Meeting the Challenge of Complexity

Proceedings of a Special Workshop on Land-Use/Land-Cover Change
October 4–7, 2001, Irvine, California

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Meeting the Challenge of Complexity

Proceedings of a Special Workshop on Land-Use/Land-Cover Change

October 4–7, 2001, Irvine, California

Organized in conjunction with the National Academies of Science Arthur M. Sackler Colloquium on Agent-Based Models by the Center for Spatially Integrated Social Science (CSISS) at the University of California at Santa Barbara, the Focus 1 Office of the IGBP/IHDP Land Use and Cover Change (LUCC) Project at Indiana University, and the Center for the Study of Institutions, Population, and Environmental Change (CIPEC) at Indiana University.

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Preface

William J. McConnell

Interest in the application of agent-based models to the study of land change has been growing rapidly in recent years, as more researchers seek to apply increasingly sophisticated models to understand and project the land-use dynamics that give rise to changes in the Earth's land cover. This growing interest was presaged and fostered by the recognition and promotion of this line of research by both the international Land Use and Cover Change Project and the U.S. National Research Council in their respective research strategy reports (Lambin et al. 1999, NRC 2001).

The Land Use and Cover Change (LUCC) Project is a program element of two major global change research programs: the International Geosphere-Biosphere Programme (IGBP); and the International Human Dimensions Programme on Global Environmental Change (IHDP). LUCC's mandate is to provide information about past changes in the Earth's land cover; to help explain the land-use dynamics responsible for these changes; to assist in the development of projections of future land-use and land-cover dynamics; and to identify critical regions that are particularly vulnerable to global environmental change. The ultimate goal of the LUCC Project is to improve the understanding of, and gain new knowledge on, regionally based interactive changes between land uses and land covers. In part, the project develops new integrated and regional models that are informed by empirical assessments of the patterns of land use and case studies that explain the processes underpinning such configurations of land-use and land-cover change over varying spatial and temporal scales. Specifically, LUCC seeks the development of improved means for projecting and backcasting land uses and land covers. The following are highlights from the LUCC Implementation Strategy (Lambin et al. 1999). (For a detailed explanation of the LUCC Project, its programmatic design, and its current research, please refer to the International Project Office website: http://www.geo.ucl.ac.be/LUCC/lucc.)

The study of land-use dynamics—a major determinant of land-cover changes—involves the consideration of human behavior. Crucial roles are played by decision makers, institutions, initial conditions of land cover, and the inter-level integration of processes at one level with those at other levels of aggregation. Without understanding the dynamics behind land-use change, we cannot understand changes in land cover, nor estimate the utility of policy intervention.

In order to understand the dynamics of land use, it is necessary to identify trajectories of change across a sample of the world's regions, including a broad diversity of land-use strategies. These trajectories inform global models, which integrate biophysical data with the human aspects of global changes in land cover. However, global models alone are not sufficient, as they are likely to simplify (deliberately) the drivers of human behavior. The same processes that are responsible for explaining most of the variances at different levels of analysis change over time and in space. Creating a direct link between spatially explicit land-cover information, as derived by remote sensing, and information on land-use change processes requires the development of new methods and models which merge landscape data with data on human behavior. It is necessary to develop models that are more sensitive to regional variability, and more effective in identifying the best points for policy intervention and inter-level articulation. For example, a human community connected by paved roads to world markets will feel the pressure of international commodity price shifts a great deal more than communities with poor road infrastructure, and are likely to make very different decisions about land use. The most critical element in land use is the human agent. It is the agent (an individual, household, or institution) that takes specific actions according to its own decision rules which drive land-cover change. These agents are engaged in a very complex game in which they evaluate economic and non-economic alternatives.

Accordingly, the study of land-use/land-cover change must undertake the following:

- development of intelligent agent-based models of local land use and regional land use. This involves the use of spatially explicit models of agents' behavior in a topographically explicit landscape wherein they encounter new challenges, their decision environment is uncertain, their behavior is adaptive, and they learn over time.
- development of regional models based on aggregate behavior, as expressed through the interplay of market forces, institutions, and demographic structural change.

