Multi-Agent Systems for the Simulation of Land-Use and Land-Cover Change: A Review

Dawn C. Parker,* Steven M. Manson,** Marco A. Janssen,***
Matthew J. Hoffmann,**** and Peter Deadman*****

**Departments of Geography and Environmental Science and Policy, George Mason University*
***Department of Geography, University of Minnesota*
****Center for the Study of Institutions, Population, and Environmental Change, Indiana University*
*****Department of Political Science and International Relations, University of Delaware*
******Department of Geography, University of Waterloo*

This article presents an overview of multi-agent system models of land-use/cover change (MAS/LUCC models). This special class of LUCC models combines a cellular landscape model with agent-based representations of decision making, integrating the two components through specification of interdependencies and feedbacks between agents and their environment. The authors review alternative LUCC modeling techniques and discuss the ways in which MAS/LUCC models may overcome some important limitations of existing techniques. We briefly review ongoing MAS/LUCC modeling efforts in four research areas. We discuss the potential strengths of MAS/LUCC models and suggest that these strengths guide researchers in assessing the appropriate choice of model for their particular research question. We find that MAS/LUCC models are particularly well suited for representing complex spatial interactions under heterogeneous conditions and for modeling decentralized, autonomous decision making. We discuss a range of possible roles for MAS/LUCC models, from abstract models designed to derive stylized hypotheses to empirically detailed simulation models appropriate for scenario and policy analysis. We also discuss the challenge of validation and verification for MAS/LUCC models. Finally, we outline important challenges and open research questions in this new field. We conclude that, while significant challenges exist, these models offer a promising new tool for researchers whose goal is to create fine-scale models of LUCC phenomena that focus on human-environment interactions. *Key Words: agent-based modeling, cellular automata, complexity theory, land-use and land-cover change, multi-agent systems.*

Recently, global environmental challenges and the development of advanced computer-based modeling and analysis tools have expanded interest in the application of computational approaches to the study of human systems. Researchers are beginning to use these tools to address the challenges outlined by Openshaw (1994, 1995) to develop methodologies within human geography that seek computational solutions to problems involving both numeric and symbolic data. These new computational tools can be applied to various areas in geography, such as industrial location, transportation, biogeography, or the study of land-use/cover change (LUCC), and may complement existing quantitative and qualitative modeling approaches in human geography. This article focuses specifically on application of these techniques to the study of LUCC.

Land is a dynamic canvas on which human and natural systems interact. Understanding the many factors influencing LUCC has been the focus of scientific study across multiple disciplines, locations, and scales. But direct measurements alone are not sufficient to provide an understanding of the forces driving change. Linking observations at a range of spatial and temporal scales to empirical models provides a comprehensive approach to understanding land-cover change (Turner et al. 1995). One promising class of models designed to simulate and analyze LUCC are multi-agent system models of land-use/cover change (MAS/LUCC models). This article aims to provide a broad overview of the history of these models, offer our perspective on their potential role in LUCC modeling, discuss some key issues related to their development and implementation, and briefly review ongoing research based on this modeling paradigm.

MAS/LUCC models combine two key components into an integrated system. The first component is a cellular model that represents the landscape over which actors make decisions. The second component is an agent-based model that describes the decision-making architecture of the key actors in the system under study. These two components are integrated through specification of interdependencies and feedbacks between the agents and their environment. This approach to the study of systems with

Annals of the Association of American Geographers, 93(2), 2003, pp. 314–337

Published by Blackwell Publishing, 350 Main Street, Malden, MA 02148, and 9600 Garsington Road, Oxford OX4 2DQ, U.K.

many discrete, interacting components that generate observable behavior at multiple levels both draws from and facilitates comparisons to broader studies in complexity research (Manson 2001).

All of the authors of this article are involved in development of various MAS/LUCC models. During the planning and development stages of our projects, we have considered several key questions:

- What alternative techniques are available for LUCC modeling? What are the potential limitations of these techniques? Can MAS/LUCC models overcome some of these limitations?
- What are some ongoing applications of this modeling technique, and why have the developers chosen to use the new approach?
- What are the unique strengths of MAS/LUCC modeling techniques? How can these strengths guide researchers in selecting the most appropriate modeling technique for their particular research question?
- What is the appropriate role for MAS/LUCC models? Are these models best used in a highly abstract form to demonstrate potential theoretical causes for qualitatively assessed real-world phenomena? Alternatively, can they be used to create well-parameterized empirical simulations appropriate for scenario and policy analysis?
- How can these models be empirically parameterized, verified, and validated?
- What are some remaining challenges and open questions in this research area?

By providing answers to these questions, we hope to offer guidance to researchers considering the utility of this new modeling approach. We also hope to spark a healthy debate among researchers as to the potential advantages, limitations, and major research challenges of MAS/LUCC modeling. As MAS modeling studies are being undertaken by geographers in other research fields—including transportation, integrated assessment, recreation, and resource management—many of the issues raised in this article may be relevant for other applications as well. The remainder of this article sequentially addresses the questions outlined above.

Approaches to Modeling Land-Use/Cover Change

This section examines myriad LUCC modeling approaches and offers MAS as a means of complementing other techniques. We briefly discuss the strengths and weaknesses of seven broad, partly overlapping categories of models: mathematical equation-based, system dynamics, statistical, expert system, evolutionary, cellular, and hybrid. This review is not exhaustive and only serves to highlight ways in which present techniques are complemented by MAS/LUCC models that combine cellular and agent-based models. More comprehensive overviews of LUCC modeling techniques focus on tropical deforestation (Lambin 1994; Kaimowitz and Angelsen 1998), economic models of land use (Plantinga 1999), ecological landscapes (Baker 1989), urban and regional community planning (U.S. EPA 2000), and LUCC dynamics (Briassoulis 2000; Agarwal et al. 2002; Veldkamp and Lambin 2001; Verburg et al. forthcoming).

Equation-Based Models

Most models are mathematical in some way, but some are especially so, in that they rely on equations that seek a static or equilibrium solution. The most common mathematical models are sets of equations based on theories of population growth and diffusion that specify cumulative LUCC over time (Sklar and Costanza 1991). More complex models, often grounded in economic theory, employ simultaneous joint equations (Kaimowitz and Angelsen 1998). One variant of such models is based on linear programming (Weinberg, Kling, and Wilen 1993; Howitt 1995), potentially linked to GIS information on land parcels (Chuvieco 1993; Longley, Higgs, and Martin 1994; Cromley and Hanink 1999). A major drawback of such models is that a numerical or analytical solution to the system of equations must be obtained, limiting the level of complexity that may practically be built into such models. Simulation models that combine mathematical equations with other data structures are considered below.

System Models

System models represent stocks and flows of information, material, or energy as sets of differential equations linked through intermediary functions and data structures (Gilbert and Troitzsch 1999). Time is broken into discrete steps to allow feedback. Human and ecological interactions can be represented within these models, but they depend on explicit enumeration of causes and functional representation, and they accommodate spatial relationships with difficulty (Baker 1989; Sklar and Costanza 1991).

Statistical Techniques

Statistical techniques are a common approach to modeling LUCC, given their power, wide acceptance, and relative ease of use. They include a variety of regression techniques applied to space and more tailored spatial statistical methods (Ludeke, Maggio, and Reid 1990; Mertens and Lambin 1997). Unless they are tied to a theoretical framework, statistical techniques may downplay decision making and social phenomena such as institutions. Spatial econometrics provides successful examples of combining theory and statistics (Chomitz and Gray 1996; Geoghegan, Wainger, and Bockstael 1997; Geoghegan et al. 1998; Leggett and Bockstael 2000; Munroe, Southworth, and Tucker 2001).

Expert Models

Expert models combine expert judgment with non-frequentist probability techniques, such as Bayesian probability or Dempster-Schaefer theory (Eastman 1999), or symbolic artificial-intelligence approaches, such as expert systems and rule-based knowledge systems (Gordon and Shortliffe 1984; Lee et al. 1992). These methods express qualitative knowledge in a quantitative fashion that enables the modeler to determine where given land uses are likely to occur. It can be difficult to include all aspects of the problem domain, however, which leaves room for gaps and inconsistencies.

Evolutionary Models

Within the field of artificial intelligence, symbolic approaches such as expert systems are complemented by a biologically inspired evolutionary paradigm. Exemplars of this field, such as artificial neural networks and evolutionary programming, are finding their way into LUCC models (e.g., Mann and Benwell 1996; Balling et al. 1999). In brief, neural networks are silicon analogs of neural structure that are trained to associate outcomes with stimuli. Evolutionary programming mimics the process of Darwinian evolution by breeding computational programs over many generations to create programs that become increasingly able to solve a particular problem.

Cellular Models

Cellular models (CM) include cellular automata (CA) and Markov models. Each of these models operates over a lattice of congruent cells. In CA, each cell exists in one of a finite set of states, and future states depend on transition rules based on a local spatiotemporal neighborhood. The system is homogeneous in the sense that the set of possible states is the same for each cell and the same transition rule applies to each cell. Time advances in discrete steps, and updates may be synchronous or asynchronous (Hegselmann 1998). More general versions of CA use nonlocal neighborhoods (Takeyama and Couclelis 1997) and graph networks (O'Sullivan 2001). In Markov models, cell states depend probabilistically on temporally lagged cell state values. Markov models may be combined with CA for LUCC modeling, as evidenced by joint CA-Markov models (Li and Reynolds 1997; Balzter, Braun, and Kohler 1998).

Cellular modeling methods underlie many LUCC models. Tobler (1979) was one of the first to suggest the use of CM to model geographical processes. This was followed by GIS research that applied CM—particularly CA—to a number of research questions (Couclelis 1985; Cecchini and Viola 1990). Sophisticated CA models of ecological processes exist for rangeland dynamics (Li and Reynolds 1997), species composition (Silvertown et al. 1992), forest succession (Hogeweg 1988; Alonso and Sole 2000), global LUCC in response to climate change (Alcamo 1994), and a host of other biological phenomena (Ermentrout and Edelstein-Keshet 1993; Gronewold and Sonnenschein 1998).

Many CM inductively assume that the actions of human agents are important but do not expressly model decisions. Others explicitly posit a set of agents coincident with lattice cells and use transition rules as proxies to decision making. These efforts succeed when the unit of analysis is tessellated, decision-making strategies are fixed, and local neighbors affect heterogeneous actors in a simple, well-defined manner. A good example is modeling residential choice and land use in urban areas, where actors are assumed, for analytical simplicity, to be evenly arrayed—as in homes—and their decision making stems from interactions with immediate neighbors (Schelling 1971; Hegselmann 1998). Other work loosens the tessellation of actors to make more realistic models (Portugali, Benenson, and Omer 1997; Benenson 1998).

When actors are not tied to location in the intrinsic manner of CA cells, however, there may be a problem of *spatial orientedness* (Hogeweg 1988)—the extent to which neighborhood relationships do not reflect actual spatial relationships. The remedy lies in techniques that have nonuniform transition rules and can dynamically change the strength and configuration of connections between cells. As these characteristics lie beyond the capacities of rigidly defined CA, the pure, traditional CA method may not be broadly suited to modeling LUCC. A LUCC model may require multiple mobile agents ranging widely over space, agent heterogeneity, agents organized among institutions and social networks, or agents that control large and varying portions of space.

In sum, cellular models have proven utility for modeling ecological aspects of LUCC, but they face challenges when incorporating human decision making. It is necessary to use complex, hierarchical rule-sets to differentiate between the kinds of decision making that apply to groups of cells, such as local land-tenure structure (e.g., Li 2000; White and Engelen 2000). While effective, these deviations from generic cellular automata come at the potential cost of moving away from the advantages of the generic approach. In particular, "in order to converse with other disciplines, from biology and physics to chemistry, it may be necessary that the form of . . . CA preserve as many features of strict and formal CA models as possible" (Torrens and O'Sullivan 2001, 165).

Hybrid Models

Hybrid models combine any of the above-mentioned techniques, each of which is a fairly discrete approach unto itself. A prime example is estuarine land-use/cover transition modeling that has an explicit, cellular model tied to a system dynamics model (Costanza, Sklar, and Day 1986). Another similar combination is DELTA, which integrates submodels of human colonization and ecological interactions to estimate deforestation under different immigration and land-management scenarios (Southworth, Dale, and O'Neill 1991). Other examples that combine statistical techniques with cellular models and system models include larger-scale models, such as GEOMOD2 (Hall et al. 1995), the CLUE family (Veldkamp and Fresco 1996), and endangered-species models developed at the Geographic Modeling Systems Lab at the University of Illinois (Trame et al. 1997; Westervelt et al. 1997).

A distinct variant of hybrid models is dynamic spatial simulation (DSS), which portrays the landscape as a two-dimensional grid in which rules represent the actions of land managers based on factors such as agricultural suitability (Lambin 1994; Gilruth, Marsh, and Itami 1995). DSS typically does not represent heterogeneous actors, institutional effects on decision making, or multiple production activities. However, due to its ability to represent individual decision making and temporal and spatial dynamics, it constitutes an important advance over previous models (Lambin 1994). The orientation toward individual decision making in DSS—that some form of land managers act over a landscape—is shared by agent-based models. Thus, these models are logical precursors to MAS/LUCC.

Agent-Based Models

Where cellular models are focused on landscapes and transitions, agent-based models focus on human actions. Agents are the crucial component in these models. Several characteristics define agents: they are autonomous; they share an environment through agent communication and interaction; and they make decisions that tie behavior to the environment. Agents have been used to represent a wide variety of entities, including atoms, biological cells, animals, people, and organizations (Liebrand, Nowak, and Hegselmann 1988; Epstein and Axtell 1996; Conte, Hegselmann, and Terna 1997; Weiss 1999; Janssen and Jager 2000).

