflating pattern and process and reconciling simplicity and complexity; and policy issues posed by the science-policy gap and post-normal science.

More can be done, however, as meeting these challenges requires broader strategies for calibrating, verifying, and validating models of geographic complexity. The interplay between system sensitivity and metastability define scale limits in model evaluation. Interdisciplinary research with a distinctly geographic cast supports triangulation among, and replication of, varied approaches. Better communication of geographic complexity methods and theory within the science and policy communities will lead to better model evaluation.   More broadly, we must appreciate and accommodate the limited extent to which models can answer certain questions about complex systems. Even if scientists could somehow deliver unequivocal technical and scientific answers to questions posed by issues such as global environmental change, there will usually remain trans-scientific aspects of these issues that require a political component to answer the moral or ethical questions, and the rubric of model evaluation can help frame the answers.

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Figures

Figure 1. Axiomatic, normal science, and semantic conceptions of the relationship between theory, models, and reality

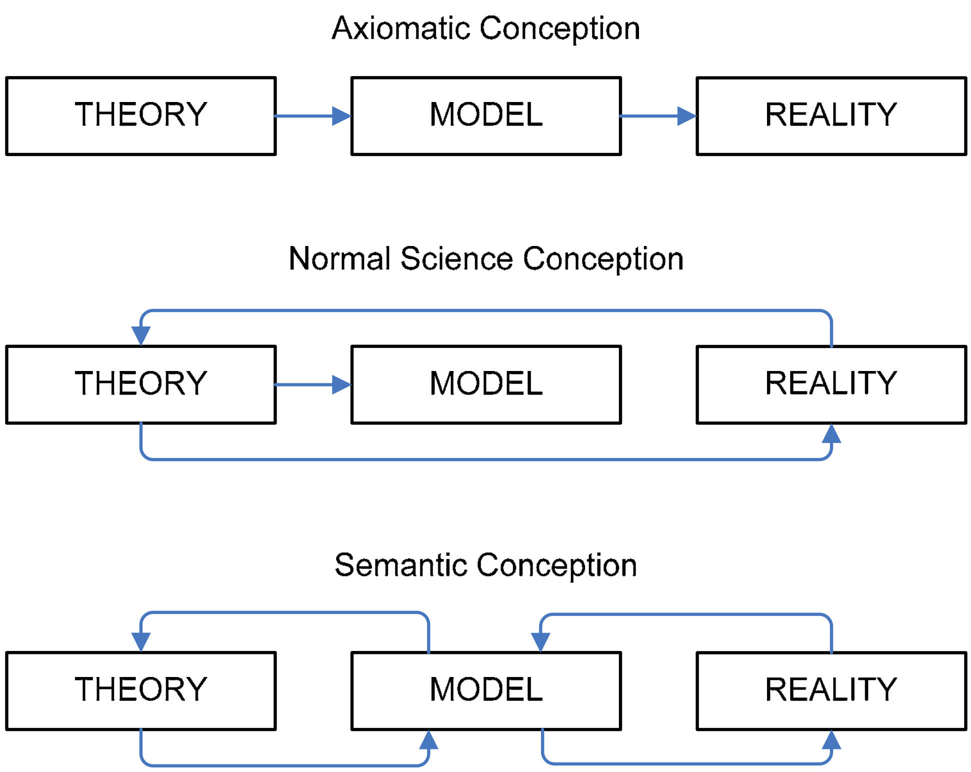

Figure 2. Semantic conception for geographic complexity.

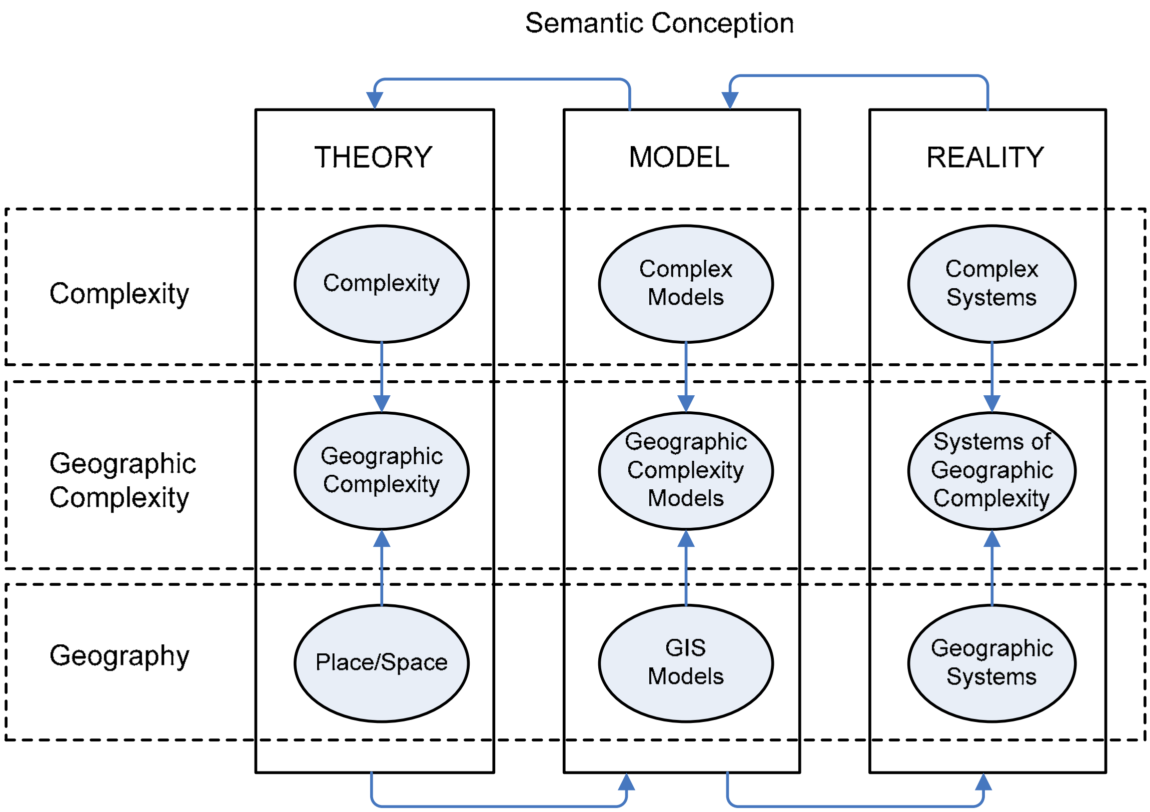

Figure 3. Relationships between various challenges to modeling geographic complexity.