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

Dawn C. Parker, Steven M. Manson, Marco A. Janssen, Matt Hoffman, and Peter Deadman

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Author Contact Information:

Dawn Cassandra Parker
Postdoctoral Fellow in Modeling
Center for the Study of Institutions, Population, and Environmental Change
Indiana University
408 N. Indiana, Bloomington, IN 47408
812-855-5178
[link to dawparke@indiana.edu] / [link to http://php.indiana.edu/~dawparke/]

Steven M. Manson
Graduate School of Geography, Clark University
950 Main St., Worcester MA 01610
508-793-7336
[link to smanson@clarku.edu] / [link to www.stevenmanson.com]

Marco A. Janssen
Department of Spatial Economics (Afdeling Ruimtelijke Economie)
Free University (Vrije Universiteit)
De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands
+31-(0)20-44.46092/90
[link to mjanssen@econ.vu.nl] / [link to http://www.feweb.vu.nl/re/medewerkers/mjanssen/marco.htm]

Mathew Hoffman
Department of Political Science and International Relations
University of Delaware
404 Smith Hall, Newark, DE 19716
302 831 2598
[link to mjhoff@udel.edu] / [link to http://www.udel.edu/poscir/mjhoff/cv.html]

Peter Deadman
Department of Geography
University of Waterloo
Waterloo, Ont. Canada, N2L 3G1
(519) 888-4567 ext. 2791
[link to pjdeadma@fes.uwaterloo.ca] / [link to http://www.fes.uwaterloo.ca/geography/Faculty/deadman.html]
1. Introduction

Recently, several major developments have encouraged interest in empirically focused models of land use and land-cover change. These developments include both real-world influences on research and the development of advanced tools for modeling and analysis. Global environmental challenges have lead to a growing interest in environmental policy analysis. This interest has spurred increased support for interdisciplinary research projects designed to address these challenges. Further, sophisticated tools for computer simulation modeling, including geographic information systems and sophisticated mathematical modeling software, have been developed. In tandem, many sophisticated theoretical models of human decision making and behavior have also been developed.

These factors have combined to influence development of a special class of models designed to simulate and analyze land-use and land-cover change (LUCC). We refer to these models as "Multi-agent system models of land use/land cover change" (MAS/LUCC models). The goal of this paper is to provide a broad overview of the history of these of 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 generally integrated through specification of interdependencies and feedbacks between the agents and their environment.

The authors are all involved in development of MAS/LUCC models. During the planning and development stages of our projects, we needed to consider several key questions:

- What techniques are available for LUCC modeling? What are the potential limitations of these techniques? Can MAS/LUCC models potentially overcome some of these limitations?

- 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 measured 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 ongoing applications of this modeling technique, and how have they tackled the challenges outlined above?

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 its potential and limitations in the context of the major research challenges of MAS/LUCC models.

2. **Multi-agent systems**

Land-use/cover change modeling techniques may be categorized by technique, use, intent, or a criterion like scale. Overviews focus on tropical deforestation (Lambin 1994), economic models of deforestation (Kaimowitz and Angelsen 1998; Plantinga 1999), ecological landscapes (Baker 1989), urban and regional community planning (EPA 2000), and land-use/cover change dynamics (Agarwal et al. 2000). We offer six broad categories of models: mathematical equation-based, statistical, expert system, system dynamics, cellular, and hybrid. The section concludes that a combination of cellular models and agent-based models is particularly apt for the purposes of multi-agent system models of land-use/cover change.

**Equation-based models**

Most models are in some way ‘mathematical,’ 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 land-use/cover change over time (Sklar and Costanza 1991). More complex models, often grounded in economic theory, employ simultaneous joint equations (Kaimowitz and Angelsen 1998). Another variant is linear programming linked to GIS information on land parcels (Chuvieco 1993; Longley, Higgs and Martin 1994).

**Statistical techniques**

Statistical techniques are a common approach to modeling land-use/cover change 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. Successful examples of combining theory and statistics are provided by spatial econometrics (Chomitz and Gray 1996; Geoghegan et al. 1996; 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-Schafer 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.

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 are dependent on explicit enumeration of causes and, functional representation, and they accommodate spatial relationships with difficulty (Baker 1989; Sklar and Costanza 1991).

Cellular models of land-use/cover change

Cellular models (CM) include cellular automata (CA), generalized cellular automata (GCA), and Markov models. Each of these models operates over a lattice of congruent cells. Cellular automata are the most commonly used form of cellular models. In a 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). GCA are a more general version of a cellular automata that use non-local neighborhoods (Takeyama and Couclelis 1997). Markov models are similar to cellular automata for land-use/cover change modeling as evidenced by joint CA-Markov models (Li and Reynolds 1997; Balzter, Braun and Kohler 1998).