Autonomy means that agents have control over their actions and internal state in order to achieve goals. Wooldridge (1999) defines intelligent agents as being able to act with flexibility, which implies that agents are goal-directed and capable of interaction with other agents and a common environment, meant, in a wide sense, as anything outside of the agents. In a LUCC context, a shared landscape where the actions of one agent can affect those of others is likely to be the unifying environment. A land market is another example of an important environment through which agents interact.

Agents must act according to some model of cognition that links their autonomous goals to the environment through their behavior. The term "cognition" ranges in applicability to situations ranging from relatively simple stimulus-response decision making to the point where actors are proactive, take initiative, and have larger intentions. At a minimum, an autonomous agent needs strategies that allow it to react to changes in environment, given the importance of the environment to goals and actions. Reaction can be scripted and still be considered a cognitive model in a narrow sense, as long as the agent can respond to changes (Russell and Norvig 1995). Beyond pure reaction, some of the most well-developed formal models of human decision making are based on rational-choice theory. These models generally assume that actors are perfectly rational optimizers with unfettered access to information, foresight, and infinite analytical ability. These agents are therefore capable of deductively solving complex mathematical optimization problems in order to maximize their well-being and can balance long-run vs. short-run payoffs even in the face of uncertainty. While rational-choice models can have substantial explanatory power, some of the axiomatic foundations of rational choice are contradicted by experimental evidence, leading prominent social scientists to question the empirical validity of rational-choice theory (Selten 2001).

It is an open question whether models of perfect rationality are appropriate for agent-based models applied to LUCC, given the importance of spatial interdependencies and feedbacks in these systems. For instance, if the value of an action to every perfectly rational agent depends on both her actions and those of her neighbors, then she faces a high-dimensional, fully recursive programming problem if she strategically seeks to anticipate the actions of her neighbors. Recognition of the complex environment in which human decision making occurs has resulted in a movement toward agent-based models that employ some variant of bounded rationality (Simon 1997; Gigerenzer and Todd 1999). In general, boundedly rational agents have goals that relate their actions to the environment. Rather than implementing an optimal solution that fully anticipates all future states of the system of which they are part, they make inductive, discrete, and evolving choices that move them toward achieving goals (Tversky and Kahneman 1990; Rabin 1998; Bower and Bunn 2000).

Good examples of decision-making models can be found in the emerging field of agent-based computational economics, where these approaches have been applied to financial markets, macroeconomics, innovation, environmental management, and labor economics (Tesfatsion 2001). Boundedly rational forms of decision making have been modeled using genetic algorithms (Arifovic 1994, 2001; Miller 1996; Beckenbach 1999; Dawid 1999; Chen and Yeh 2001), heuristics (Arthur 1993, 1994a; Gigerenzer and Todd 1999; Gigerenzer and Selten 2001), simulated annealing (Kollman, Miller, and Page 1997), classifier systems (Holland 1990), and reinforcement learning (Bower and Bunn 2000; Duffy 2001; Kirman and Vriend 2001).

Before continuing, it is important to address one key difference between agent-based modeling and other techniques. The discussion of systems models, cellular models, and agent-based models leads naturally to the question of the relationship between general systems theory, agent-based modeling, and complexity theory (Phelan 1999). During the heyday of general systems theory, on which systems models are partially based, some researchers found the theory useful for modeling environmental systems (Bennett and Chorley 1978), while others found it wanting (Chisholm 1967). Complexity research differs from general systems theory in several respects (Manson 2001). Complex systems are often characterized by nonlinear relationships between constantly changing entities, while systems theory typically studies static entities linked by linear relationships defined by flows and stocks of energy, information, or matter. Similarly, systems theory emphasizes quantities of flow, not necessarily their quality, while complexity research attempts to examine qualitative attributes, such as learning and communication. As discussed below, complex behavior is seen as emerging from interactions between system components, while system models tend to favor parameterized flows and stocks that assume that the system exists in equilibrium due to fixed relationships between system elements. Agent-based modeling relies on the idea that emergent or synergistic characteristics are understood by examining subcomponent relationships. Finally, complexity research takes advantage of the increasing sophistication of computer-simulation tools that allow *exploratory simulation* (Conte and Gilbert 1995). Silicon-based simulation allows exploration of system outcomes that are not preordained and deterministic (Thrift 1999).

Multi-Agent Systems for Land-Use/Cover Change

The exploration of modeling thus far has raised three key points that the remainder of this article explores. First, of the host of methods used to model LUCC, dynamic spatial simulation offers a promising degree of flexibility. Second, as noted above, cellular models successfully replicate aspects of ecological and biogeophysical phenomena, but they may not always be suited to modeling decision making. Third, as explored more fully below, agent-based modeling is a promising means of representing disaggregated decision making. When all three points are taken together, they suggest the use of a dynamic, spatial simulation-like MAS/LUCC model that consists of two components. The first is a cellular model that represents biogeophysical and ecological aspects of a modeled system. The second is an agent-based model that represents human decision making. The cellular model is part of the agents' environment, and the agents, in turn, act on the simulated environment. In this manner, the complex interactions among agents and between agents and their environment can be simulated in a manner that assumes no equilibrium conditions. Rather, equilibria or transient but reoccurring patterns emerge through the simulated interactions between agents and their environment. The following sections highlight the advantages of this combination for modeling LUCC and a number of existing examples.

Current Applications of MAS/LUCC Modeling

In this section, we briefly discuss recent studies that apply multi-agent systems to studying LUCC for practical cases. We do not intend to provide a complete review of all possible studies, since this field is newly emerging and a detailed review would be quickly outdated. We discuss why researchers have chosen to use MAS/LUCC models in four overlapping topic areas: natural-resource management, agricultural economics, archaeology, and urban simulations. In Table 1, we list a number of published studies that demonstrate the broad range of applications. For more details, we refer to recent overviews by Kohler (2000), Gimblett (2002), Janssen (forthcoming), and

Table 1. Characteristics of a Number of Land-Use/Cover Change Studies that Use the Combination of Agents and Cellular Models

Publication(s)	Type(s) of Land Use	Issue	Time Period	Type(s) of Agents	Type(s) of Decisions	Geographic Location
Balmann (1997); Balmann et al. (2002)	Agriculture	Diffusion of new practices	2001–2020	Farms	Investment, production, land-renting	Hohenlohe, Germany
Berger (2001)	Agriculture	Diffusion of new practices	1997–2015	Farm households	Investment, tenure, production	Chile
Rouchier et al. (2001)	Rangelands	Emergent relationships between farmers and herdsmen	400 units of time	Herdsmen, farmers, and village leader	Negotiations on location for herding, selling animals	North Cameroon
Dean et al. (2000)	Settlements	Societal collapse	800–1360	Households	Location to farm, harvest, store harvest, marriage	Long House Valley, Arizona, U.S.
Hoffmann, Kelley, and Evans (2002)	Forests, agriculture	Trends in deforestation and reforestation	1850–present	Landowners	Farm, fallow, harvest timber	Indiana, U.S.
Kohler et al. (2000)	Settlements	Settlement pattern	900–1300	Households	Agricultural production decisions, marriage, choice of new residential location	Mesa Verde Region, U.S.
Ligtenberg, Bregt, and van Lammeren (2001)	Urban	Modeling spatial planning	30 years	Stakeholders	Voting for preferred land use	Nijmegen, the Netherlands
Lim et al. (2002)	Forests	Trends in tropical deforestation	1961–present	Farmers	Cropping decisions	Brazilian Amazon
Lynam (2002)	Savanna	Sustainability of agricultural practices	30 years	Households	Cropping decisions	Kanyurira Ward, Zimbabwe
Manson (2000; forthcoming)	Forests, agriculture	Trends in tropical cultivation and deforestation	1960–2010	Households, institutions	Crop/land allocation	Yucatán Peninsula, Mexico.
Polhill, Gotts, and Law (2001)	Not specified	Study of imitation strategies	200 years	Land managers	Land-use decisions and land market	No specific location
Rajan and Shibasaki (2000)	Forests, agriculture, urban	Land-use/cover change at the national level	1980–1990	Decision maker on spatial grid	Land use and migration	Thailand
Sanders et al. (1997)	Urban	Evolution of settlements	2000 years	Spatial entity	Transition rules for settlement type change	No specific location
Torrens (2001)	Urban	Residential location dynamics	Not specified	Home sellers and home buyers	When to sell and buy	No specific location

Parker, Berger, and Manson (forthcoming) that incorporate work on MAS/LUCC models.

Natural-Resource Management

Within the field of natural-resource management there is substantial interest in using MAS models to understand common-pool resource problems. The question of interest concerns what type of institutional rules may direct individuals to act in the benefit of the collective. Bousquet and colleagues (1998) have developed a number of models in which collective-choice models influence LUCC. For example, Rouchier and colleagues (2001) study how herdsmen search for suitable grazing locations in the dry season and negotiate with farmers for the use of their land. Depending on the criteria by which the herdsmen pursue access to rangelands, different carrying capacities for cattle result, although the physical characteristics of the system are held constant. In the long term, decisions based on cost differentials lead to lower numbers of cattle, while decisions that take into account the history of interactions lead to a higher carrying capacity.

Agricultural Economics

Several agricultural economists have performed studies on how new agricultural practices are adopted by a population of farmers in an agricultural region (Balmann 1997; Berger 2001; Polhill, Gotts, and Law 2001; Balmann et al. 2002). Such an adoption process is typically bottom-up, since landowners vary in their preferences and abilities to adopt technological innovations, land quality and availability are spatially heterogeneous, and information on new practices spreads via social interactions of agents. These scholars have developed simulations that include farmers' investment decisions in new technologies, land markets, and crop-choice decisions. The resulting models can be used to assess the impacts of various governmental policies on the adoption of new agricultural practices and the structure of the farm economy.

Archaeology

Archaeologists are not able to perform repeated, controlled experiments. Therefore, since the early 1970s, archaeologists have used models to test possible explanations for observed phenomena, basing their modeling on the limited information available from the past. These models have focused mainly on how complex societies have emerged and collapsed. Archeologists are now beginning to use MAS/LUCC as a means of incorporating spatial information into their models.

Dean and colleagues (2000) study the cause of the collapse of the Anasazi around A.D. 1300 in Arizona. Scholars have argued for both social and environmental causes (drought) for the collapse of this society. Simulating individual decisions of households on a very detailed landscape of physical conditions of the local environment, the authors refute the hypothesis that environmental factors alone account for the collapse. Kohler and colleagues (2000) study the reasons why there have been periods during which Pueblo people lived in compact villages, while in other times they lived in dispersed hamlets. These model results show the importance of environmental factors related to water availability for these settlement changes.

Urban Simulation

Torrens (2002) discusses the drawbacks of traditional spatial-interaction and discrete-choice models of urban landscapes and argues that these drawbacks provide motivation for scholars of urban studies to undertake multi-agent simulations. Drawbacks of traditional models include poor representation of dynamics in urban simulations and poor handling of details in spatial and socioeconomic representations. He also argues that the top-down approach in traditional urban models conflicts with the bottom-up perspective of complex systems.

Torrens (2002) argues that a new wave of urban models provides a detailed, decentralized, and dynamic view of urban systems. While most are based on cellular automata, a few MAS and CA-MAS oriented models are being developed. CA models have been used for assessing the role of density constraints in land development (Batty, Xie, and Sun 1999), describing the evolution of urban forms (Clarke, Hoppen, and Gaydos 1997; Wu 1998), and simulating land-use transitions (White and Engelen 1997). Torrens himself (2001) combines CA and MAS models in an exploratory study.

Why Use MAS/LUCC Models?

As discussed above, many well-developed techniques for modeling land-use/cover dynamics exist. However, each of these techniques has some limitations. Equation-based models may require simplifying assumptions to achieve analytical or computational tractability, and they are often based on empirically implausible assumptions regarding static market equilibria. System models directly address the shortcomings of equation-based models in terms of representing feedbacks and dynamic processes, but these models also operate at a very aggregated level, or, equivalently, at a very coarse temporal and spatial resolution. Therefore, where local heterogeneity and interactions are important, such models may have limited explanatory power.

Some insight into the impacts of spatial heterogeneity, neighborhood effects, and spatial spillovers can be gleaned through estimation of statistical models. However, these models distill information into parameter estimates that represent average effects over available data. Thus, such models may be useful for projecting spatial dynamics and interactions only for processes that are stationary and uniform over space and time. While the impacts of spatial influences occurring at hierarchical spatial scales can be represented to some extent through statistical techniques that account for regional heterogeneity (such as generalized least-squares, fixed-effect, and random-effect models), feedbacks across scales cannot be effectively modeled. While cellular modeling techniques offer greater flexibility for representing spatial and temporal dynamics, these dynamics are also based on stationary transition probabilities. Therefore, such models have limited ability to reflect feedbacks in the system under study, as global changes in the system do not influence transitions at the cellular level. Perhaps most significantly, none of the above modeling techniques can represent the impacts of autonomous, heterogeneous, and decentralized human decision making on the landscape.

MAS/LUCC models can potentially overcome many of these limitations. In particular, they might be well suited for representing socioeconomic and biophysical complexity. They also might be well suited for the related goal of modeling interactions and feedbacks between socioeconomic and biophysical environments. In the following section, we offer our perspective on the general strengths of MAS/LUCC models. This discussion may guide researchers in selecting the modeling framework most appropriate for their particular research.