A major issue in the development of these models concerns the definition of appropriate spatial units (or levels of aggregation) to establish the correspondence between biophysical and socioeconomic variables. This has to take into account the unit of decision making, human mobility (e.g., pastoralism or the dispersal of household plots), units of landscape transformation, the spatial scale of ecological processes (e.g., a watershed) and data availability. Consumers, producers, commodities, and resources each must be represented at suitable and mutually consistent levels of aggregation. For regional modeling of land-use/land-cover changes, a suitable aggregation must provide for an enhanced level of detail with respect to land managers, land resources, and land-intensive activities such as agriculture and forestry. Several studies have demonstrated that key relationships between driving forces and physical land-use/land-cover change are scale-dependent. Therefore, multi-scale approaches are necessary and should be promoted. For each group of agents, modeling the key behavioral responses and constraints is necessary. This calls for innovative thinking on the application of decision theory, microeconomic principles, social dynamics simulation concepts, and spatial statistical analysis. For example, representing the role of decision agents and decision strategies in models requires a much wider approach than econometric analysis.

Social, institutional and economic analyses of land use requires a socioeconomic data set which is comprehensive and internally consistent. Classifications of agents, production sectors, factor inputs to production, incomes, and expenditures must be complete and all-inclusive. One such format for this is the Social Accounting Matrix (SAM), which has proven to be a useful format in which to group the required data. In all cases, information about markets for land must be added to the usual production, consumption, income, and trade data, and all at a regional level of spatial disaggregation.

Technological progress in land-based production sectors has resulted in intensification along multiple dimensions. For instance, higher yields per hectare of harvested area have resulted from improved seeds, increased application of fertilizers, better plant protection, improved tools and mechanization, and biotechnological engineering. Given that the larger part of incremental food production is projected to come from intensification, models must be sensitive to technological change, which is treated with only simple exogenous assumptions in most existing regional or global models. In addition, it is necessary to develop scenarios of technological development specific to different land-based sectors and environments.

In LUCC research, it is important to know not only how land is allocated among uses in a given area, but also how the usage pattern varies within that area. This is especially true when a given study area is heterogeneous and large in size. The integration of spatial heterogeneity must be linked with the development of integrated land-use change models. Research on mid- and long-term prospects of land-use/land-cover change cannot be limited to observation and description. Development of causal models can lead to an improved understanding of the current and recent situation and at the same time provide credible, geographically referenced predictions. The length of time over which a prediction is valid is a function of the persistence of the observed phenomena. There is evidence to suggest that the majority of land-cover change is consistent over 10- to 15-year intervals. However, changes in political, institutional, and economic conditions can cause rapid changes in the rate or direction of land-cover change.

There is a need to develop regional scenarios and assessments for identifying land-use patterns with certain optimal characteristics that simultaneously satisfy various economic, social, and environmental goals. Shifting from empirical models, which just highlight spatial and temporal associations between variables, to system models that represent causal relationships provides a comprehensive approach to understanding land-cover change and, at the same time, provides important inputs to policy. An important aspect of the work described here is the link between direct observations, case studies, and models in an effort to test or identify dominant processes in land use/land-cover changes. There is also the issue of uncertainty and thresholds in land-use/land-cover change: Under what conditions do the dynamics of a land-use system become unpredictable or radically change its mode of functioning?

There are large uncertainties regarding the long-term evolution of key driving forces, such as population growth and distribution, or per capita income growth. For assessments of land-use/land-cover change, it is important to establish a number of well-defined and spatially explicit scenarios of socioeconomic development. These will provide the basis for assessing and framing the plausible range of land-use/land-cover changes and their environmental impacts over a time horizon of 30 to 50 years and beyond.