Cellular modeling methods underlie many land-use/cover change 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 cellular models, particularly CA, to a number of research questions (Couclelis 1985; Cecchini and Viola 1990). Sophisticated cellular automata 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 land-use/cover change in response to climate change (Alcamo 1994), and a host of other biological phenomena (Ermentrout and Edelstein-Kesht 1993; Gronewold and Sonnenschein 1998).

Many cellular models inductively assume 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 (divided into lattice of congruent and identical
cells), and heterogeneous actors are affected by local neighbors in a simple, well-defined manner. A good example is modeling residential choice and land-use in urban areas since actors are evenly arrayed, such as in homes, and their decision making stems from interactions with immediate neighbors. Cell states relate to different characteristics of the agents such as social class and orientation (Schelling 1971; Hegselmann 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. Remedy lies in techniques that have non-uniform transition rules and can dynamically change the strength and configuration of connections between cells. As these characteristics lie beyond the capacities of rigidly defined cellular automata, this method may not be broadly suited to model land-use/cover change. 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 land-use/cover change, 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).

**Hybrid Models**

Hybrid models may combine any of above-mentioned techniques. A prime example is estuarine land-use/cover transition modeling that has an explicit, cell-based spatial component tied to a system dynamics model (Costanza, Sklar and Day 1986). Another is DELTA, which integrates sub-models of human colonization and ecological interactions to estimate deforestation under different immigration and land management scenarios (Southworth, Dale and O’Neill 1991). Other examples 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 model is dynamic spatial simulation (DSS), which portrays the landscape as a two-dimensional grid where rules represent the actions of land-managers based on factors such as agricultural suitability (Gilruth, Marsh and Itami 1995). DSS typically do not represent heterogeneous actors, institutional effects on decision making, or multiple production activities. They may still be, however, the “most advanced modeling approach for a complex, dynamic and spatial problem such as tropical deforestation” (Lambin 1994, p. 92).
Key to the definition of dynamic spatial simulation is that some form of land-managers act over a landscape. This orientation towards individual decision making is shared by agent-based models. Since dynamic spatial simulation is one of the most advanced means of modeling land-use/cover change, and it simulates the actions of land-managers, it is a logical precursor to multi-agent system models of land-use/cover change.

**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. Autonomy means that agents have control over their actions and internal state in order to achieve some goal or goals. As such, agents have been used to represent animals, people or organizations (Liebrand, Nowak and Hegselmann 1988; Epstein and Axtell 1996; Conte, Hegselmann and Terna 1997; Weiss 1999; Janssen 2000)

Agents share a common environment, meant in a wide sense as anything outside of the agents. In a land-use/cover change context, a shared landscape where the actions of one agent can affect those of others is likely to be the unifying environment. For LUCC models, a land market may provide a second important environment in which agents interact. A more complex environment involves more direct communication and interaction. The field of distributed artificial intelligence in particular concerns intercommunicating agents coexisting in a common environment (Bond and Gasser 1988). Cooperation and communication are also an important component of the environment and are often explored within the context of game theory, institutions, and economics (Holland 1993; Riolo 1997; Macy and Skvoretz 1998).

Most importantly, agents must have some form of cognition that links their autonomous goals to the environment through their behavior. Traditional economic models assume actors are perfectly rational optimizers with unfettered access to information, foresight, and infinite analytical ability. It is an open question whether models of perfect rationality will ever be practical or appropriate for ABM models of land-use/cover change given the importance of spatial interdependencies and feedbacks. 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.

This complexity has resulted in a movement towards agent-based models that employ some variant of bounded rationality (Simon 1997). In general, agents under bounded rationality 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, however, they make inductive, discrete, and evolving choices that move them towards achieving goals (Tversky and Kahneman 1990; Bower and Bunn 2000). Good examples of decision-making models are 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). Bounded rationality forms of decision making have been
modeled using genetic algorithms (Arifovic 1994; Miller 1996; Beckenbach 1999; Dawid 1999; Arifovic 2001; Chen and Yeh 2001), heuristics (Arthur 1993; Arthur 1994), simulated annealing (Kollman, Miller and Page 1997), classifier systems (Holland 1990), and reinforcement learning (Bower and Bunn 2000; Duffy 2001; Kirman and Vriend 2001). The key challenge to 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 multi-agent system modeling to become a viable long term field, there needs to be more comparison between different research efforts. There is a particular need for research that demonstrates that these models can reach equilibria similar to that found by extant theory, practice, and observation of the real world.

Multi-agent system for land-use/cover change

The exploration of modeling thus far has raised three key points. First, of the host of methods used to model land-use/cover change, dynamic spatial simulation is very promising. Second, cellular models successfully replicate ecological and biogeophysical phenomena, but they may not always be suited to modeling decision making. Third, agent-based modeling is a promising means of representing decision making that may answer the shortcomings of other techniques.