MAS/LUCC Models as a Simulated Social Laboratory

Perhaps the greatest general advantage of MAS/LUCC models is their flexibility. Because the models need not be solved for closed-form analytical equilibrium solutions, details critical to the system under study can be built in. These details may include endogeneity related to agent decision making and disaggregated spatial relationships. As suggested by Casti (1999), these models can then serve as a social laboratory in which to explore links between land-use behaviors and landscape outcomes. Once the mechanisms of the model are programmed, researchers have greater flexibility to design and execute experiments to explore alternative causal mechanisms than they would if a solution to a set of equilibrium conditions were required.

Representing Complexity

The flexibility possible within MAS/LUCC models means that such models can be designed to represent complex land-use and land-cover systems. While no precise definition of a complex system exists (Auyang 1998; Batty and Torrens 2001; Ziemelis and Allen 2001), complex systems are generally discussed as dynamic systems that exhibit recognizable patterns of organization across spatial and temporal scales. Complex systems are often defined in terms of the strength of dynamic linkages between components. Systems with very strong dynamic linkages may immediately move to and remain at a stable equilibrium. Systems with weak dynamic linkages are often chaotic, and changes in the system due to small perturbation are large and often difficult to track. In contrast, systems with moderate linkages between components may exhibit transient but recurrent patterns of organization. Such complex systems are often said to reside at the *edge of chaos* (Waldrop 1992).

Structurally, complex systems are characterized by interdependencies, heterogeneity, and nested hierarchies among agents and their environment (Arthur, Durlaf, and Lane 1997; Holland 1998; Epstein 1999; Kohler 2000; LeBaron 2001; Manson 2001). Many examples of these three key sources of complexity can be identified in human-influenced landscapes. Complexity arises from both human decision making and the explicitly spatial aspects of the landscape environment.

Interdependencies exist among agents, between agents and their biophysical environment, across time, and across space. Agents may rely on information from past decisions—their own and those of other agents—to update decision-making strategies. This process leads to temporal interdependencies among agents. Agent decisions likely will have temporally dynamic impacts on the biophysical environment, including impacts on soil health, biodiversity, and the type and succession of vegetation cover. Brander and Taylor (1998) and Sanchirico and Wilen (1999) present examples of bioeconomic models that incorporate ecological interdependencies. If each agent's behavior potentially affects other agents' decisions uniformly, and agents' actions are not spatially linked, these dynamics potentially could be modeled in an aspatial context.

However, many spatial interdependencies potentially have an impact on individual decision making. These include spatial influences on agent behavior, such as flows of information, diffusion of technology, spatial competition, local coordination, social networks, and positive and negative externalities among neighbors (see Miyao and Kanemoto 1987; Case 1991, 1992; Lansing and Kremer

1993; Krider and Weinberg 1997; Ray and Williams 1999; Parker 2000; Irwin and Bockstael 2002). Many biophysical spatial interdependencies are also potentially important, such as downstream watershed impacts, habitat connectivity, metapopulation dynamics, and ecological edge effects. Furthermore, biophysical and social processes interact at a spatially explicit level. For example, residential development patterns may impact surface runoff and thereby lead to changes in hydrologic networks. Alternatively, local changes in ecological conditions may drive human migration.

Heterogeneity may also be present across agents, the biophysical environment, space, and time. Agents may vary according to experience, values, ability, and resources. This heterogeneity may change over time due to agent learning and demographic changes. Biophysical heterogeneity can also drive changes in land-use decisions and the resulting land cover. Differences in soil quality, topography, vegetation, water quality, and water availability all influence the relative success of various land-use choices.

While models with substantial heterogeneity may be analytically tractable, when heterogeneity and interdependencies are combined, analytical solutions become very difficult to obtain. Assumptions of agent homogeneity are commonly invoked to obtain analytical tractability. When agent heterogeneity is a critical driver of model outcomes, assumptions of homogeneity are not appropriate. Technology adoption is a simple example in which both agent heterogeneity and spatial interdependencies are important. The benefits of a new technology are often uncertain. Therefore, an agent with greater access to resources to ensure a subsistence level of consumption (such as stored wealth or access to credit) may be more willing to risk adoption of a new technology. The success or failure of the new technology will provide information about the payoffs from the technology to other agents, potentially reducing uncertainty. If information diffuses spatially, risk-averse neighbors of the early adopter may now adopt the technology. Further, the distribution of agent types over space may impact the spatial extent of adoption. Thus regions of adoption and nonadoption may emerge as a result of local agent heterogeneity and spatial interdependencies between agents.

In models of complex systems, interdependencies and heterogeneity often lead to what are called nonconvexities—an irregular and rugged abstract surface describing the relationship between the parameters of the system and possible outcome states. In systems with such mathematical properties, many possible stable equilibria can exist (Burrows 1986; Bond and Gasser 1988). For many systems, the particular equilibrium that a system reaches depends on the initial conditions of the model. Such systems are said to exhibit path-dependency (Arthur 1988, 1994b). A simple extension of the technology-adoption example illustrates this concept. The presence of a single agent willing to take risks may be required to instigate a cascade of technology adoption. The system therefore has two equilibria, one with adoption and one without, and initial condition of the distribution of risk preferences among agents may determine whether the technology is in fact adopted in a local region.

In addition to heterogeneity and interdependencies, both social and biophysical systems are characterized by hierarchical, nested structures. For example, family members interact to form a household, which may interact with other households in a village through political and economic institutions. City governments collectively influence and are influenced by county and regional governments, which, in turn, interact at a national level. On the biophysical side, individual waterways join to define nested watersheds, and populations formed of individual species members aggregate to form communities, which, in turn, collectively define ecosystems. These nestings imply that an individual agent or parcel is likely influenced by, and in turn influences, processes occurring at multiple spatial scales. These spatial complexities are very difficult to model in a purely analytical or statistical framework. Further, they may complicate the situation of multiple equilibria and path-dependence discussed above, as feedbacks within the system may change the shape of the outcome surface, rendering previously stable equilibria unstable (Kauffman 1994). Returning to the example of technology adoption, regional policies that offer inducements for adoption may influence the decisions of individual landowners—a downward linkage. The subsequent development of a critical mass of adopters may then lead to the creation of a formal market for the good produced using the new technology—an upward linkage.

Adaptation

Complex systems are often described as being adaptive. Adaptive mechanisms may influence outcomes at both micro- and macroscales. At the level of an individual agent, learning behavior and the evolution of strategies may be built into the decision-making structure. At the system level, the aggregate population evolution may be influenced by the birth, death, migration, and bankruptcy of agents (Epstein and Axtell 1996; Kohler et al. 2000; Berger 2001). Finally, rules and institutions may evolve over time in response to changing social and environmental conditions (Lansing and Kremer 1993; Janssen and Ostrom forthcoming).

Modeling Emergence

If researchers are specifically interested in modeling the complex dynamics of a LUCC system, they also may be specifically interested in understanding the macroscopic, or emergent, phenomena that could result. While "emergence" has become a popular buzzword in discussions of complexity, there are numerous concrete manifestations of the concept, many of which are potentially useful foci for empirical researchers. However, it is important to acknowledge that a widely accepted formal mathematical definition of emergence has not been established, and the topic remains a point of lively debate among modelers. Below, we briefly summarize the diverse ways in which emergence has been defined in the literature and discuss the relevance of the concept for MAS/LUCC modeling.

Emergent phenomena are described as aggregate outcomes that cannot be predicted by examining the elements of the system in isolation. This description is often summarized as a whole that is greater than the sum of its parts. Holland (1998) describes emergence simply as much coming from little. Epstein and Axtell (1996, 6) suggest that emergence is characterized by "organization into recognizable macroscopic social patterns." Baas and Emmeche (1997) explicitly identify emergence as a function of synergism, whereby systemwide characteristics result, not from the additive effects of system components (superposition), but from interactions among components. Auyang (1998) similarly defines emergent phenomena as higher-level structures that are both qualitatively different from their lower-level components and not obtainable through aggregation, averaging, or other superposition of microlevel components.

Definitions of emergence usually concern macroscale phenomena that arise from microinteraction. Therefore, the concept of emergence is directly related to the phenomenon of nested hierarchies that characterize complex systems. Emergent phenomena at one level potentially define the units of interaction at the next higher level. However, the macrostructure potentially also affects units at the microscale. Castelfranchi (1998), for example, discusses how emergent networks of dependence between agents' decisions constrain and influence agents' subsequent actions. There are definitions of emergence that necessitate that lower-level elements remain unaware of their role in emergent phenomena (Forrest 1991). MAS models based on such principles may fail to capture reality if they do not allow reflexivity or model individuals who reason about features of which they are part. Conversely, MAS models are sufficiently flexible to capture both upward and downward linkages, and may therefore be a useful tool for exploring such linkages. Emergent structures may change form in response to exogenous shocks or a key state of the system reaching a level of critical mass. This restoration of discernible structure in response to system perturbations represents an outcome-oriented interpretation of adaptation.

Some definitions specifically associate emergence with surprise or novelty (Batty and Torrens 2001). The concept of surprise is potentially consistent with the concept of an emergent property as one that could not be predicted by examining the components of the system in isolation. However, definition in terms of the fundamentally subjective concept of surprise is potentially problematic. If a phenomenon must be surprising, how can it be replicable? Is it then not emergent upon reobservation? Auyang (1998) specifically rejects the concept of surprise as a defining characteristic of emergence, but provides a helpful discussion of the relationship between novelty and emergence. The concept of surprise, though, may provide a counterfactual way of defining emergence: a pattern the appearance of which is an obvious consequence of the properties of the underlying components may not be regarded as emergent.

Various authors identify many concrete examples of emergence. For example, both market-clearing price and the aggregate distribution of economic activity have been identified as emergent properties of economic systems (Epstein and Axtell 1996). Location models have focused on spatial segregation and patterns of settlement and migration as emergent properties of spatially explicit complex systems (Schelling 1978; Kohler et al. 2000). Patterns of land use have also been identified as emergent properties of land markets (White and Engelen 1993, 1994; Parker, Evans, and Meretsky 2001). The distribution of farm sizes has been identified as an emergent property of agricultural land markets (Balmann 1997; Berger 2001). In each of these examples, the macroscopic outcome depends on interactions between agents, as well as individual agent characteristics.

If researchers assume that modeled systems reach their theoretical equilibria, some of these macroscale phenomena can be derived from a set of equilibrium conditions, given a set of assumptions about agent interactions that are not explicitly modeled. For example, in the classic economic model of a purely competitive economy, a market-clearing price can be derived from a set of equilibrium conditions that hold under certain restrictive assumptions (Laffont 1988). If these phenomena can be modeled using simple analytical techniques, why would a more complicated technique be justified? There are two answers to this question. First, by relying on simplifying assumptions regarding agent interactions, heterogeneity, and hierarchical structures, the analytical techniques may predict outcomes that hold only as special cases. Second, in many cases, a set of equilibrium conditions that define the emergent outcome cannot be analytically solved, or cannot be solved for a unique equilibrium. This second answer often holds for spatial problems. Analytical spatial-equilibrium models are very difficult to construct in cases in which the relationship of each neighbor to every other neighbor must be modeled. Even if impacts are limited to a local neighborhood, these models quickly become intractable. Thus, an emergent phenomenon such as landscape pattern may be practically modeled only with computational tools, such as MAS models.

Modeling Dynamic Paths

Many temporally dynamic analytical models are solved only for a steady state (a dynamic equilibrium in which the rate of change of system components is zero). A very long time horizon may be required for the model to reach a steady state. Realistically, however, steady states are highly dependent on parameter values that are not stable over time, and thus theoretical steady states may not be a reasonable modeling target. Further, policy makers may be most interested in short-run changes in the system under study. Therefore, analysis of the dynamic path (or paths) of the system may be of more relevance than information about a theoretical long-run equilibrium. When spatial heterogeneity impacts path-dependent outcomes, policy makers may be interested in differential impacts on local stakeholders. MAS models can be used to analyze the path of the system within any timeframe. Further, parameter values can be perturbed to examine how the path of the system changes in response to exogenous shocks.

Participatory Models

Oreskes, Shrader-Frechette, and Belitz (1994, 644) claim that "[F]undamentally, the reason for modeling is a lack of full access, either in time or space, to the phenomena of interest." Such a lack of access is endemic in many LUCC-relevant policy areas. Participatory approaches to model development and implementation offer promise as a means to increase the utility of simulation models by closely tailoring the model and subsequent analysis to the needs of stakeholders. Participatory approaches have been applied to problems in geography, ecology, and natural-resource management (Grimble and Wellard 1997; Steins and Edwards 1999; Luz 2000; Craig, Harris, and Weiner 2002). Such participatory models vary from heuristic models that give policy makers and stakeholders a voice in model development and a feel for the general dynamics of a system to detailed models designed to mimic actual systems and provide potential futures. MAS models are potentially useful for active/interactive policy-testing and learning in resource-management areas, precisely because the MAS approaches can model both decision making *and* social-physical-biological processes. The visual communication provided by spatially explicit cellular models, particularly those coupled with GIS, can assist in communicating model results to a wide range of stakeholders and policy makers. Finally, the flexibility of representation and implementation inherent in MAS/LUCC models makes them well suited to interactive scenario analysis.