The National Research Council (NRC) was organized by the U.S. National Academy of Science (NAS) to associate the broad community of science and technology with the Academy's goals of furthering knowledge and advising the federal government. In response to a request from the U.S. National Science Foundation, the NRC formed a committee to identify the most important environmental research challenges of the next decade. The following are highlights from the resulting report related to the development of agent-based models of land-use/land-cover change (NRC 2001). For more information on the NRC, see http://www.nas.edu/nrc.

- Theory and assessment models used to address land dynamics are mainly static, economic sector–based, and non-spatial, and do not account for neighboring uses, the roles of institutions that manage land and resources, or biophysical changes and feedbacks in land use and land cover, including climate change and anthropogenic changes in terrestrial ecosystems. Such inadequacies must be redressed if we are to achieve a robust understanding of these phenomena and provide the kinds of projections required to conduct environmental planning and to ensure the sustainability of critical ecosystem functions. In particular, it is necessary to improve understanding of how, where, and why specific land units change.

- The research community is now poised to develop at least four types of spatially explicit, integrative, explanatory land-change models: (a) those based on behavioral and/or structural theory linked to specific geographic locations, (b) those drawn from changes registered in remotely sensed imagery, (c) hybrids of these two types, and (d) dynamic spatial simulations that offer projections under different sets of assumptions.

The Center for Spatially Integrated Social Science (CSISS) is funded by the National Science Foundation under its program of support for infrastructure in the social and behavioral sciences. Its programs focus on the methods, tools, techniques, software, data access, and other services needed to promote and facilitate a novel and integrating approach to the social sciences.

The CSISS Mission is founded on the principle that analyzing social phenomena in space and time enhances our understanding of social processes. Hence, CSISS cultivates an integrated approach to social science research that recognizes the importance of location, space, spatiality, and place. The goal of CSISS is to integrate spatial concepts into the theories and practices of the social sciences by providing infrastructure to facilitate: (1) the integration of existing spatial knowledge, making it more explicit, and (2) the generation of new spatial knowledge and understanding.

CSISS Objectives:

1. To encourage and expand applications of new geographic information technologies and newly available geographically referenced data in social science.

2. To introduce the next generation of scholars to this integrated approach to social science research.

3. To foster collaborative interdisciplinary networks that address core issues in the social sciences using this approach.

4. To develop a successful clearinghouse for the tools, case studies, educational opportunities, and other resources needed by this approach.

Because of this recognition of the importance of ABM to the development of land-change science, LUCC, CSISS, and the NAS have undertaken to support researchers in this area. This workshop is one result of their collaboration.

Acknowledgments

The editors wish to gratefully acknowledge the support and contributions of the many individuals and organizations who contributed to this collaboration. For organization of the National Academy of Sciences Sackler Colloquium on Adaptive Agents and their support and assistance in organizing our companion workshop, we thank Brian Berry, Douglas Kiel, and Euel Elliot. We also would like to thank the workshop co-organizers as well as the sponsoring organizations, the LUCC Focus 1 project, CIPEC, and CSISS, for organizational, financial, and administrative support. These organizations acknowledge financial support through the U.S. National Science Foundation grants SBR9521918 (CIPEC) and 9978058 (CSISS). Ann Ricchiazzi did an outstanding job of creating and maintaining the workshop website, and Don Janelle provided helpful support during the workshop. Nat McKamey and Amanda Evans provided invaluable administrative assistance in support of the workshop, and William McConnell and Amanda Evans provided consistent and patient administrative and organizational support during the production and review processes for the LUCC report version of this document. We thank internal reviewers Richard Aspinall and Dan Brown, as well as other conference participants, for timely feedback on an early draft. The proceedings also has benefited from comments from external reviewers from the LUCC organization. We also issue a special thanks to Joanna Broderick for her technical editing efforts. Finally, the content of this publication reflects the enthusiastic and insightful input of the conference participants, and we thank them for their participation and contributions to both the workshop and the proceedings.