When all three points are taken together, it is not difficult to envision a dynamic spatial simulation that is a multi-agent system with 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 to represent 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 suitable for hypothesis creation, deductive testing, and inductive exploration of observed behavior. Section 6 highlights efforts that take advantage of some form of this combination for modeling land-use/cover change.

3. When are MAS/LUCC models most appropriate?

As discussed above, many well-developed techniques for analyzing land-use/land-cover change exist. However, each of these techniques has some limitations that are potentially overcome by MAS/LUCC models. In particular, MAS/LUCC models may be particularly well-suited for the representation of socioeconomic and biophysical complexity. They may also 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 models can then serve as a simulated social laboratory in which to test hypotheses that link land-use behaviors to landscape outcomes. Once the mechanisms of the model are programmed, researchers can easily design and execute experiments to explore alternative hypotheses.

**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. Complex systems are characterized by interdependencies, heterogeneity, and nested hierarchies among both 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.

Interdependencies exist among agents, between agents and their biophysical environment, across time, and across space. In a temporal context, bounded rationality agents may rely on information from past decisions, both their own and those of other agents, to update decision-making strategies. This process leads to temporal interdependencies among agents. Further, agent decisions will likely have dynamic impacts on the biophysical environment, including impacts on soil health, biodiversity, and the type and succession of vegetation cover ((see Brander and Taylor 1998; Sanchirico and Wilen 1999) for examples of traditional economic models that incorporate ecological interdependencies). Many spatial interdependencies potentially impact individual decision making. These include spatial influences among agents, such as flows of information, diffusion of technology, local coordination, social networks, and positive and negative externalities among neighbors (see Kanemoto 1987; Case 1991; Case 1992; Parker 1999; Ray and Williams 1999; Parker 2000; Irwin and Bockstael 2001; Parker 2001). Many biophysical spatial interdependencies are also potentially important, such as downstream watershed impacts, habitat connectivity, metapopulation dynamics, and ecological edge effects.

Heterogeneity may also be present across agents, the biophysical environment, across space, and across 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. In economics, 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. A simple example in which both heterogeneity and interdependencies are important is technology adoption. 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. As a consequence, agents having a higher level of risk aversion may now adopt the technology. Berger (2001) uses an MAS model to analyze diffusion of technology among heterogeneous farm households.)

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 impacted by, county and regional governments, which in turn interact at a national level. On the biophysical side, individual waterways feed together to define nested watersheds, and populations, formed of individuals 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 framework.

In complex systems, interdependencies and heterogeneity often lead to what are called non-convexities – an irregular and rugged abstract surface describing the possible states of the system. 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. A simple extension of the previous technology adoption example illustrates this concept. 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.

Modeling “Emergence”

If researchers are specifically interested in modeling the complex dynamics of a LUCC system, they may also be specifically interested in understanding the macroscopic, or “emergent” phenomena that may result. While “emergence” has become a popular buzz word in discussions of complexity, there are many concrete manifestations of the concept, many of which are potentially useful focal points for empirical researchers.

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) suggest that emergence is characterized by “organization into recognizable macroscopic social patterns”. Bass and Emche (1997) explicitly identify emergence as a function of synergism, whereby system-wide characteristics do not result from the additive effects of system components (superposition) but instead from interactions among components.
Definitions of emergence usually concerned macro-scale phenomena that arise from micro-interaction. 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 macro-structure potentially also affect units at the micro-scale. Seeing social norms as emerging from agent interaction, for instance, does not adequately address how norms affect agents. There are definitions of emergence that necessitate that lower level elements remain unaware of their role in emergent phenomena (Forrest 1991). As a result, agent-based models 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.

There are 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 as an emergent property of spatially explicit complex systems (Schelling 1978). Patterns of land use have also been identified as emergent properties of land markets (White and Engelen 1993; White and Engelen 1994; Parker, Evans and Meretsky 2001).

Some of these macro-scale 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. The first answer is that the analytical techniques, by relying on simplifying assumptions regarding agent interactions, heterogeneity, and hierarchical structures, may predict a set of equilibrium outcomes that hold only as special cases. The second answer is that 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 holds often for spatial problems. Analytical spatial equilibrium models are very difficult to construct in cases where 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, emergent phenomena such as landscape pattern may be practically modeled only with tools such as multi-agent systems 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. Further, policy makers may be most interested in short-run changes in the system under study. Therefore, analysis of the path towards equilibrium may be of more relevance.
than information about a theoretical long-run equilibrium. MAS models can be used to analyze the path of the system within any time frame. Further, parameter values can be perturbed to examine how the path of the system changes in response to exogenous shocks.