Three general types of participatory models, distinguished by the level of participation involved, are prevalent in the literature. One type is explicitly concerned with participation at all stages of model development (Hare et al. 2002; Lynam et al. 2002; Bousquet et al. 2002). Stakeholders and modelers work together to build MAS models of the systems in question, and the model-building and model-running exercises facilitate learning about the interactions and dynamics in the system being addressed. With the second type of participatory model, stakeholder participation is not necessarily incorporated into model-building, but stakeholders participate in the model-running, acting as agents in the model (Barreteau, Bousquet, and Attonaty 2001; Gilbert, Maltby, and Asakawa 2002). In this type of model, stakeholders play the game by interacting with artificial agents in a MAS model in order to learn more about the system at hand. Finally—and most commonly—MAS models are designed to be presented to policy makers as a fully functioning scenario-analysis tool (Rajan and Shibasaki 2000; Antona et al. 2002; Ligtenberg et al. 2002). With this type of model, stakeholders can alter variables and parameters of models that either are heuristic or closely mimic real systems in order to test policy alternatives.

In summary, MAS models are likely to be a useful tool for theoretical exploration and development of hypotheses when complex phenomena have an important influence on model outcomes. MAS models may be particularly appropriate when important interdependencies between agents and their environment are present, when heterogeneity of agents and/or their environment critically affect model outcomes, when upward and downward linkages among hierarchical structures of organization exist, and when adaptive behaviors at the individual or system level are relevant for the system under study. They are also potentially useful for examining the path of a system in cases in which the timescale to reach equilibrium is beyond the timeframe of interest to the researcher. Finally, these may be well suited for development and implementation of participatory models designed to assist decision making in complex circumstances. In cases where these complexities are not present, simpler and more transparent modeling techniques may be appropriate.

Potential Roles of MAS/LUCC Models

The numerous, diverse applications and noted advantages of MAS/LUCC notwithstanding, a series of questions for modelers remains. What kind of science are we practicing when we use MAS models? What, if anything, do the results of our models tell us? What role does our simulation play in our investigations? In light of the observation that "[I]n every case of simulating complex adaptive systems, the emergent properties are strictly dependent on the 'rules' preprogrammed by the investigator" (Fogel, Chellapilla, and Angeline 1999, 146), how much can we learn with this method? The answers to these questions are far from clear. Indeed, recent commentaries caution modelers to take care with the claims they make about their models and to reflect on the utility of them as a tool for exploring empirical phenomena (Oreskes, Shrader-Frechette, and Belitz 1994; Casti 1997).

Beyond a common goal of understanding something about the world by creating simulations, there are multiple ways to conceive of the utility of the modeling enterprise. While MAS/LUCC models appear to be useful tools, it is imperative that we consider the kinds of information and knowledge that we can potentially extract from them. This is not a trivial task, because MAS models do not easily fit into the classic deductive/inductive categories familiar to scientists. Consistent with deduction, a MAS modeler begins with a set of assumptions regarding agent behaviors and interactions. In contrast to classical deduction, however, the modeler cannot prove the results using formal mathematics or logic. Instead, the modeler may generate data in different simulation experiments, which are then analyzed with inductive methods similar to those employed for analysis of empirical data. In contrast to the case with pure induction, however, one does not work with real-world data. Judd (1997) discusses ways in which computational methods can be useful for theoretical analysis, even when such methods do not meet the theorem/proof criteria for pure deduction. Axelrod (1997a) concurs that simulation is neither purely deductive nor inductive, and alternatively characterizes it as a third way of doing science. Thus, it is not immediately clear what role this new scientific approach should play in our analysis of LUCC issues.

In sorting out roles for MAS/LUCC models, we turn to an interesting distinction Casti (1997) has drawn between models, which relies on the analogy of the difference between a photographic portrait and a Picasso portrait: one attempts to mimic reality; the other, while capturing parts of reality, focuses in on particular aspects in the hopes of emphasizing fundamental features. This is a useful metaphor for discussing the role of MAS/LUCC models. This section condenses various uses of MAS into similar categories—explanatory approaches (Picasso) and descriptive approaches (photographic)—and discusses the types of knowledge hoped for and the advantages and disadvantages of both.

Explanatory Approaches

Explanatory approaches conceive MAS to be a social laboratory. This type of modeling strives to explore theory and generate hypotheses. Modelers begin with a theoretical framework and formalize it in computer code in order to examine the ramifications of their framework and potentially generate new hypotheses to explore empirically. As with any theoretical enterprise, explanatory models may emphasize some details about a phenomenon and ignore others. Akin to Picasso's portraits, these models focus on particular processes or dynamics in order to achieve fundamental understanding about aspects of a phenomenon.

One way to conceive of this type of modeling is as a method for testing candidate explanations. Epstein (1999) is perhaps the best proponent of this approach, arguing that we need to pursue *generative social science*. Candidate-explanation modeling entails describing (through a model) how the "decentralized local interactions of heterogeneous, boundedly rational, autonomous agents generate" a regularity (Epstein 1999, 41). Tesfatsion (2001, 282) also suggests this role for agent-based models in economics, noting that one key role for such models is to demonstrate how market regularities can emerge from "repeated local interactions of autonomous agents acting in their own perceived self interest."

Using MAS models to develop candidate explanations follows simple logic. There is a target empirical, macroscopic phenomenon (or pattern or regularity), which often represents an emergent property of a complex system, such as the spatial organization inherent in patterns of human settlement. The modeler develops a series of rules, interactions, and specifications for the agents and their environment, and then allows agents to interact within a simulation environment. If the macrophenomenon that results resembles the empirical phenomenon of interest, then the modeler has uncovered, at the very least, a candidate explanation for the empirical phenomenon (see Axtell and Epstein [1994] for a discussion of the difficulty in determining what constitutes resemblance). When used in this manner, MAS allows modelers to assess the ramifications and boundary conditions of theories and hypotheses, as it facilitates a plausibility check on the empirical expectations that flow from theories. Further, MAS models provide the opportunity to systematically test alternative explanations.

This type of modeling can be considered normative, in that it attempts to encapsulate critical mechanisms in order to function as a virtual laboratory. Again, when outcomes from theoretically based constructions mimic reality, the theory gains support. These models purport to be explanatory by stating how reality should or would be under idealized circumstances. Explanatory MAS/LUCC models do not attempt to reproduce actual land-use systems; instead, they concentrate on specific aspects and on modeling fundamental dynamics, in the hope that such laboratory explorations will lead to empirically relevant insights.

Beyond simulating the ramifications of given theories, explanatory approaches also hope to find novel hypotheses. Researchers may construct a model with the specific goal of examining the possible (but unknown) macroscopic implications of a particular set of microlevel interactions. The early prisoner's-dilemma computer tournaments, in which researchers competed by submitting agent-based programs representing strategies, comprise a prime example of this type of modeling (Axelrod 1984, 1997b). It was far from clear at the outset which strategies would be most successful, and most researchers would have argued initially that cooperative outcomes would be unlikely candidates. The fact that tit for tat—a strategy that entails cooperation—emerged as successful opened up a productive empirical research avenue in politics and economics. MAS/LUCC models can potentially play the same role. Models that explore fundamental processes can potentially be used to derive novel testable hypotheses that relate landowner/manager decisions to land-use and land-cover outcomes.

Thus, in general, explanatory modeling approaches allow modelers to (1) demonstrate that a set of rules can lead to the outcome of interest—test theory, (2) explore other possible causes that could lead to the same outcome—formally exploring the robustness of the proposed causal explanations, and (3) discover outcomes not originally anticipated. The potential drawback of this approach is the lack of a clear method for evaluating the empirical utility of the simulations. Because abstract concepts make up the building blocks of these models, and general patterns and phenomena are the goal, it is difficult to establish what the models tell us about reality. While they can tell us a great deal about our theorizing and thinking, they may supply less understanding of specific real-world systems.

Descriptive Approaches

Descriptive approaches follow a fundamentally different logic and are more concerned with empirical validity and/or predictive capacity. Like the photograph in Casti's (1997) metaphor, these approaches attempt to mimic real-world systems to facilitate direct empirical and policy scenario research.

In LUCC modeling terms, empirically based MAS/LUCC models may be constructed to achieve a variety of goals, including: to replicate landscape composition and function; to examine the impact on the biophysical environment of policies that influence socioeconomic behavior; and to demonstrate the value of using information on spatial heterogeneity and interactions, among others. Such models would be as fully parameterized with real-world data as possible and, ideally, would incorporate links with models representing important biophysical processes, such as hydrologic flows, vegetation-growth models, soil fertility, and transport and fate of pollutants. Within a GIS-based model, socioeconomic and biophysical inputs could be linked through common spatial identifiers. To the extent possible, given data availability, the scale at which social and biophysical processes operate in the model would match researchers' understanding of the scale at which they operate in the real world.

Using MAS methods for this type of modeling may be more effective in several areas than using existing empirical models. First, by modeling at a fine resolution, such models may make the best statistical use of available information. Second, as noted above, by accounting for heterogeneity and interdependencies, the models can reflect important endogenous feedbacks between socioeconomic and biophysical processes. Last, since the models are not constructed to meet a set of equilibrium criteria, they can produce discontinuous and nonlinear phenomena, such as extinctions, regime shifts, and exponential growth of populations.

Descriptive models can often be identified by claims made of their replicative ability, particularly when applied to LUCC. Herein lies both their advantage (noted above) and their disadvantage. For many of these fitting models, MAS practitioners may point out ways in which their models provide insight into real-world processes. This provides hope for real relevance in terms of policy making. These intuitive insights, however, can potentially come at the cost of more general rules, and descriptive models may thereby move us away from developing normative statements (Judson 1994).

A different type of problem arises from a fundamental fact regarding modeling. With MAS/LUCC techniques, we can create an infinite number of models, while reality remains singular. Thus, we must be on guard and temper our conclusions, as it is possible to develop a model that can reproduce a statistically correct metaphenomenon with a model structure that does not capture real processes. The most dangerous situation, of course, is when we achieve metaverisimilitude with a model mechanism that is close enough to be perceived as being correct when, in fact, it is not. Rather than nullifying the utility of descriptive approaches, these disadvantages instead necessitate a recognition of the underlying uncertainty in any modeling enterprise and caution in claims, especially where policy prescriptions are concerned (Oreskes, Shrader-Frechette, and Belitz 1994).

Moving Forward

The explanatory and descriptive approaches described above represent a continuum, rather than a dichotomous, mutually exclusive choice. There will always be aspects of both photographs and Picasso in any model built to explore LUCC questions. At issue is the question of how precise we should make our re-creations of specific social/environmental systems and what information we hope to glean from our simulations. If the goal of our modeling endeavors is the re-creation of actual land use in specific locations over time for use in policy-scenario modeling and prediction, then the descriptive approach is indicated. If, instead, we hope to understand generic patterns of LUCC over time, so that we can find and apply insights to a wide range of specific empirical situations, then an explanatory approach is appropriate. To some extent, our choices are constrained by the data available and the theoretical sophistication already achieved. However, it is crucial that the larger question of modeling philosophy, explanatory versus descriptive, be acknowledged and understood.

Building an Empirically Grounded Model

Modeling and simulation are useful approaches to exploring LUCC, but their utility depends on adequate verification and validation. Verification and validation concern, respectively, the correctness of model construction and the truthfulness of a model with respect to its problem domain. In other words, verification means building the system right, and validation means building the right system. Verification techniques range from debugging the computer program that underlies the simulation to ensuring that model structure is adequate. Once a model is verified and works correctly, then the modeler is concerned with validation—comparing model outcomes to outside data and expectations. It is important to note that these definitions of validation and verification are model-centric terms that do not immediately address larger epistemological questions of modeling in general (e.g., Oreskes, Shrader-Frechette, and Belitz 1994).

Verification

The greatest simultaneous advantage and shortcoming of agent-based models is their flexibility of specification and design. Verification reduces the problematic nature of flexibility by vetting model structure and the rules employed. In particular, success in verifying a model lies in striking a balance between theory and data. Fortunately, a hallmark of MAS is the ability to map the concepts and structures of real world onto the model in a way that preserves natural objects and connections (Batty 2001; Kerridge, Hine, and Wigan 2001).

Apart from examining the balance between theory and data, verification essentially involves attempts to break the model by varying model configurations. This process leads to debugging—careful assessment of model objects and linkages among them. Effective communication of model design to others can assist in verification. Most modeling publications do not contain a description of the simulation sufficient to permit the reader to fully understand model design and therefore the appropriateness of verification procedures. Furthermore, a general lack of published code for LUCC models and a lack of common modeling platforms render replication difficult. A growing tradition of publishing software code along with manuscripts, however, exists within the agent-based modeling community. It behooves MAS/LUCC research to continue this tradition. Similarly, as more models adopt common standards, verification will become easier.

Key to verification is sensitivity analysis of relationships between model parameters and the state or time path of variables endogenous to the modeled system. Incremental parameter changes are mapped against model outcomes in order to ascertain the spatial or temporal limits of a model's applicability and to identify programming artifacts. Common techniques, borrowed from closed-form analytical modeling, include the *comparative static* (Silberberg 1990) and *comparative dynamic* (Kaimowitz and Angelsen 1998) methods. Closely allied to sensitivity analysis is the study of error propagation and uncertainty, a topic often left unconsidered in LUCC modeling (Robinson

1994). Work within this topic ranges from studying the effects on errors of mathematical operations (Alonso 1968) to error classification in remote sensing (Riley et al. 1997) and treatment of error and uncertainty in geographic information systems (Eastman 1999; Heuvelink 2002).