Part 1 Introduction and Conceptual Overview

An increasing number of scholars are exploring the potential of agent-based or multi-agent system tools for modeling human land-use decisions and subsequent land-cover change. As defined here, an agent-based model of land-use/land-cover change (ABM/LUCC) consists of two key components. The first is a cellular model that represents the landscape under study. This cellular model may draw on a number of specific spatial modeling techniques, such as *cellular automata*, *spatial diffusion models*, and *Markov models*. The second component is an agent-based model (ABM) that represents human decision making and interactions. An agent-based model consists of autonomous decision-making entities (agents), an environment through which agents interact, rules that define the relationship between agents and their environment, and rules that determine sequencing of actions in the model. Autonomous agents are composed of rules that translate both internal and external information into internal *states*, decisions, or actions. Agent-based models are usually implemented as multi-agent systems, a concept originated in the computer sciences that allows for a very efficient design of large and interconnected computer programs.

In the context of a LUCC model, an agent may represent a land manager who combines individual knowledge and values, information on soil quality and topography (the biophysical landscape environment), and an assessment of the land-management choices of neighbors (the spatial social environment) to calculate a land-use decision. The model agents also may represent higher-level entities or social organizations such as a village assembly, local governments, or a neighboring country. In the place of *differential equations* at an aggregate level, ABM/LUCC include the decision rules, such as income maximization or minimum subsistence levels, of each human actor, their environmental feedbacks, and carryover of spatially distributed resources. For an ABM/LUCC, a shared landscape defined through the cellular model provides a key environment through which agents interact. Land markets, social networks, and resource management institutions may provide other important interaction environments. While agent interactions may lead to recognizably structured outcomes in ABM/LUCC, a set of global equilibrium conditions is not employed in these models, in contrast to modeling techniques such as conventional *mathematical programming* or *econometrics*. Thus, agent-based models offer a high degree of flexibility that allows researchers to account for heterogeneity and interdependencies among agents and their environment. Further, when coupled with a cellular model representing the landscape on which agents act, these models are well suited for explicit representation of spatial processes, spatial interaction, and multi-scale phenomena. These potential strengths are discussed in following sections. A detailed discussion of the components of an ABM/LUCC, alternative models of human decision making, and further issues related to the development of these models, is provided by Parker et al. (in press).

This document is based on presentations and discussions that occurred at the Special Workshop on Agent-Based Models of Land-Use/Land-Cover Change, held October 4–7, 2001, in Irvine, California. The workshop was motivated through a shared interest in exploring the potential of agent-based models of land use by representatives of several organizations: the Land-Use and Land-Cover Change Program; the Center for Spatially Integrated Social Science; the Center for the Study of Institutions, Population, and Environmental Change; and the National Academy of Sciences. The informal, invited workshop was held in conjunction with the National Academy of Sciences Sackler Colloquium, "Adaptive Agents, Intelligence and Emergent Human Organization: Capturing Complexity through Agent-Based Modeling," and was organized by Michael F. Goodchild, William J. McConnell, Dawn C. Parker, and B. L. Turner II. The goals of the workshop were (1) to facilitate communication among researchers engaging in the newly developing field of agent-based land-use modeling; (2) to discuss the potential and limitations of this new modeling technique; (3) to identify important methodological questions related to development of ABM/LUCC; and (4) to identify areas where concentrated research, communication, and infrastructure efforts would be useful. Detailed information on the workshop program and participant presentations is available at http://www.csiss.org/events/other/agent-based/.

Workshop organizers determined that a traditional conference format consisting of research paper presentations would not be appropriate because of the relative youth of this research field. Alternatively, the workshop format consisted of a combination of structured discussions on a set of pre-defined topics and short presentations by participants engaged in developing ABM/LUCC. The structure of these proceedings is based on the structure of meeting discussions and presentations.