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 impact model outcomes, and when forward and backward linkages among hierarchical structures of organization exist. They are also potentially useful for examining the path of a system in cases where the time scale to reach equilibrium is beyond the time frame of interest to the researcher. In cases where these complexities are not present, simpler and more transparent modeling techniques may be appropriate.

**MAS/LUCC models as an empirical tool**

We have argued that MAS/LUCC models have significant advantages when the goal of research is to specifically model complexity. These models also have some potentially strong advantages for empirical modeling, especially when the models are coupled with a geographic information system. Because MAS/LUCC models can easily incorporate interdependencies, they are well-suited to modeling feedbacks between socioeconomic and biophysical processes. Within a GIS-based model, socioeconomic and biophysical inputs can be linked through common spatial identifiers.

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, a common understanding of how to address scale in integrated systems is needed (Gibson, Ostrom and Ahn 2000).

One disadvantage of many dynamic systems models is that data must be aggregated, or scaled up, spatially. This aggregation results in a loss of statistical information. MAS/LUCC models, however, can theoretically be structured so as to match the scale and structure of the available spatial data. However, this observation leads to another caveat, discussed below in more detail. If spatial data are not available at a scale fine enough to be compatible with the minimum spatial decision-making unit, then parameterization of an MAS model may be difficult, and MAS results may need to be scaled up for comparisons with actual data.
4. The Appropriate Role for MAS/LUCC Models

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 “in 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 p. 146) how much can we learn with this method? The answers to these questions are far from clear. Beyond a common goal of understanding something about the world by creating simulations, there are multiple ways to conceive the utility of modeling enterprise. This section condenses the varying ways of using MAS into two categories—generative approaches and fitting approaches—and discusses their advantages and disadvantages.

Generative approaches

Generative 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 put it in computer format in order to examine the ramifications of their framework, and potentially generate new hypotheses to explore empirically. A useful way to conceive of this type of modeling is as a method for testing candidate explanations. Joshua Epstein is perhaps the best proponent of using models to develop candidate explanations, 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). Tesfatsion also suggests this role for agent-based models, 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” (2001, p.282).

Using multi-agent systems models to develop candidate explanations follows simple logic. There is a target empirical macroscopic phenomenon (or pattern or regularity that often represents an emergent property of a complex system). The modeler develops a series of rules, interactions, and specifications for the agents in the model to follow and then allows agents to interact within a simulation environment. If the macro phenomenon that results resembles the empirical phenomenon of interest, then the modeler has uncovered in the very least a candidate explanation for the empirical phenomenon. When used in this manner, MAS allows modelers to check the ramifications of their theories and hypotheses, as it facilitates checking the plausibility of the empirical expectations that flow from our theories.

This type of modeling is “normative” in that it attempts to encapsulate critical mechanisms in order to function as a virtual laboratory. Again, when the modeled subjects mimic reality, and they are based on theory, support is lent to the theory. These models purport to be explanatory by stating how reality should or would be under ideal conditions.

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1 Deciding what constitutes resemblance is a far from facile enterprise. See Epstein and Axtell "Understanding our Creations" for more on this.
circumstances. Rational choice economic models, discussed earlier, are examples of such normative models (Tesfatsion 2001).

In addition, beyond simulating the ramifications of given theories, generative approaches also hope to find novel hypotheses. A potential role for MAS/LUCC models is deriving potentially novel testable hypotheses that relate land owner/manager decisions to land-use and land-cover outcomes. The modeler begins with a set of expectations, or a theoretical framework, structures the model accordingly, and then through simulation may discover outcomes not originally expected.

In general, generative modeling approaches allow modelers to: 1) demonstrate that a set of rules can lead to the outcome of interest—test theory and; 2) explore other possible causes that could lead to the same outcome—formally exploring the robustness of the proposed causal explanations and searching for new hypotheses.

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 understand 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.

**Fitting approaches**

Fitting approaches follow a fundamentally different logic and are more concerned with empirical validity and/or predictive capacity. These approaches attempt to mimic real world systems in such a way as to achieve some level of matching with reality, thus facilitating direct empirical as well as policy research.

In land-use/land-cover change modeling terms, empirically-based MAS/LUCC models may be constructed to replicate landscape composition and function, and to demonstrate the value of using information on spatial heterogeneity and interactions. This is the same sort of role as is now served by spatially disaggregated (fine-scale) econometric models. Such a model would be as fully parameterized with real-world data as is 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. Using MAS methods for this type of modeling may be more effective than existing empirical models in two areas. First, by modeling at the same scale as available data, such models may make best statistical use of available information. Second, as noted above, by accounting for heterogeneity and interdependencies, the models can reflect important endogenous feedbacks in the system. Since the models are not constrained to meet a set of equilibrium criteria, they can be constructed to produce discontinuous and non-linear phenomena, such as extinctions and exponential growth of populations.