Validation

Validation concerns how well model outcomes represent real system behavior. Therefore, validation involves comparing model outputs with real-world observations or the product of another model or theory assumed to adequately characterize reality. Mounting interest in verification and validation of LUCC models is evidenced by a recent special issue of *Agriculture, Ecosystems and Environment* (Veldkamp and Lambin 2001). Data are drawn from other models, theories, and observations of the target system, provided by surveys, role-playing games, interviews, censuses, and remote sensing (Manson 2000; Deadman and Schlager 2002). Outcomes of interest may be demographic, such as aggregated spatial distribution of population or migration. They may include patterns and degree of natural-resource exploitation, such as groundwater quality, patterns of soil degradation, species population health and distribution, and spatial patterns of land cover. Also of interest are measures of economic well-being, such as the value of output, income distribution, and trade flows. For many of these measures, researchers may be concerned with how both aggregate and spatial outcomes unfold over time.

Model outcomes are compared to real outcomes using a variety of aspatial and spatial measures. Statistics is home to an array of techniques geared toward description and hypothesis testing appropriate for analyzing aspatial outcomes. In terms of spatial measures, the complexity of LUCC suggests the use of a variety of tests to measure spatiotemporal outcomes (Turner, Costanza, and Sklar 1989). This need is evidenced through many authors' use of spatial statistical approaches (point-pattern and landscape metrics) to compare modeled outcomes and data (White and Engelen 1993; Batty and Xie 1994; Alberti and Waddell 2000; Manson 2000; Parker 2000; Herold and Menz 2001; Parker, Evans, and Meretsky 2001; Irwin and Bockstael 2002). While pattern and texture metrics are useful for their ties to ecological characteristics, such as biotic diversity (Giles and Trani 1999), their use is tempered by uncertainty about the linkage between fractal metrics and ecological processes (Li 2000). Location- based methods, such as error-matrix analysis or the kappa statistics, are now joined by measures that better differentiate between location prediction and quantity prediction (Pontius 2000; Pontius and Schneider 2001).

Pitfalls in Verification and Validation

As has been widely recognized throughout geography, there are scale-related problems held in common by verification and validation for MAS/LUCC models. Change analysis of spatial data, for instance, is affected by changing resolution (Lam and Quattrochi 1992) and extent (Saura and Millan 2001). Scale effects can be statistically causal, since variables differentially co-vary as a function of the scale at which they are measured (Bian 1997). For MAS/LUCC researchers, the need for a sufficient sample size to ensure statistical significance, the resolution at which the MAS/LUCC model operates, and the resolution of available data may influence the choice of spatial resolution for comparison of modeled and real-world outputs. Researchers making spatial comparisons are cautioned to be aware of potential issues related to both scale and spatial correlation, as discussed by the authors above. There is a long history of research into issues of scalar, spatial, and temporal corollaries of verification and validation techniques upon which researchers may draw (Cliff and Ord 1973; Openshaw 1977; Anselin 1988; Pontius and Schneider 2001; Heuvelink 2002).

Finally, assumptions necessary for verification and validation, such as normality and linearity, can be at odds with models designed to accommodate complex behaviors caused by sensitivity to initial conditions, self-organized criticality, path-dependency, or nonlinearities (Arthur 1988; Kauffman 1994; Manson 2001). In effect, the very synergies that make complex systems interesting also make them difficult to analyze. Therefore, a need exists for techniques such as active nonlinear testing, which seeks out sets of strongly interacting parameters in a search for relationships across variables that are not found by traditional verification and validation (Miller 1998). Furthermore, researchers should be careful to ensure that abrupt changes in system behavior and unexpected outcomes are ultimately explained by the conceptual framework embodied in the model. Outcomes must be traced back to a unique set of precursors, not model artifacts.

A final challenge lies in abstraction, since many outcomes of human interaction, such as trust or learning, are imputed or abstract. Validating abstract outcomes is difficult, since they are ill defined or not easily measured. One solution involves expert and stakeholder interviews that provide a sense of how emergent outcomes are related to model structure and processes (Bousquet et al. 1998).

The various challenges faced in model validation and verification highlight the need for more sophisticated approaches. Verification and validation of agent-based models will be aided by better communication of model design through adoption of common languages, standard techniques, and better linkages to other software used in LUCC research, such as GIS and statistical packages. Otherwise, two broad questions will continue to guide the development of verification and validation. First, what do we learn when different model configurations enjoy varying levels of success across different forms of verification and validation? Second, does a model behave as expected when key components or their interdependencies are varied? Does the removal of a key resource institution, for example, result in an anticipated or documented LUCC? It is the role of both verification and validation to determine which components are important and why.

Challenges and Conclusions

This article has outlined many of the issues researchers face when constructing multi-agent system models of LUCC. There remain a number of fundamental challenges for which no clear solutions exist. These issues must be addressed in the coming years in order for MAS/LUCC modeling to evolve into a mature scientific field.

General Modeling Challenges

Many of these challenges mirror those faced when undertaking any modeling endeavor. In order to identify an appropriate degree of abstraction for the model, researchers must have a clear idea of the goal of their modeling effort. Is it a stylized representation of an abstract system that may produce results that are easily generalized to a wide variety of circumstances, or a carefully parameterized empirical model appropriate for scenario and policy analysis? Researchers may even choose to create models at both ends of the spectrum, in order to allow the development of one model to inform development of the other. Whatever the goal of modeling efforts, balancing the utility of abstraction against the need to include the critical components of the system under study is a major challenge of modeling. Developing techniques to understand the relationship between model components and outcomes is a major challenge, and success in this area is likely to have an impact on the acceptance of model results by the broader scientific community.

Most MAS/LUCC models are, by their nature, interdisciplinary. Therefore, researchers building these models face a formidable set of challenges unique to interdisciplinary research. A major challenge relates to building an experimental frame that can be used to answer questions of interest to multiple disciplines. A second challenge lies in unifying models that may operate—perhaps appropriately—at different spatial and temporal scales. This challenge occurs both at the time of model construction and when model outcomes are analyzed.

Building an Experimental Frame. Since the real world is far too complex to model in its entirety, we must define an experimental frame that we can use to guide our data-collection, modeling, and validation efforts. In defining such an experimental frame, we place boundaries around a subset of the real world. These boundaries can be defined in a variety of ways based on the spatial extent of a study area, the institutions or other human systems considered, and the temporal period of interest. Experimental frames are also defined in reference to particular research questions and bodies of knowledge. A real-world system can have any number of experimental frames associated with it. For example, the experimental frames for a particular fishery would be different for an ecologist, a fisheries biologist, or an economist. When the purpose of the modeling effort is specifically interdisciplinary, the boundaries of the experimental frame will be broadened, but challenges inherent to the definition of any model—defining the appropriate degree of abstraction and identifying which factors will be endogenous to the model—remain.

Scale Considerations. While MAS/LUCC models can theoretically integrate submodels across disciplines, a caveat is that models representing these processes must work according to compatible spatial and temporal scales. Frequently, processes in different disciplines operate over different scales, and relevant boundaries of scale do not coincide. These incompatibilities potentially occur over both spatial and temporal scales. Thus, representing and integrating processes across scale is a major modeling challenge. While issues of scale are central to the discipline of ecology (Levin 1992), within the social sciences the significance of scale is only beginning to be explored. In order to link ecological and social processes, we need a common understanding of how to address scale in integrated systems (Gibson, Ostrom, and Ahn 2000).

Theoretically, MAS/LUCC models can be structured to match the scale and structure of the available spatial data. However, if spatial data are not available at a scale fine enough to be compatible with the minimum spatial unit at which human decision making and/or ecological processes operate, then parameterization of a MAS model may be difficult, and MAS results may need to be scaled up for comparisons with actual data. The result may be a statistical loss of information.

When landscapes are directly compared, issues of spatial scale become potentially important in analyzing model outcomes. Within a defined geographical area, spatial heterogeneity that is apparent at a fine spatial scale may not show up as an aggregate, cross-region measure. Thus, if scale-dependent phenomena are present in the landscape of interest, the choice of spatial unit of analysis becomes quite important when comparing model outputs. This potential scale-dependence in measuring results highlights the importance of identifying the appropriate spatial scale for decision making in the model.

Specific Challenges

Understanding Complexity. Many of the challenges we have discussed are specific to MAS/LUCC models. These include the need to understand and represent complexity. While we have argued that MAS/LUCC models are an excellent tool for modeling complexity in human-influenced landscapes, it also must be acknowledged that the theory that defines complexity is still in the developmental stage. Thus, modeling and understanding complexity will surely be an iterative process. As researchers, we may find that the road we have taken changes even as we are in the middle of our journey.

Individual Decision Making. We have seen that many competing models of decision making exist. One of the strengths of MAS/LUCC modeling lies in the diversity of disciplinary perspectives that it brings together. Yet the result of this diversity is that radically different approaches have been used to represent human behavior through agent-based models. Within the community of multi-agent simulation, most researchers embrace a variant of bounded rationality for modeling human decision making. The resulting problem is an almost infinite number of possible formulations of agents.

A key challenge for researchers designing an agent-based model is to decide among the sheer number of competing techniques and theories for modeling decision making. In order for MAS modeling to become a viable long-term field, more comparison between different research efforts is needed. There is a particular need for research that compares these decision-making models to extant theory, practice, and observation of the real world. Such research would focus on the macroscale implications of particular microscale decision-making strategies and would examine whether particular agent decision-making formulations are appropriate for particular decision-making situations. This research would simultaneously support current approaches when there is agreement and point the way for improvements (in both general MAS and MAS/LUCC work) when there is disagreement.

Modeling Institutions. Institutions—the formal and informal rules between agents—constrain the actions of agents to derive an improved collective outcome. The last twenty years have seen much improved understanding of the factors that influence collective action problems (Ostrom 1998). However, formal models of the empirical insights are lacking. Nevertheless, numerous studies have focused on the evolution of cooperation in collective-choice problems (Axelrod 1984). These game-theory-oriented studies focus on the selection of a limited set of rules. The importance of social norms and reputation has been investigated, but important aspects such as the creation of rules, social memory, and the role of symbols and communications have not been incorporated in formal models. Many of these phenomena play a potentially important role in LUCC systems, but development of formal models remains a challenge.

Empirical Parameterization and Model Validation. Due to their complexity and ability to represent detail, MAS/LUCC models may face unique challenges of parameterization and validation. To a high degree, development of techniques for understanding output lags behind development of the tools that produce output. On the cellular modeling side, fine-resolution data appropriate for model validation are just beginning to become widely available, and the availability of social-science data lags behind the availability of natural-science data. Confidentiality concerns related to fine-resolution data on land use contribute to this lag. On the agent-based modeling side, massive advances in computing power have meant that sophisticated tools have become widely used before researchers have had time to consider and develop methods to link these models to data.

These challenges represent exciting opportunities for researchers. There is no end to interesting interdisciplinary research questions for which MAS/LUCC models are appropriate tools. We live in an era of both increased computing power and increased availability of spatial data. While many unanswered questions remain, researchers have the ability to draw on and combine knowledge from many disciplines—including landscape ecology, spatial statistics, and econometrics—in order to develop creative new tools for empirical analysis.

Communication. For some scholars, who argue that analytical proofs are required for the scientific method to be upheld, MAS/LUCC models have the image of pseudoscience. Multi-agent simulations produce colorful moving output, which might give the impression that they involve nothing more than playing games. Since most practitioners of MAS modeling purposely incorporate uncertainty and path dependence in their modeling efforts, each simulation might produce different results. Robust solutions can be derived with multiple experiments, but they do not have the power of mathematical proofs. Thus, effective and convincing communication of our results is a challenge.

Several strategies may assist in this goal. The first is to attempt to replicate findings using more than one modeling approach. This strategy has been followed by a number of authors whose work compares experimental and computational results (Axelrod 1986; Arthur 1991; Duffy 2001). A second approach attempts to replicate analytical findings in a simulation environment (Marimon, McGratten, and Sargent 1990; Marks 1992; Miller and Shubik 1992; Andreoni and Miller 1993; Arifovic 1994; Nyarko, Woodford, and Yannelis 1994; Weibull 1995; Epstein and Axtell 1996). These approaches demonstrate, under a set of simplifying assumptions, that a computational model can replicate a well-established analytical result. Within LUCC modeling, researchers may choose to make comparisons between the many alternative land-use modeling strategies described in the second section of this paper and the results from MAS/LUCC models.

A second strategy is to continue development of empirically parameterized and tested models. Historically, while many empirical cellular models of LUCC phenomena exist, agent-based models have been, by and large, theoretical. As empirical models are developed and tested, the circle of the scientific method will be completed for this new approach, and models will likely gain greater acceptance and use.

A final strategy is to encourage and facilitate clear communication of model mechanisms and results. Provision of modeling source code can be encouraged when possible. Currently, MAS/LUCC models are implemented in diverse programming languages and platforms, in order to meet the specialized needs of particular projects (Parker, Berger, and Manson forthcoming). In order to encourage cross-fertilization and comparisons between models, however, it may be important to have a common language through which model mechanisms can be communicated. Documentation of models using Unified Modeling Language may serve as a partial remedy to this communication gap (Fowler and Scott 1999). While we encourage journal and volume editors to provide space for extensive model documentation, we recognize that this space is costly. Therefore, a centralized repository for source code and documentation could be a valuable infrastructure addition for the MAS/LUCC community.

Conclusions

This article began with a set of questions designed to focus our exploration of MAS/LUCC modeling. In the course of the article, we endeavored to answer but did not fully succeed in answering all of the questions, because, indeed not all of the final answers are yet available. Instead, the utility of this article has been in delineating the uses, obstacles, advantages, and disadvantages associated with this particular methodology. We demonstrated that, in principle, MAS/LUCC models offer tools that can facilitate progress in understanding processes of LUCC. We delineated the type of issues and processes that MAS/LUCC models can address and those where traditional methods will likely suffice. We outlined the deliberation that must take place in choosing a modeling strategy—namely, what type of role is the model expected to play in a research project? We discussed the crucial issues of verification and validation, noting the challenges that lie ahead in empirical applications of these models. Finally, we noted the broad and open questions that MAS/LUCC research must address if this methodology is to become accepted. This exercise in clarifying the questions, challenges, and possibilities surrounding MAS/LUCC builds a foundation for further progress.