The editors envision several goals for this document. The first is to provide a contextual summary of meeting discussions. The second is to provide an introduction to the current state of research on ABM/LUCC to scholars interested in using this modeling technique. The third is to provide a structured comparison of ongoing ABM/LUCC efforts. The editors recognize that scholars from multiple disciplines are interested in this modeling technique, and any one scholar may be unfamiliar with relevant methodological issues in another discipline. Thus, while the report content summarizes the main content of the meeting, it also expands on this content in each topic area. Our goal is not to provide an original and comprehensive review in each area, but rather to familiarize the reader with key issues and provide a basic set of bibliographic references. We also hope this publication will provide a template for evaluation and comparison of ABM/LUCC research projects.

This introductory section continues with a friendly challenge related to the challenges of ABM/LUCC by Helen Couclelis. It continues with a response to this challenge by the editors and a discussion of modeling needs for the land-use/land-cover change community that may potentially be met through ABM/LUCC. It concludes with synthesis and expansion of the first workshop discussion topic: What are the potential strengths and appropriate roles for ABM/LUCC?

Section 2 examines three methodological issues that deserve careful consideration when building an ABM/LUCC: spatial concepts and methods; the structure of the software model; and model calibration, verification, and validation. Contributions in the section pay particular attention to the special challenges and requirements of ABM/LUCC. Section 3 presents a structured series of project descriptions based on ongoing research. While these projects are representative of ongoing work, the collection should not be considered comprehensive, as other interesting efforts also are underway. Section 4 provides a synthetic discussion of these ongoing works and discusses a series of key open research questions related to ABM/LUCC.

1.1. WHY I NO LONGER WORK WITH AGENTS: A CHALLENGE FOR ABMs OF HUMAN-ENVIRONMENT INTERACTIONS

Helen Couclelis

My work with ABMs dates from the mid-1980s when I published two papers exploring the possibilities of agents in spatial modeling. The first paper developed a formal model of a way-finding agent operating within a complex building where other similar agents also were present. The objective there was to express a sequence of models of human decisions of increasing complexity in terms of the formal hierarchy of systems specifications developed by Zeigler (1976). This helped clarify the nature of the relationship between these different models, ranging from elementary stimulus-response to rational decision to reactive and intelligent agents (Couclelis 1986). The second paper described a cellular automata (CA) model of urban development in which developers were making investment decisions based on complex rules expressed in predicate calculus (Couclelis 1989). Since that time I have not done any research involving agents even though I have followed with interest the rapid growth of the field. In this note I explain briefly why I became skeptical of the whole paradigm following that early enthusiasm. At the same time I wish to express my willingness, if not hope, to change my mind regarding the relevance of ABMs to spatial modeling following this workshop.
As a former engineer turned scientist I am acutely aware of the subtle but profound differences, practical as well as conceptual, between the synthetic stance of the design disciplines and the analytic stance of the sciences. One major difference in practical terms is that when you design something you have direct (partial or total) control on the outcome, whereas when you analyze

something that’s “out there” you can only hope that you guessed correctly. That distinction also is discussed at length in Parker et al. (in press) under the rubrics of “explanatory” vs. “descriptive” (or fitted) models.

My view of how that distinction impacts agent-based modeling of land-use and land-cover change is as follows. Agent-based models fundamentally involve one or several agents interacting with an environment. Combined with the “explanatory” vs. “descriptive” (or designed vs. analyzed) models distinction this gives four cases:

1. Agents and environment both designed. This describes the “social laboratories,” the self-contained microworlds (such as Sugarscape) that researchers build from scratch. These models can achieve complete validity within the artificial microworlds they set up, but outside of these they serve as abstract thought experiments at best (Axelrod 1997).
2. Agents designed, environment analyzed. This describes the engineering applications of the ABM paradigm whereby software or hardware robots are designed to operate within pre-existing environments. These are problem-solving applications where the agents’ behavior rules may or may not be anthropomorphic. These kinds of agent models clearly can be extremely effective in practice though they often can be defeated by the complexity of the real environments within which they operate.
3. Agents analyzed, environment designed. This is the case of behavioral experiments where natural subjects (human or animal) are observed within controlled laboratory conditions. Reasonably reliable behavioral and decision rules may be inferred under these circumstances (notably, through the methods of experimental psychology), but it is always questionable whether the rules thus derived will also be valid “out there” in the real world.
4. Agents and environment both analyzed. This is the only one of the four cases that directly concerns land-use/land-cover modeling. Here the relevant kinds of models are the traditional types recognized in the philosophy of science: descriptive, predictive, or explanatory models. Building a descriptive model (i.e., one that fits observations) is technically no trivial task but, in principle, it can always be done given enough free *parameters*. Such models can be very useful as data summaries but beyond that their utility is limited. They may sometimes be used as predictive models to the extent that trend extrapolation is warranted, but true predictive models must be structurally appropriate; i.e., they need to correspond to the mechanisms operating in the real system(s) under study. This requires the existence of formal process theory, which simply is not available in the land-use/land-cover field (with or without agents). Predictive models based on theory are, by that token, also explanatory models, though not all explanatory models are predictive (e.g., the causal relations identified may change over time in unpredictable ways). Reasonably reliable predictive and explanatory models of land-use change would be of tremendous value to planning and policy making, but after forty years of efforts in that area the success stories are still quite limited.

Agent-based modeling meets an intuitive desire to explicitly represent human decision making when modeling systems where we know for a fact that human decision making plays a major role. However, by doing so, the well-known problems of modeling a highly complex, dynamic spatial environment are compounded by the problems of modeling highly complex, dynamic decision-making units interacting with that environment and among themselves in highly complex, dynamic ways. The question is whether the benefits of that approach to spatial modeling exceed the considerable costs of the added dimensions of complexity introduced into the modeling effort. The answer is far from clear and in, my mind, it is in the negative. But then I am open to being persuaded otherwise.

1.2. ABM/LUCC: CAN WE MEET THE CHALLENGE OF COMPLEXITY?

Dawn C. Parker

The preface to this volume discusses a series of questions and objectives that might guide exploration of land-use and land-cover change. The hypothesis that “agents, such as individuals, households, and firms . . . take specific actions according to their own calculus or decision rules that drive land-cover change” is presented. A series of requirements of models that will answer questions of interest to the land-use/land-cover modeling community are suggested. These include:

- Process-based explanations
- Spatially explicit models of agent behavior
- Representation of socioeconomic-environmental linkages
- Representation of a diversity of human agent types
- Representation of impacts of heterogeneous local conditions on human decisions
- Ability to analyze the response of a system to exogenous influences: technological innovations, urban-rural dynamics, and policy and institutional changes (scenario analyses)
- Integration and feedbacks across hierarchical spatial and temporal scales
- Improved means for projecting and backcasting land uses and land covers

These questions and methodological modeling challenges can be summarized in terms of complex human behavior interacting with a complex environment. As defined above, ABM/LUCC offer the flexibility necessary to represent and integrate both sources of complexity, and thus may be a useful tool for addressing the questions of importance to the LUCC community. This said, one of the most fundamental challenges of model building lies not in replication of the system under study, but in identification of an appropriate level of abstraction. A model is an abstract representation of a real-world system that must possess sufficient detail related to the problem under study to analyze key dynamics but, at the same time, be sufficiently transparent so key mechanisms and drivers of change can be identified.

In section 1.1, Couclelis acknowledges that human decision making plays a major role in land-use change. She raises, however, well-founded skepticism regarding the possible success of a model of land-use change designed to integrate complexity in human decision making with complexity in environmental interactions. Her skepticism rests on two main arguments. First, formal process theories of human-environment interactions are not yet developed, and this deficit has hindered development of projective land-use change modeling. Second, she doubts that the explanatory benefits of a combined model exceed the costs of the perhaps exponentially magnified complexities of combing representations of human and environmental dynamics.