Fitting models (also labeled descriptive) can be identified, particularly as applied to land-use/cover change, by claims made of their projective ability. For the bulk of these fitting
models, practitioners of agent-based modeling are prone to pointing out how their models give “insight” into real-world processes. However, this intuitive insight can come at the cost of more general rules. In other words, these models can move us away from developing normative statements (Judson 1994). This seems particularly common – we create a model that can reproduce a statistically correct meta-phenomenon but at the cost of ignoring others, or through a model structure that is patently unreal. The most dangerous situation, of course, is when we achieve meta-verisimilitude with a model mechanism that is close enough to perceive as being correct when in fact it is not.

The two categories outlined above represent a continuum rather than a dichotomous, mutually exclusive choice. 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 recreation of actual land use in specific locations over time for use in policy scenario modeling and prediction, then the fitting approach is indicated. If instead, we hope to understand generic patterns of land-use/land-cover change over time, such that we can find and apply insights to a wide range of specific empirical situations, then a generative 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, generative vs. fitting, be acknowledged and understood.

5. Building an Empirically Grounded Model

One of the great advantages of computer experiments is that they allow researchers to explore a variety of questions associated with the behavior of a real-world system, without having to directly manipulate the real system. Modeling and simulation can become a useful tool for exploring hypotheses, but the utility of any model is dependent upon it possessing some degree of validity. When we assess the validity of a model, as expressed through the simulation that brings it to life, we are examining how well the model represents the corresponding real system. The enterprise of modeling and simulation often becomes an iterative process, as successive versions of a simulation are assessed for their validity, and modified in response to the results of those tests.

There are a great number of challenges associated with validation of MAS/LUCC models that must be considered. Since the real world is far too complex to model in its entirety, we must define an experimental frame that we can use to focus our data collection, modeling, and validation efforts upon. 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, and referenced to particular 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 may be different for an ecologist, a fisheries biologist, or an economist. When the purpose of the modeling effort is specifically interdisciplinary, the definition of the experimental frame will be broadened, but challenges inherent to the definition of any model – defining an appropriate degree of abstraction and identifying which factors will be endogenous to the model – remain.
Even when one has defined a relatively narrow experimental frame, the potential for model complexity is high. In such cases, model validation becomes a difficult task with many uncertainties. Path dependencies in the model can result in large changes in output as small changes are made to input parameters. Hence statistically significant measures of validation may be difficult to obtain, leaving the researcher to assess qualitative similarities. This can be particularly true when validating the human systems components of the simulation. Even if valid data can be produced from the perspective of land-use changes over time, validating the social processes that lead to those changes may be more difficult. Further, models containing stochastic elements can further complicate the validation process, as the distribution of model behavior may be difficult to establish.

Simultaneously the greatest advantage and shortcoming of agent-based models is their flexibility in specification and design. Researchers must ensure that model structure and rules employed therein are derived equally from theory and data in order to avoid introducing artifactual mistakes. Emerging agent-based research in pedestrian modeling, for example, consciously attempts to combine field data with the best of theory in response to past efforts that leaned too heavily in one direction at the expense of the other (Batty 2001; Kerridge, Hine and Wigan 2001).

Nonetheless, a good deal of attention must be paid to the twinned concerns of verification and validation. Verification describes the relationship that exists between the model and the simulation that is used to bring that model to life. Verification asks whether the simulation is correctly enacting the rules of behavior that are specified in the model. Is the model doing what we think it is doing? Verification procedures can include an object-by-object testing of behavior, or full simulation runs, under known conditions.

Validation issues are often left unconsidered in LUCC modeling (Robinson 1994). Treatment of this topic ranges from studying the effects on errors of mathematical operations (Alonso 1968) and error classification in remote sensing (Riley et al. 1997) to more sophisticated treatment of error and uncertainty in econometrics and geographic information systems (Eastman 1999).

Any validation exercise requires the comparison of data from the simulation with data from the real system. The data collected for the purposes of model design and validation may come from outside the experimental frame, as when experimental evidence (economic and psychological) is used to motivate agent specifications (Deadman and Schlager Forthcoming). Survey and interview data, as well as results from statistical models, that are outside the experimental frame can also be of value. For theoretical modeling exercises, such data may be quite suitable. However, many LUCC modeling investigations are focused on specific physical real-world locations. In such cases, data such as that from surveys, interviews, or a census, as well as data obtained through remote sensing or other geographic information systems techniques, may provide data to inform the model. An example of this approach is provided by Manson (2000), where parameters of a multi-criteria objective function are estimated separately and are used to directly parameterize an agent decision-making model. Alternatively, the same objective function is solved locally using a genetic search algorithm.
There are varying degrees of strength in validation. Ziegler (1976) identifies three levels of model validation, replicative, predictive, and structural. Replicative validity determines whether a model can represent data that has already been acquired. Predictive validity measures whether or not a model matches data that is acquired subsequent to model development. Structural validity measures whether or not the structure of the model matches the structure of the real system under study.