The authors of this article represent a range of social-science disciplines, and our review is necessarily somewhat weighted by our disciplinary perspectives and expertise. We have seen, however, that no one methodological approach dominates this nascent field. Rather, a wide range of techniques for model development and empirical assessment are used, and, in many cases, insightful comparisons have resulted when multiple approaches are used to tackle a single research question. Further, modeling efforts fall along a spectrum from highly abstract to highly empirical applications. Ideally, this diversity will spur a dialog between modelers working at each end of the spectrum, with lessons from one end being used to inform the other. Finally, it is clear that this modeling field will benefit from the development of a set of common metrics that can be used to test simulations and from continued effort to validate models of human decision making. While challenges remain, the many recent developments reflect an encouraging trend towards integrating the multiple tools and disciplines required to develop a new methodology for dynamic spatial modeling of human-environment interactions.

Acknowledgments

This article has benefited from in-depth discussions with and comments from members of the Center for the Study of Institutions, Population, and Environmental Change (CIPEC) biocomplexity project at Indiana University, participants in the 2001 Special Workshop on agent-based models of land use, Elinor Ostrom, James Wilson, and five anonymous reviewers. All errors and omissions are the authors' responsibility. The authors gratefully acknowledge financial support from the CIPEC through National Science Foundation (NSF) grants SBR9521918 and SES008351, the Resilience Alliance, the National Aeronautics and Space Administration (NASA) Earth System Science Fellowship program, the National Science Foundation (NSF) doctoral dissertation improvement grant 9907952, NASA's LCLUC program (NAG 56406), and NSF grant 9521914 through the Carnegie Mellon University Center for Integrated Study of the Human Dimensions of Global Change.

References

Agarwal, C., G. M. Green, J. M. Grove, T. P. Evans, and C. M. Schweik. 2002. A review and assessment of land-use change models: Dynamics of space, time, and human choice. UFS Technical Report NE-297. Burlington, VT: U.S. Department of Agriculture Forest Service, Northeastern Forest Research Station. Also available at http://www.fs.fed.us/ne/newtown_square/publications/technical_reports/pdfs/2002/gtrne297.pdf (last accessed 1 May 2003).

Alberti, M., and P. Waddell. 2000. An integrated urban development and ecological simulation model. *Integrated Assessment* 1 (3): 215–27.

Alcamo, J. ed. 1994. *IMAGE 2.0: Integrated modeling of global climate change*. Dordrecht: Kluwer Academic Publishers.

Alonso, D., and R. V. Sole. 2000. The DivGame simulator: A stochastic cellular automata model of rainforest dynamics. *Ecological Modelling* 133 (1/2): 131–41.

Alonso, W. 1968. Predicting best with imperfect data. *Journal of the American Institute of Planners* 34:248–55.

Andreoni, J. A., and J. H. Miller. 1993. Rational cooperation in the finitely repeated prisoner's dilemma: Experimental evidence. *Economic Journal* 103 (418): 570–85.

Anselin, L. 1988. *Spatial econometrics: Methods and models*. Dordrecht: Kluwer Academic Press.

Antona, M., P. Bommel, F. Bousquet, and C. L. Page. 2002. Interactions and organization in ecosystem management: The use of multi-agent systems to simulate incentive environmental policies. In *Third workshop on agent-based simulation*, ed. C. Urban, 85–92. Ghent, Belgium: SCS-European Publishing House.

Arifovic, J. 1994. Genetic algorithm learning and the cobweb model. *Journal of Economic Dynamics and Control* 18: 3–28.

———. 2001. Evolutionary dynamics of currency substitution. *Journal of Economic Dynamics and Control* 25 (3–4): 395–417.

Arthur, W. B. 1988. Self-reinforcing mechanisms in economics. In *The economy as an evolving complex system*, ed. P. W. Anderson, K. J. Arrow, and D. Pines, 9–33. Redwood City, CA: Addison-Wesley.

———. 1991. Designing economic agents that act like human agents: A behavioral approach to bounded rationality. *American Economic Review, Papers and Proceedings* 81 (2): 353–59.

———. 1993. On designing economic agents that behave like human agents. *Journal of Evolutionary Economics* 3 (1): 1–22.

———. 1994a. Inductive reasoning and bounded rationality. *American Economic Review, Papers and Proceedings* 84 (2): 406–11.

———. 1994b. Path dependence, self-reinforcement, and human learning. In *Increasing returns and path dependence in the economy*, ed. W. B. Arthur, 135–58. Ann Arbor: University of Michigan Press.

Arthur, W. B., S. N. Durlaf, and D. Lane, eds. 1997. *The economy as an evolving complex system II*. Reading, MA: Addison-Wesley.

Auyang, S. Y. 1998. *Foundations of complex systems theories: In economics, evolutionary biology, and statistical physics*. New York: Cambridge University Press.

Axelrod, R. M. 1984. *The evolution of cooperation*. New York: Basic Books.

———. 1986. An evolutionary approach to norms. *American Political Science Review* 80:1096–111.

———. 1997a. Advancing the art of simulation in the social sciences. In *Simulating social phenomena*, ed. R. Conte, R. Hegselmann, and P. Terna, 21–40. Berlin: Springer-Verlag.

———. 1997b. *The complexity of cooperation. Agent-based models of competition and collaboration*. Princeton, NJ: Princeton University Press.

Axtell, R. L., and J. M. Epstein. 1994. Agent-based modeling: Understanding our creations. *The Bulletin of the Santa Fe Institute* 28–32.

Baas, N. A., and C. Emmeche. 1997. *On emergence and explanation*. Santa Fe Institute Publication 97-02-008. Santa Fe, NM: Santa Fe Institute.

Baker, W. L. 1989. A review of models in landscape change. *Landscape Ecology* 2 (2): 111–33.

Balling, R. J., J. T. Taber, M. Brown, and K. Day. 1999. Multiobjective urban planning using a genetic algorithm. *ASCE Journal of Urban Planning and Development* 125 (2): 86–99.

Balmann, A., 1997. Farm-based modelling of regional structural change. *European Review of Agricultural Economics* 25 (1): 85–108.

Balmann, A., K. Happe, K. Kellermann, and A. Kleingarn. 2002. Adjustment costs of agri-environmental policy switchings: A multi-agent approach. In *Complexity and ecosystem management: The theory and practice of multi-agent approaches*, ed. M. A. Janssen, 127–57. Northampton, MA: Edward Elgar Publishers.

Balzter, H., P. W. Braun, and W. Kohler. 1998. Cellular automata models for vegetation dynamics. *Ecological Modelling* 107 (2/3): 113–25.

Barreteau, O., F. Bousquet, and J. M. Attonaty. 2001. Role-playing games for opening the black box of multi-agent systems: method and lessons of its application to Senegal River Valley irrigated systems. *Journal of Artificial Societies and Social Simulation* 4 (2). http://jasss.soc.surrey.ac.uk/4/2/5.html (last accessed 10 February 2003).

Batty, M. 2001. Agent-based pedestrian modeling. *Environment and Planning B* 28 (3): 321–26.

Batty, M., and P. M. Torrens. 2001. Modelling complexity: The limits to prediction. *Cybergeo* 21. http://www.cybergeopresse.fr/ectqg12/batty/articlemb.htm (last accessed 10 February 2003).

Batty, M., and Y. Xie. 1994. Modeling inside GIS. Part 1: Model structures, exploratory spatial data analysis, and aggregation. *International Journal of Geographic Information Systems* 8 (3): 291–307.

Batty, M., Y. Xie, and Z. Sun. 1999. Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment, and Urban Systems* 23 (3): 205–33.

Beckenbach, F. 1999. Learning by genetic algorithms in economics. In *Computational techniques for modelling learning in economics*, ed. T. Brenner, 73–100. Boston: Kluwer Academic Publishers.

Benenson, I. 1998. Multi-agent simulations of residential dynamics in the city. *Computers, Environment, and Urban Systems* 22 (1): 25–42.

Bennett, R. J., and R. J. Chorley. 1978. *Environmental systems: Philosophy, analysis, and control*. Princeton, NJ: Princeton University Press.

Berger, T. 2001. Agent-based spatial models applied to agriculture: A simulation tool for technology diffusion, resource-use changes, and policy analysis. *Agricultural Economics* 25 (2–3): 245–60.

Bian, L. 1997. Multiscale nature of spatial data in scaling up environmental models. In *Scale in remote sensing and GIS*, ed. D. A. Quattrochi and M. F. Goodchild, 13–26. New York: Lewis Publishers.

Bond, A. H., and L. Gasser. 1988. *Readings in distributed artificial intelligence*. San Mateo, CA: Morgan and Kauffman.

Bousquet, F., I. Bakam, H. Proton, and C. L. Page. 1998. Cormas: Common-pool resources and multi-agent systems. *Lecture Notes in Artificial Intelligence* 1416:826–37.

Bousquet, F., F. O. Barreteau, P. d'Aquino, M. Etienne, S. Boissau, S. Auber, C. L. Page, D. Babin, and J. C. Castella. 2002. Multi-agent systems and role games: An approach for ecosystem co-management. In *Complexity and ecosystem management: The theory and practice of multi-agent approaches*, ed. M. A. Janssen, 249–85. Northampton, MA: Edward Elgar Publishers.

Bower, J., and D. W. Bunn. 2000. Model-based comparisons of pool and bilateral markets for electricity. *Energy Journal* 21 (3): 1–29.

Brander, J. A., and M. S. Taylor. 1998. The simple economics of Easter Island: A Ricardo-Malthus model of renewable resource use. *The American Economic Review* 88 (1): 119–38.

Briassoulis, H. 2000. Analysis of land-use change: Theoretical and modeling approaches. In *The Web book of regional science* (http://www.rri.wvu.edu/regscweb.htm, last accessed 1 May 2003), ed. Scott Loveridge. Morgantown, MV: Regional Research Institute, West Virginia University.

Burrows, P. 1986. Nonconvexity induced by external costs of production: Theoretical curio or policy dilemma? *Journal of Environmental Economics and Management* 13: 101–28.

Case, A. 1991. Spatial patterns in household demand. *Econometrica* 59 (4): 953–65.

———. 1992. Neighborhood influence and technological change. *Regional Science and Urban Economics* 22:491–508.

Castelfranchi, C. 1998. Modelling social action for AI agents. *Artificial Intelligence* 103:157–82.

Casti, J. L. 1997. Can you trust it? On the reliability of computer simulation models. *Complexity* 2 (5): 8–11.

———. 1999. The computer as a laboratory. *Complexity* 4 (5): 12–14.

Cecchini, A., and F. Viola. 1990. Eine stadtbausimulation (A stimulation of urban development). *Wissenschaftliche Zeitschrift der Hocheschule fur Architektur und Bauwesen* 36: 159–162.

Chen, S. H., and C. H. Yeh. 2001. Evolving traders and the business school with genetic programming: A new architecture of the agent-based artificial stock market. *Journal of Economic Dynamics and Control* 25 (3–4): 363–93.

Chisholm, M. 1967. General systems theory and geography. *Transactions of the Institute of British Geographers* 42: 45–52.

Chomitz, K. M., and D. A. Gray. 1996. Roads, land use, and deforestation: A spatial model applied to Belize. *The World Bank Economic Review* 10 (3): 487–512.

Chuvieco, E. 1993. Integration of linear programming and GIS for land-use modeling. *International Journal of Geographical Information Systems* 7 (1): 71–83.

Clarke, K. C., S. Hoppen, and L. Gaydos. 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B* 24:247–61.

Cliff, A. D., and J. K. Ord. 1973. *Spatial autocorrelation*. London: Pion.

Conte, R., and N. Gilbert. 1995. Computer simulation for social theory. In *Artificial societies: The computer simulation of social life*, ed N. Gilbert and R. Conte, 1–15. London: UCL Press.

Conte, R., R. Hegselmann, and P. Terna, eds. 1997. *Simulating social phenomena*. Berlin: Springer-Verlag.

Costanza, R., F. H. Sklar, and J. W. Day, Jr. 1986. Modeling spatial and temporal succession in the Atchafalaya/Terrebonne Marsh/estuarine complex in South Louisiana. In *Estuarine variability*, ed. D. A. Wolfe, 387–404. Orlando: Academic Press.

Couclelis, H. 1985. Cellular worlds: A framework for modeling micro-macro dynamics. *Environment and Planning A* 17: 585–96.

Craig, W. J., T. M. Harris, and D. Weiner, eds. 2002. *Community participation and geographic information systems*. London: Taylor and Francis.

Cromley, R. G., and D. M. Hanink. 1999. Coupling land-use allocation models with raster GIS. *Journal of Geographic Systems* 1:137–53.

Dawid, H. 1999. *Adaptive learning by genetic algorithms: Analytical results and applications to economic models*. Berlin: Springer-Verlag.

Deadman, P. J., and E. Schlager. 2002. Models of individual decision making in agent-based simulation of common-pool-resource management institutions. In *Integrating geographic information systems and agent-based modeling techniques for simulating social and ecological processes*, ed. H. R. Gimblett, 137–69. New York: Oxford University Press.