In these proceedings, we hope to address her healthy skepticism. First, we propose that ABM/LUCC potentially can serve all four of the categories that she describes, exploring both abstract and empirical combinations of human-environment interactions. Each model variant may serve a particular role in gaining a clearer understanding of land-use and land-cover change. As such, ABM/LUCC can be a tool for developing the process theory of LUCC that she argues is still absent in the literature. While a comprehensive process theory is not yet developed, sophisticated models of individual process components, such as human decision making and spatial diffusion processes, are increasingly well developed. An agent-based model of land-use/land-cover change offers a means to link these processes to develop integrated theories of causal relationships. We envision an iterated exchange between designed (theoretical/abstract) and analyzed (empirical) models that may help reveal the complex dynamics of linked human-environment systems.

We also suggest that the costs of model development and model analysis have fallen radically due to increased computing power, innovative software tools, and development of platforms specifically designed for agent-based modeling. Further, while data procurement remains a challenge, especially regarding spatially disaggregated socioeconomic data, the availability of satellite images and advent of remote sensing techniques have relaxed constraints on available data on the environmental side. Special data sampling strategies for LUCC models (Berger and Ringler 2002) as well as newly developed econometric techniques based on maximum entropy (Howitt and Reynaud 2001) also may hold considerable potential to provide consistent disaggregate data.

Finally, since there is broad agreement regarding the influence of human decision making on land-use and land-cover change, we must attempt to build integrated models that link the incentives of human decision makers to the environmental impacts of land-cover change. In particular, there is growing recognition of the importance of cross-scale linkages and interactions between regional and local drivers of land-use change. We see ABM/LUCC as promising means of creating models that link processes operating at different spatial and temporal scales. In the final cost/benefit calculus, the costs of not attempting to build models that capture the complexities we believe drive critical environmental outcomes far exceed the costs of traveling down an uncertain path.

1.3. POTENTIAL STRENGTHS AND APPROPRIATE ROLES FOR ABM/LUCC

Dawn C. Parker, Steven M. Manson, and Thomas Berger

Diverse communities engage in modeling land-use and land-cover change, including land-use planners, urban and regional modelers, and researchers interested in the impacts of global climate change on land-use and related human responses. These communities employ a variety of modeling techniques and have diverse modeling goals. Members of each community likely have two main questions regarding ABM/LUCC: First, what role might ABM/LUCC play in addressing their major concerns and research questions? Second, how might ABM/LUCC relate to the existing tools used by these communities, such as cellular automata, spatial econometrics, remote sensing, and mathematical programming?

1.3.1. Roles, Scope, and Methodology of Models

Workshop participants proposed several interrelated continua along which ABM/LUCC could be categorized (see Figure 1). These characterizations relate to the roles, scope, and methodology behind the model.[1] Along with the matrix that will be developed in section 3.1, this framework provides a useful context for relating ABM/LUCC to previous LUCC modeling work. The continuum can be defined in most general terms as running from purely theoretical to purely empirical. Theoretical models also are often constructed to serve as explanatory tools, and thus results are often generalizable to a range of research applications. In contrast, empirical models are often designed to closely match the details of a particular case study, and as such, their conclusions are often specific to that case. However, both theoretical and empirical models potentially can serve as exploratory tools, as discussed further below.

Theoretical models can often be characterized as deductive, in the sense that they use a logical procedure to derive some very specific results from basic and unquestioned assumptions (axioms). Inductive methods, in contrast, filter patterns from empirical data to identify some general laws behind them. Thus, in principle, the spectrum also could be seen as running from deductive to inductive. However, there is substantial debate as to whether computer simulation methods such as ABM can be characterized as purely deductive and/or purely inductive. Consistent with deduction, an ABM modeler begins with a set of assumptions regarding agent behaviors and interactions, but in contrast to classical deduction, the modeler cannot prove the results using formal mathematics or logic. Instead, the modeler may generate data in different simulation experiments that are then analyzed with inductive methods similar to those employed for analysis of empirical data. In contrast to pure induction, however, one does not work with real-world data. Zwicker (1981) therefore characterizes simulation modeling as "pseudo-inductive." Axelrod (1997) concurs that simulation is neither purely deductive nor inductive, and alternatively characterized it as a "third way of doing science." He stresses several potential useful roles for simulation: to aid intuition, to demonstrate an existence proof, and to discover new mechanisms or laws that have so far not been empirically inferred. 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.