As far as replicative or predictive validity is concerned, researchers may be interested in a variety of both non-spatial and spatial outcomes from MAS/LUCC models. These measures may be demographic, such as levels and spatial distribution of population and inward and outward migration. They may include both patterns and degree of natural resource exploitation, such as groundwater levels and quality, patterns of soil degradation, species population health and distribution, and spatial patterns of land use and land cover. Researchers are often interested in measures of economic well-being, such as the value of output, income distribution, and trade flows. For many of these measures, researchers may be interested in the time path of both aggregate and spatial outcomes.

Formal statistical comparisons of model output to real-world data require sufficient variation within measures to identify parameters and a sufficient sample size to potentially obtain statistical significance. Having multiple temporal observations for both data and model output is one strategy to produce this variation, as long as temporal dependencies are accounted for in the analysis. However, often only cross-sectional comparisons are possible. Several authors propose spatial statistical approaches (point-pattern and landscape statistics) 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; Irwin and Bockstael 2001; Parker, Evans and Meretsky 2001). When comparisons are done using micro-scale measures, such as nearest-neighbor distances between parcels or parcel-level landscape statistics, a reasonable sample size is easily obtained. However, when landscapes are compared via aggregate, index measures, such as class or landscape level pattern indices, sample size is likely to be insufficient for conducting formal statistical tests. A potential remedy is to subdivide the landscape into separate neighborhoods and compare the distribution of statistics across neighborhoods. In this case, issues of spatial dependency become potentially problematic, in parallel with issues of temporal dependencies that must be accounted for in time-series models. However, active research developing methods to deal with these spatial dependencies is occurring in multiple disciplines.

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. First, decision-making units must occur at a sufficiently fine scale so that empirically
relevant spatial heterogeneity can emerge. Second, model validation may need to occur at multiple spatial scales.

The spatiotemporal complexity of LUCC modeling suggests use of different tests to evaluate results according to a variety of spatial and aspatial criteria (Turner, Costanza and Sklar 1989). A simulation should be equipped with an array of tests (e.g., Manson 2000) that are used to measure key aspects such as spatial location and composition statistics (Pontius 2000), pattern measures (Frohn 1997), multi-resolution measures (Costanza 1989), and uncertainty measures (Ogneva-Himmelberger 1998). Further, simulation results should be potentially linked with packages that facilitate formal statistical analysis.

The validation process may also include an examination of how model performance changes with model configuration. This may include sensitivity analysis, where parameters are varied across repeated runs of the simulation so as to observe changes in model performance. For models with closed-form analytical solutions, "comparative static" (Silberberg 1990) and "comparative dynamic" (Kaimowitz and Angelsen 1998) analyses are frequently used as tools for structural validation. These techniques formally analyze the relationship between model parameters and state or time path (respectively) of variables endogenous to the modeled system. These analysis techniques are often used not only to understand model behavior, but also to derive testable hypotheses that relate differences in model parameters and outcomes. While such analysis is often possible only for simplified versions of multi-agent models that can be analytically represented and solved, simulation techniques offer an alternative for MAS models. Models can be run through many iterations, varying a particular parameter incrementally. Parameter changes can then be mapped against model outcomes, providing a limited understanding of the influence of particular parameters on system outcomes. However, there is a major caveat in using this approach for complex systems. As discussed earlier, complex systems are characterized by substantial interdependencies, and these interdependencies can often lead to non-convexities, which imply that the relationship between a model parameter and variables of interest may be highly dependent on the values of other variables (Miller 1998). In effect, the very synergies that make complex systems interesting also make them very difficult to analyze. Thus, a more sophisticated approach to model validation than the traditional comparative static/comparative dynamic approach must be developed.

The process of assessing structural validity of a model may move beyond sensitivity analysis, potentially tracking how outcomes change as different components of the model are added or removed. The results of the other validation phases inform structural validation. Experts in a variety of disciplines engage in an iterative process to answer two key questions. First, what do we learn from how different socioeconomic models enjoy varying levels of success across the tests in validation? To what extent is a significant difference in one metric between two models due to a difference in approach or theory? Second, do different models behave as expected when key components are added or removed? Does the removal of a key resource institution, for example, result in an anticipated or documented land-use/cover change? Similarly, there is still a fair deal of uncertainty and disagreement in the literature on the relative contribution of phenomena
such as roads or population to land-use/cover change. It is the role of structural validation to determine which components are important and when they are important.