Dean, J. S., G. J. Gumerman, J. M. Epstein, R. L. Axtell, A. C. Swedlund, M. T. Parket, and S. McCarroll. 2000. Understanding Anasazi cultural change through agent-based modeling. In *Dynamics in human and primate societies*, ed. T. A. Kohler and G. J. Gumerman, 179–206. New York: Oxford University Press.

Duffy, J. 2001. Learning to speculate: Experiments with artificial and real agents. *Journal of Economic Dynamics and Control* 25 (3–4): 295–319.

Eastman, R. 1999. *Guide to GIS and image processing*. Worcester, MA: Clark University.

Epstein, J. M. 1999. Agent-based models and generative social science. *Complexity* 4 (5): 41–60.

Epstein, J. M., and R. Axtell. 1996. *Growing artificial societies: Social science from the ground up*. Washington, DC: Brookings Institution Press.

Ermentrout, G. B., and L. Edelstein-Keshet. 1993. Cellular automata approaches to biological modeling. *Journal of Theoretical Biology* 160 (1): 97–113.

Fogel, D., K. Chellapilla, and P. Angeline. 1999. Inductive reasoning and bounded rationality reconsidered. *IEEE Transactions on Evolutionary Computation* 3 (2): 142–43.

Forrest, S., ed. 1991. *Emergent computation: Self-organization, collective, and cooperative phenomena in natural and artificial computing networks*. Cambridge, MA: MIT Press.

Fowler, M., and K. Scott. 1999. *UML distilled: Applying the standard object modeling language*. New York: Addison Wesley Longman.

Geoghegan, J., L. J. Pritchard, Y. Ogneva-Himmelberger, R. Roy Chowdury, S. Sanderson, and B. L. Turner II. 1998. "Socializing the pixel" and "pixelizing the social" in land-use/cover change. In *People and pixels*, ed. D. Liverman, E. F. Moran, R. R. Rindfuss, and P. C. Stern, 51–69. Washington, DC: National Research Council.

Geoghegan, J., L. Wainger, and N. Bockstael. 1997. Spatial landscape indices in a Hedonic framework: An ecological economics analysis using GIS. *Ecological Economics* 23: 251–64.

Gibson, C. C., E. Ostrom, and T. K. Ahn. 2000. The concept of scale and the human dimensions of global change: A survey. *Ecological Economics* 32:217–39.

Gigerenzer, G., and R. Selten. 2001. *Bounded rationality: The adaptive toolbox*. Cambridge, MA: MIT Press.

Gigerenzer, G., and P. Todd. 1999. *Simple heuristics that make us smart*. Oxford: Oxford University Press.

Gilbert, N., S. Maltby, and T. Asakawa. 2002. Participatory simulations for developing scenarios in environmental resource management. In *Third workshop on agent-based simulation*, ed. C. Urban, 67–72. Ghent, Belgium: SCS-European Publishing House.

Gilbert, N., and K. G. Troitzsch. 1999. *Simulation for the social scientist*. London: Open University Press.

Giles, R. H., Jr., and M. K. Trani. 1999. Key elements of landscape pattern measures. *Environmental Management* 23 (4): 477–81.

Gilruth, P. T., S. E. Marsh, and R. Itami. 1995. A dynamic spatial model of shifting cultivation in the highlands of Guinea, West Africa. *Ecological Modelling* 79:179–97.

Gimblett, H. R., ed. 2002. *Integrating geographic information systems and agent-based modeling techniques for simulating social and ecological processes*. New York: Oxford University Press.

Gordon, J., and E. Shortliffe. 1984. The Dempster-Shafer theory of evidence: Rule-based expert systems. In *The MYCIN experience of the Stanford Heuristic Programming Project*, ed. B. Buchanan and E. Shortliffe, 272–92. Reading, MA: Addison Wesley.

Grimble, R., and K. Wellard. 1997. Stakeholder methodologies in natural resource management: A review of principles, contexts, experiences and opportunities. *Agricultural Systems 55:173–93.*

Gronewold, A., and M. Sonnenschein. 1998. Event-based modelling of ecological systems with asynchronous cellular automata. *Ecological Modelling* 108 (1): 37–52.

Hall, C. A. S., H. Tian, Y. Qi, G. Pontius, and J. Cornell. 1995. Modelling spatial and temporal patterns of tropical land-use change. *Journal of Biogeography* 22 (4/5): 753–57.

Hare, M., D. Medugno, J. Heeb, and C. Pahl-Wostl. 2002. An applied methodology for participatory model building of agent-based models for urban water management. In *Third workshop on agent-based simulation*, ed. C. Urban, 61–66. Ghent, Belgium: SCS-European Publishing House.

Hegselmann, R. 1998. Modeling social dynamics by cellular automata. In *Computer modeling of social processes*, ed. W. B. G. Liebrand, A. Nowak, and R. Hegselmann, 37–64. London: SAGE Publications.

Herold, M., and G. Menz. 2001. Landscape metric signatures (LMS) to improve urban land-use information derived from remotely sensed data. In *A decade of trans-European remote sensing cooperation: Proceedings of the 20th EARSeL Symposium, Dresden, Germany, 14–16 June 2000*, ed. M. F. Buchroithner, 251–56. Lisse, The Netherlands: A. A. Balkema Publishers.

Heuvelink, G. 2002. Developments in statistical approaches to spatial uncertainty and its propagation. *International Journal of Geographical Information Science* 16 (2): 111–13.

Hoffmann, M., H. Kelley, and T. Evans. 2002. Simulating land-cover change in South-Central Indiana: An agent-based model of deforestation and afforestation. In *Complexity and ecosystem management: The theory and practice of multi-agent approaches*, ed. M. A. Janssen, 218–47. Northampton, MA: Edward Elgar Publishers.

Hogeweg, P. 1988. Cellular automata as a paradigm for ecological modelling. *Applied Mathematics and Computation* 27 (1): 81–100.

Holland, J. H. 1990. Concerning the emergence of tag-mediated lookahead in classifier systems. *Physica* 42D:188–201.

———. 1998. *Emergence: From chaos to order*. Reading, MA: Perseus Books.

Howitt, R. E. 1995. Positive mathematical programming. *American Journal of Agricultural Economics* 77 (2): 329–42.

Irwin, E., and N. Bockstael. 2002. Interacting agents, spatial externalities, and the evolution of residential land-use patterns. *Journal of Economic Geography* 2 (1): 31–54.

Janssen, M. A., ed. Forthcoming. *Complexity and ecosystem management: The theory and practice of multi-agent approaches*. Northampton, MA: Edward Elgar Publishers.

Janssen, M. A., and W. Jager. 2000. The human actor in ecological economic models. *Ecological Economics* 35 (3): 307–10.

Janssen, M. A., and E. Ostrom. Forthcoming. Adoption of a new regulation for the governance of common-pool resources by a heterogeneous population. In *Inequality, cooperation, and environmental sustainability*, ed. J. M. Baland, P. Bardhan, and S. Bowles. New York: Russell Sage Foundation.

Judd, K. L. 1997. Computational economics and economic theory: Substitutes or complements. *Journal of Economic Dynamics and Control* 21 (6): 907–42.

Judson, O. P. 1994. The rise of the individual-based model in ecology. *Trends in Ecology and Evolution* 9 (1): 9–14.

Kaimowitz, D., and A. Angelsen. 1998. *Economic models of tropical deforestation: A review.* Jakarta: Centre for International Forestry Research.

Kauffman, S. 1994. Whispers from Carnot: The origins of order and principles of adaptation in complex nonequilibrium systems. In *Complexity: Metaphors, models, and reality*, ed. G. Cowan, D. Pines, and D. Meltzer, 83–160. New York: Addison Wesley.

Kerridge, J., J. Hine, and M. Wigan. 2001. Agent-based modelling of pedestrian movements: The questions that need to be asked and answered. *Environment and Planning B* 28 (3): 327–42.

Kirman, A. P., and N. J. Vriend. 2001. Evolving market structure: An ACE model of price dispersion and loyalty. *Journal of Economic Dynamics and Control* 25 (3–4): 459–502.

Kohler, T. A. 2000. *Dynamics in human and primate societies*. New York: Oxford University Press.

Kohler, T. A., J. Kresl, C. V. West, E. Carr, and R. H. Wilshusen. 2000. Be there then: A modeling approach to settlement determinants and spatial efficiency among late ancestral pueblo populations of the Mesa Verde region, U.S. Southwest. In *Dynamics in human and primate societies*, ed. T. A. Kohler and G. J. Gumerman, 145–78. New York: Oxford University Press.

Kollman, K., J. H. Miller, and S. E. Page. 1997. Political institutions and sorting in a Tiebout model. *American Economic Review* 87 (5): 977–92.

Krider, R. E., and C. B. Weinberg. 1997. Spatial competition and bounded rationality: Retailing at the edge of chaos. *Geographical Analysis* 29 (1): 16–34.

Laffont, J.-J. 1988. *Fundamentals of public economics*. Cambridge, MA: MIT Press.

Lam, N., and D. A. Quattrochi. 1992. On the issues of scale, resolution, and fractal analysis in the mapping sciences. *The Professional Geographer* 44:88–98.

Lambin, E. F. 1994. *Modelling deforestation processes: A review.* Luxemburg: European Commission.

Lansing, J. S., and J. N. Kremer. 1993. Emergent properties of Balinese water temple networks: Coadaptation on a rugged fitness landscape. *American Anthropologist* 95 (1): 97–114.

LeBaron, B. 2001. A builder's guide to agent-based financial markets. *Quantitative Finance* 1 (2): 254–61.

Lee, R. G., R. Flamm, M. G. Turner, C. Bledsoe, P. Chandler, C. DeFerrari, R. Gottfried, R. J. Naiman, N. Schumaker, and D. Wear. 1992. Integrating sustainable development and environmental vitality: A landscape ecology approach. In *Watershed management: Balancing sustainability and environmental change*, ed. R. J. Naiman, 499–521. New York: Springer-Verlag.

Leggett, C. G., and N. E. Bockstael. 2000. Evidence of the effects of water quality on residential land prices. *Journal of Environmental Economics and Management* 39:121–44.

Levin, S. A. 1992. The problem of pattern and scale in ecology. *Ecology* 73 (6): 1943–67.

Li, B.-L. 2000. Fractal geometry applications in description and analysis of patch patterns and patch dynamics. *Ecological Modelling* 132 (1/2): 33–50.

Li, H., and J. F. Reynolds. 1997. Modeling effects of spatial pattern, drought, and grazing on rates of rangeland degradation: A combined Markov and cellular automaton approach. In *Scale in remote sensing and GIS*, ed. D. A. Quattrochi and M. F. Goodchild, 211–30. New York: Lewis Publishers.

Liebrand, W. B. G., A. Nowak, and R. Hegselmann, eds. 1988. *Computer modeling of social processes*. London: Sage Publications.

Ligtenberg, A., A. K. Bregt, and R. van Lammeren. 2001. Multi-actor-based land-use modelling: Spatial planning using agents. *Landscape and Urban Planning* 56:21–33.

Ligtenberg, A., A. K. Bregt, M. Wachowicz, A. Beulens, and D. L. Kettenis. 2002. Multi-agent land-use change simulation: Modeling actors perception. In *Third workshop on agent-based simulation*, ed. C. Urban, 93–98. Ghent, Belgium: SCS-European Publishing House.

Lim, K., P. Deadman, E. Moran, E. Brondizio, and S. McCracken. 2002. Agent-based simulations of household decision-making and land-use change near Altamira, Brazil. In *Integrating geographic information systems and agent-based modeling techniques for simulating social and ecological processes*, ed. H. R. Gimblett, 137–69. New York: Oxford University Press.

Longley, P., G. Higgs, and D. Martin. 1994. The predictive use of GIS to model property valuations. *International Journal of Geographical Information Systems* 8 (2): 217–35.

Ludeke, A. K., R. C. Maggio, and L. M. Reid. 1990. An analysis of anthropogenic deforestation using logistic regression and GIS. *Journal of Environmental Management* 31:247–59.

Luz, F. 2000. Participatory landscape ecology—A basis for acceptance and implementation. *Landscape and Urban Planning* 50:157–66.

Lynam, T. 2002. Complex and useful but certainly wrong: A multi-agent agro-ecosystem model from the semi-arid areas of Zimbabwe. In *Complexity and ecosystem management: The theory and practice of multi-agent approaches*, ed. M. A. Janssen, 188–217. Northampton, MA: Edward Elgar Publishers.

Lynam, T., F. Bousquet, P. D'Aquino, O. Barreteau, C. L. Page, F. Chinembiri, and B. Mombeshora. 2002. Adapting science to adaptive managers: Spidergrams, belief models, and multi-agent systems modeling. *Conservation Ecology* 5 (2). http://www.consecol.org/vol5/iss2/art24/ (last accessed 10 February 2003).

Mann, S., and G. Benwell. 1996. The integration of ecological, neural, and spatial modelling for monitoring and prediction for semiarid landscapes. *Computers and Geosciences* 22 (9): 1003–12.

Manson, S. M. 2000. Agent-based dynamic spatial simulation of land-use/cover change in the Yucatán peninsula, Mexico. Paper presented at the Fourth International Conference on Integrating GIS and Environmental Modeling (GIS/EM4), Banff, Canada, 2–8 September.

———. 2001. Simplifying complexity: A review of complexity theory. *Geoforum* 32 (3): 405–14.

———. Forthcoming. The SYPR integrative assessment model: Complexity in development. In *Final frontiers: Understanding land change in the southern Yucatan peninsular region*, ed. B. L. Turner II, D. Foster, and J. Geoghegan. Oxford: Clarendon, Oxford University Press.