Despite progress on some fronts, the issues associated with model validation will continue to be of vital importance to the progression of this discipline. Researchers must continue to focus their efforts on model validation and the clear communication of model design to others. Most publications do not contain a sufficient description of the simulation to permit the reader to fully understand model design or assess validation procedures. Furthermore, a general lack of published code renders replication an impossible task. Continuing efforts must be made to clearly explain model design and validation procedures.

6. Current applications of MAS/LUCC Modeling

In this section we will briefly review recent studies that apply MAS to study land-use and land-cover change for practical cases. In general, scholars in this field originate from different disciplines and have different motivations for constructing MAS/LUCC applications. Geographers have begun to become interested in ‘dynamic’ GIS, while social scientists dealing with complex ecosystem management issues have found that they can not address their problems with traditional tools, and computer scientists have become interested in applying their tools from multi-agent system technology. We do not intend to provide a complete review of all possible studies, but touch upon overlapping topic areas: natural resource management, agricultural economics, forests, urban simulations, regional analysis and archaeology. For more details we refer to recent overviews that incorporate work on MAS/LUCC models (Kohler 2000; Gimblett 2001; Janssen 2001)

Natural resource management

François Bousquet at CIRAD began study of renewable resource management using multi-agent systems in the early 1990s. His work has focused on case studies of natural resource management regimes in developing countries. Through development of a series of models, Bousquet and colleagues have developed a simulation environment called CORMAS (Common-Pool Resources and Multi-agent Systems) (http://cormas.cirad.fr). This modeling platform is based on the object-oriented language Smalltalk and consists of a library of pre-defined generic entities. Currently, CIRAD has a small research group on multi-agent modeling, and CORMAS supports a growing worldwide network of scholars using this platform for MAS on LUCC.

Bousquet and others (1998) mainly use heuristic rules for the agents and simple cellular automata for the environmental dynamics. The heuristic rules are based on intensive interaction (via workshops and interviews) with local stakeholders. One of the current focus areas is to investigate the use of role-playing games, an interaction of roles played by stakeholders in a structured game that feeds into a computer simulation to replicate the observed dynamics (Bousquet et al. 2001).
Agricultural economics

Alfons Balmann and colleagues study agricultural systems by simulating interacting farms in an agricultural region in Germany (Balmann 1997; Balmann et al. 2001). The region is hypothetical, but the data are based on statistics of representative farms in a typical region in Germany, and is represented as a spatial grid where each cell symbolizes a parcel of land. Farms, the agents, own a number of cells. They aim to maximize income through production and investment activities and compete in a rental market for land. Balmann’s work focuses on how agricultural practices may change in the region, based on governmental policies. The model initially developed by Balmann has been adapted by Thomas Berger to examine technology adoption when both agents and the biophysical environment are heterogeneous (Berger 2001).

Lynam (2001) developed a multi-agent agro ecosystem model of a complex agroecosystem in the semi-arid area of Zimbabwe, Kanyurira Ward. The model was designed to examine the interactions among social, economic and ecological conditions of the system, and to identify those components which significantly contribute to households’ ability to satisfy needs. The agents represent households and the implementation was based on various field data collection methods. The environment was represented by GIS data layer files and rainfall statistics.

Forests

In January 2001, a 5 year project was started by Indiana University, which will focus on the development of an innovative empirically parameterized and validated agent-based model of land-use change, with a particular focus on drivers of deforestation and reforestation (http://www.cipec.org/research/biocomplexity/). This modeling effort will be complemented by the development of a series of econometric models. The strengths, weaknesses, and unique advantages of each modeling approach will be compared for two case studies south-central Indiana and the Brazilian Amazon. The purpose is to take advantage of complementarities between the two modeling efforts by allowing the econometric models to inform development of the agent-based models (Hoffman, Kelley and Evans Forthcoming; Lim et al. Forthcoming)

Urban Simulation

Torrens (http://www.casa.ucl.ac.uk/sprawl/) studies the problem of urban sprawl, a form of urban growth characterized by low densities and scattered development. One of the challenges faced by this research project is to define precise spatial metrics of sprawl. Spatial econometrics is used to measure historical urban sprawl, and the multi-agent model SprawlSim will be developed to generate observed spatial metrics in order to derive a better understanding of the driving factors of urban sprawl.

Sanders et al. create an abstract model to study the evolution of settlement patterns over long time periods. Settlements are represented as agents. The rules of the agents may allow for the simulation of the urban transition from a set of homogenous, agricultural-
oriented, and scattered villages into a complex system of functionally diverse, competing, and hierarchically structured urban settlements (Sanders et al. 1997).

Ligtenberg et al. (2001) present a pilot study that uses a multi-agent system to perform scenario analysis for the city Nijmegen in the Netherlands. They simulate decision-making processes of urban planning, and allocate different kinds of power to the actors involved in the decision process.

**Regional analysis**

Our review of regional analysis focuses on models that operate on a fine enough spatial scale to examine local patterns of land use. This discussion omits substantial work that has occurred in the last ten years that focuses on the distribution of economic activity between cities (e.g., Krugman 1995; Page 1999). Literature in this “new economic geography” is likely to be of greater interest to those researchers interested in broad, macro-scale patterns of economic development.

Manson (2000; Forthcoming) developed a prototype integrated assessment model for the Yucatán Peninsula in Mexico. The goal of the model is to perform scenario analysis of tropical deforestation and cultivation and its effect on biotic diversity and carbon sequestration in the southern Yucatán peninsular region of Mexico. Using a multi-agent system, different formulations of individual decision making are analyzed. The model is calibrated and validated with household surveys, archival research, and spatial data including aerial photography, satellite imagery and geographic information system maps of land-use/cover and biophysical characteristics. The model is validated using multiple criteria that reflect both composition and pattern.

Another example is an integrated dynamic simulation model (AGENT-LUC) of Thailand by Rajan and Shibaski (2000). The model focuses on changes in land-use/land-cover patterns for the period 1980-1990. On a micro-level, agents make land-use decisions given information on existing land use, economic and demographic conditions, and biophysical conditions. Furthermore, the agents also make migration decisions. These micro-level decisions affect land use and population densities, as well as agricultural production.

**Archaeology**

Since the early 1970s, simulation models have been used within archaeology as a tool to test possible explanations for phenomena based on the limited information available from the past. The questions of archaeologists focus mainly on how complex societies have emerged and collapsed. An interesting overview can be found in Kohler and Gumerman (2000). For example, two chapters in this book use multi-agent models to explain settlement changes of the Anasazi in the Southwest of the USA. The agents represent households, and the movements of agents in the landscape are related to resource availability. The models are able to generate the population increase after 900 AD and the collapse of the system around 1300 AD.
7. Challenges and Conclusions

This paper has outlined many of the challenges that researchers face when constructing multi-agent system models of land-use and land-cover change. There are, however a number of fundamental problems for which no clear solutions exist. These issues must be addressed in the coming years in order to let this field 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 each 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. Finally, developing techniques to understand the relationship between model components and outcomes is a major challenge, and success in this area is likely to impact 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 is 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. A second challenge relates to building an experimental frame that can be used to answer questions of interest to multiple disciplines.

Challenges unique to MAS/LUCC models

Understanding Complexity

Many challenges that we have discussed are unique 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 must also be acknowledged that the theory that defines complexity is still in the development stage. Thus modeling and understanding complexity will surely be an iterative process, and, as researchers, we may find the road we have set out on changing 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. 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. It will be a challenge to derive a better understanding of what kinds of agent formulation fit with which decision-making problems, and to determine the macro scale implications of particular decision making strategies are at the macro scale. Once again, comparative modeling and empirical validation is necessary to distill the many approaches that exist, and to identify commonalities between different approaches.

Modeling Institutions

Institutions--the formal and informal rules between agents--constrain the actions of agents to derive an improved collective outcome. During the last twenty years, there has been much improved understanding of the evolution of cooperation (Axelrod 1984). These game theory oriented studies focus on the selection of a limited set of rules. Importance of social norms and reputation has been investigated, but important aspects of institutions are not understood in term of formal models. Such aspects include the creation of rules, social memory, evolution of social networks, and the role of symbols and communication. 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

MAS/LUCC models, due to their complexity and ability to represent detail, may face unique challenges of parameterization and validation. To a high degree, development of techniques for understanding output lag 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 modeling tools have become widely used before researchers have had time to consider and develop methods to link these models to data.

However, these challenges represent exciting opportunities for researchers. There is no end of interesting interdisciplinary research questions for which MAS/LUCC models are an appropriate tool. We are 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 pseudo-science. 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. Effective and convincing communication of our results is therefore 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 that, under a set of simplifying assumptions, a computational model can replicate a well-established analytical result. 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.

**Conclusions**

In this paper, we have provided an overview of a developing technique for land-use/land-cover modeling, multi-agent system models. While the authors represent a range of social science disciplines, this review is necessarily weighted somewhat by our disciplinary perspectives and expertise. We have seen 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 represent a spectrum from highly abstract to highly empirical applications. Ideally, this will spur a dialog between modelers working at each end of the spectrum, with lessons from one end being used to informing 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 many challenges remain, the many recent developments reflect an encouraging trend to integrate the many tools and disciplines required to develop a new methodology for dynamic spatial modeling of human/environment interactions.
8. References


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