Marimon, R., E. McGratten, and T. J. Sargent. 1990. Money as a medium of exchange in an economy with artificially intelligent agents. *Journal of Economic Dynamics and Control* 14:329–73.

Marks, R. E. 1992. Breeding hybrid strategies: Optimal behavior for oligopolists. *Journal of Evolutionary Economics* 2: 17–38.

Mertens, B., and E. F. Lambin. 1997. Spatial modelling of deforestation in southern Cameroon. *Applied Geography* 17 (2): 143–62.

Miller, J. H. 1996. The coevolution of automata in the repeated prisoner's dilemma. *Journal of Economic Behavior and Organization* 29:87–112.

———. 1998. Active nonlinear tests (ANTs) of complex simulation models. *Management Science* 44 (6): 820–30.

Miller, J. H., and M. Shubik. 1992. *Some dynamics of a strategic market game with a large number of agents*, Santa Fe Institute Publication 92-11-057. Santa Fe, NM: Santa Fe Institute.

Miyao, T., and Y. Kanemoto. 1987. *Urban dynamics and urban externalities*. New York: Harwood Academic Publishers.

Munroe, D., J. Southworth, and C. Tucker. 2001. The dynamics of land-cover change in western Honduras: Spatial autocorrelation and temporal variation. Paper presented at the American Agricultural Economics Association Annual Meeting, Chicago, IL, 5–8 August.

Nyarko, Y., M. Woodford, and N. C. Yannelis. 1994. Bounded rationality and learning: Introduction. *Economic Theory* 4:811–20.

Openshaw, S. 1977. A geographical study of scale and aggregation problems in region-building, partitioning, and spatial modelling. *Transactions of the Institute of British Geographers*. New Series 2:459–72.

———. 1994. Computational human geography: Towards a research agenda. *Environment and Planning A* 26: 499–508.

———. 1995. Human systems modelling as a new grand challenge area in science: What has happened to the science in social science? *Environment and Planning A* 27:159–64.

Oreskes, N., K. Shrader-Frechette, and K. Belitz. 1994. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 263:641–46.

Ostrom, E. 1998. A behavioral approach to the rational-choice theory of collective action. *American Political Science Review* 92:1–22.

O'Sullivan, D. 2001. Graph-cellular automata: A generalised discrete urban and regional model. *Environment and Planning B* 28 (5): 687–706.

Parker, D. C. 2000. Edge-effect externalities: Theoretical and empirical implications of spatial heterogeneity. Ph. D. diss., Department of Agricultural and Resource Economics, University of California at Davis.

Parker, D. C., T. Berger, and S. M. Manson, eds. 2002. *Agent-based models of land-use and land-cover change: Report and review of an international workshop, October 4–7, 2001, Irvine, California, USA*, LUCC Report Series No. 6. Bloomington, IN: Land Use and Cover Change Project. http://www.indiana.edu/%7Eact/focus1/ABM_Report6.pdf (last accessed 1 May 2003).

Parker, D. C., T. P. Evans, and V. Meretsky. 2001. Measuring emergent properties of agent-based land-use/land-cover models using spatial metrics. Paper presented at the Seventh Annual Conference of the International Society for Computational Economics, New Haven, CT, 28–29 June.

Phelan, S. E. 1999. Note on the correspondence between complexity and systems theory. *Systemic Practice and Action Research* 12 (3): 237–38.

Plantinga, A. J. 1999. *The economics of land use: A bibliography*, University of Maine Publication 744. Orono, ME: The Agricultural and Forest Experiment Station, University of Maine.

Polhill, J. G., N. M. Gotts, and A. N. R. Law. 2001. Imitative versus nonimitative strategies in a land-use simulation. *Cybernetics and Systems* 32 (1): 285–307.

Pontius, R. G., Jr., 2000. Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering and Remote Sensing* 66 (8): 1011–16.

Pontius, R. G., and L. Schneider. 2001. Land-use change model validation by a ROC method. *Agriculture, Ecosystems, and Environment* 85 (1–3): 239–48.

Portugali, J., I. Benenson, and I. Omer. 1997. Spatial cognitive dissonance and sociospacial emergence in a self-organizing city. *Environment and Planning B* 24:263–85.

Rabin, M. 1998. Psychology and economics. *Journal of Economic Literature* 36 (1): 11–46.

Rajan, K. S., and R. Shibasaki. 2000. *Land-use/cover changes and water resources—Experiences from AGENT-LUC Model.* International Center for Disaster Mitigation Engineering (INCEDE), Institute of Industrial Science, University of Tokyo Publication 19. http://incede.iis.u-tokyo.ac.jp/reports/Report_19/Rajan.pdf (last accessed 5 February 2003).

Ray, I., and J. Williams. 1999. Evaluation of price policy in the presence of water theft. *American Journal of Agricultural Economics* 81 (4): 928–41.

Riley, R. H., D. L. Phillips, M. J. Schuft, and M. C. Garcia. 1997. Resolution and error in measuring land-cover change: Effects on estimating net carbon release from Mexican terrestrial ecosystems. *International Journal of Remote Sensing* 18 (1): 121–37.

Robinson, J. 1994. Land-use and land-cover projections. In *Changes in land use and land cover: A global perspective*, ed. W. B. Meyer and B. L. Turner II, 73–92. Cambridge, U.K.: Cambridge University Press.

Rouchier, J., F. Bousquet, M. Requier-Desjardins, and M. Antona. 2001. A multi-agent model for describing transhumance in North Cameroon: Comparison of different rationality to develop a routine. *Journal of Economic Dynamics and Control* 25:527–59.

Russell, S., and P. Norvig. 1995. *Artificial intelligence: A modern approach*. Upper Saddle River, NJ: Prentice Hall.

Sanchirico, J. N., and J. E. Wilen. 1999. Bioeconomics of spatial exploitation in a patchy environment. *Journal of Environmental Economics and Management* 37 (2): 129–50.

Sanders, L., D. Pumain, H. Mathian, F. Guérin-Pace, and S. Bura. 1997. SIMPOP—A multi-agent system for the study of urbanism. *Environment and Planning B* 24:287–305.

Saura, S., and M. Millan. 2001. Sensitivity of landscape pattern metrics to map spatial extent. *Photogrammetric Engineering and Remote Sensing* 67 (9): 1027–36.

Schelling, T. 1971. Dynamic models of segregation. *Journal of Mathematical Sociology* 1:143–86.

Schelling, T. C. 1978. *Micromotives and macrobehavior*. New York: W. W. Norton.

Selten, R. 2001. What is bounded rationality? In *Bounded rationality: The adaptive toolbox*, ed. G. Gigerenzer and R. Selten, 13–36. Cambridge, MA: MIT Press.

Silberberg, E. 1990. *The structure of economics: A mathematical analysis*. New York: McGraw-Hill.

Silvertown, J., S. Holtier, J. Johnson, and P. Dale. 1992. Cellular automaton models of interspecific competition for space: The effect of pattern on process. *Journal of Ecology* 80 (3): 527–34.

Simon, H. A. 1997. Behavioral economics and bounded rationality. In *Models of bounded rationality*, ed. H. A. Simon, 267–433. Cambridge, MA: MIT Press.

Sklar, F. H., and R. Costanza. 1991. The development of dynamic spatial models for landscape ecology: A review and prognosis.

In *Quantitative methods in landscape ecology*, ed. M. G. Tuner and R. H. Gardner, 239–88. New York: Springer-Verlag.

Southworth, F., V. H. Dale, and R. V. O'Neill. 1991. Contrasting patterns of land use in Rondônia, Brazil: Simulating the effects on carbon release. *International Social Science Journal* 130:681–798.

Steins, N. A., and V. M. Edwards. 1999. Platforms for collective action in multiple-use common-pool resources. *Agriculture and Human Values* 16:241–55.

Takeyama, M., and H. Couclelis. 1997. Map dynamics: Integrating cellular automata and GIS through geo-algebra. *International Journal of Geographical Information Science* 11 (1): 73–91.

Tesfatsion, L. 2001. Introduction to the special issue on agent-based computational economics. *Journal of Economic Dynamics and Control* 25 (3/4): 281–93.

Thrift, N. 1999. The place of complexity. *Theory, Culture, and Society* 16 (3): 31–69.

Tobler, W. R. 1979. Cellular geography. In *Philosophy in geography*, ed. S. Gale and G. Olsson, 379–86. Dordrecht: D. Reidel Publishing Company.

Torrens, P. M. 2001. *Can geocomputation save urban simulation? Throw some agents into the mixture, simmer, and wait . . .*, Publication 32. London: University College, London.

———. 2002. Cellular automata and multi-agent systems as planning support tools. In *Planning support systems in practice*, ed. S. S. Geertman and J. Stillwell, 205–22. London: Springer-Verlag.

Torrens, P. M., and D. O'Sullivan. 2001. Cellular automata and urban simulation: Where do we go from here? *Environment and Planning B* 28 (2): 163–68.

Trame, A., S. J. Harper, J. Aycrigg, and J. Westervelt. 1997. *The Fort Hood avian simulation model: A dynamic model of ecological influences on two endangered species*. CERL Publication 97/88. Champaign, IL: U.S. Army Corps of Engineers. Engineer Research and Development Center, Construction Engineering Research Laboratory. http://blizzard.gis.uiuc.edu/dsm_FHASM_frame. htm (last accessed 5 February 2003).

Turner, B. L. I., D. Skole, S. Sanderson, G. Fischer, L. Fresco, and R. Leemans. 1995. *Land-use and land-cover change: Science/research plan*. IGBP Report no. 35 and HDP Report no. 7. Stockholm and Geneva: International Geosphere-Biosphere Programme: A study of Global Change (IGBP) of the International Council of Scientific Unions, and Human Dimensions of Global Environmental Change Programme (HDP) of the International Social Science Council.

Turner, M. G., R. Costanza, and F. Sklar. 1989. Methods to evaluate the performance of spatial simulation models. *Ecological Modelling* 48 (1/2): 1–18.

Tversky, A., and D. Kahneman. 1990. Rational choice and the framing of decisions. In *The limits of rationality*, ed. K. S. Cook and M. Levi, 60–89. Chicago: University of Chicago Press.

U. S. Environmental Protection Agency (EPA). 2000. *Projecting land-use change: A summary of models for assessing the effects of community growth and change on land-use patterns*. Office of Research and Development Publication EPA/600/R-00/098. Cincinnati, OH: U.S. Environmental Protection Agency.

Veldkamp, A., and L. O. Fresco. 1996. CLUE: A conceptual model to study the conversion of land use and its effects. *Ecological Modelling* 85 (2/3): 253–70.

Veldkamp, A., and E. F. Lambin. 2001. Predicting land-use change. *Agriculture, Ecosystems, and Environment* 85 (1–3): 1–6.

Verburg, P. H., P. Schot, M. Dijst, and A. Velkamp. Forthcoming. Land-use change modeling: Current practice and research priorities. *GeoJournal*.

Waldrop, M. M. 1992. *Complexity: The emerging science at the edge of order and chaos*. New York: Simon and Schuster.

Weibull, J. W. 1995. *Evolutionary game theory*. Cambridge, MA: MIT Press.

Weinberg, M., C. L. Kling, and J. E. Wilen. 1993. Water markets and water quality. *American Journal of Agricultural Economics* 75 (2): 278–91.

Weiss, G., ed. 1999. *Multi-agent systems: A modern approach to distributed artificial intelligence*. Cambridge, MA: MIT Press.

Westervelt, J. D., B. M. Hannon, S. Levi, and S. J. Harper. 1997. *A dynamic simulation model of the desert tortoise* (Gopherus agassizii) *habitat in the Central Mojave Desert*. CERL Publication 97/102. Champaign, IL: U.S. Army Corps of Engineers. Engineer Research and Development Center, Construction Engineering Research Laboratory. http://blizzard.gis.uiuc.edu/dsm_TORT_frame. htm (last accessed 5 February 2003).

White, R., and G. Engelen. 1993. Cellular automata and fractal urban form: A cellular modeling approach to the evolution of urban land-use patterns. *Environment and Planning A* 25 (8): 1175–99.

White, R., and G. Engelen. 1994. Cellular dynamics and GIS: Modelling spatial complexity. *Geographical Systems* 1 (3): 237–53.

White, R., and G. Engelen. 1997. Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B* 24:235–46.

White, R., and G. Engelen. 2000. High-resolution integrated modeling of spatial dynamics of urban and regional systems. *Computers, Environment, and Urban Systems* 24:383–400.

Wooldridge, M. 1999. Intelligent agents. In *Multi-agent systems: A modern approach to distributed artificial intelligence*, ed. G. Weiss, 27–77. Cambridge, MA: MIT Press.

Wu, F. 1998. An experiment on the generic polycentricity of urban growth in a cellular city. *Environment and Planning B* 25: 731–52.

Ziemelis, K., and L. Allen. 2001. Nature insight: Complex systems. *Nature* 410:241.

Correspondence: Departments of Geography and Environmental Science and Policy, George Mason University, Fairfax, VA 22030-4444, e-mail: dparker3@gmu.edu (Parker); Department of Geography, University of Minnesota, Minneapolis, MN 55455, e-mail: manson@umn.edu (Manson); Center for the Study of Institutions, Population, and Environmental Change, Indiana University, Bloomington, IN 47408, e-mail: maajanss@indiana.edu (Janssen); Department of Political Science and International Relations, University of Delaware, Newark, DE 19716, e-mail: mjhoff@udel.edu (Hoffman); Department of Geography, University of Waterloo, Waterloo, ON N2L 3G1 Canada, e-mail: pjdeadma@fes.uwaterloo.ca (Deadman).