In addition to this continuum, two other continua may potentially characterize LUCC models. The first is normative (describing how reality could or should be under ideal circumstances) to positive (describing links between mechanisms and outcomes without judgment as to fitness or appropriateness). The focus of this document, consistent with the bulk of meeting discussions and the approach taken by Verburg et al. (in press), remains on positive models. The second continuum is simple to complex. It is important to acknowledge that this continuum is distinct from the theoretical/empirical continuum, as a theoretical model may be relatively complex and an empirical model may be quite simple. Regardless of the style of model implemented, there is an ever-present danger of building too much complexity into any model, resulting in difficulty in

[1] While spatial models also have been characterized according to spatial and temporal scale (see Agarwal et al., 2002), this continuum does not directly relate to the conceptual discussion in this section. Jeffers (1991) also outlines a similar set of model characterizations.

understanding how processes drive outcomes. This point was stressed repeatedly by many workshop participants. Casti (1997) provides an excellent discussion of the appropriate level of detail in models of complex systems.

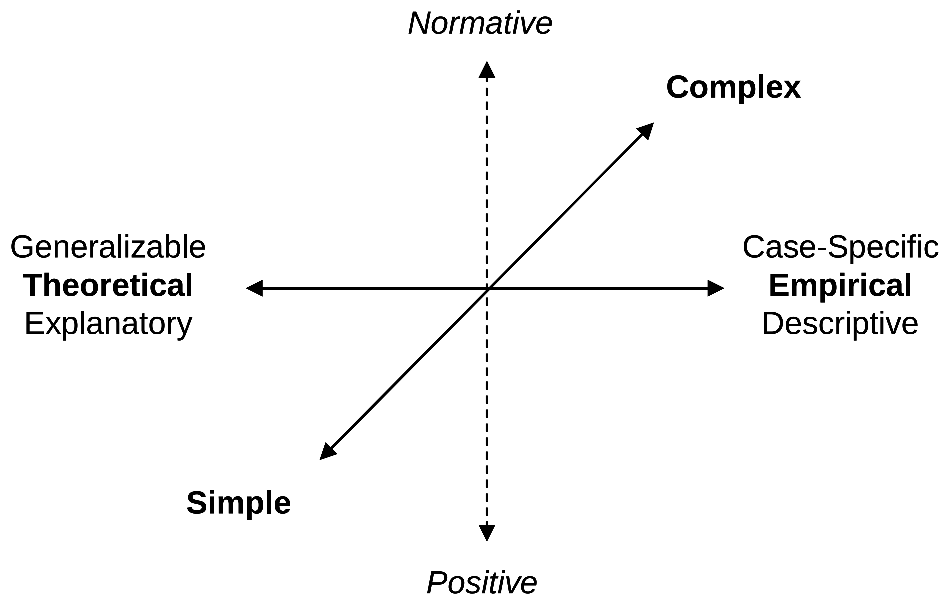

Figure 1. Continua for Categorizing Agent-Based Models

Traditionally, agent-based models have operated at the left end of this spectrum, whereas other tools used by LUCC researchers have operated at the right end of the spectrum. Thus, one possible role for ABM/LUCC is to provide explanatory, generalizable insights that may guide applied research efforts. However, ABM/LUCC also may serve to bridge the gap between abstract analytical models and applied statistical models. Specifically, if causal mechanisms are explicitly represented and parameterized as closely as possible with real-world data, such models may serve in a deductive style for applied policy analysis by linking processes to possible outcomes. Such models also may provide a means to test previously abstract models against real-world data, if theoretical models form the basis for defining processes in a simulation model that is then used to generate simulated data. If patterns from the simulated data statistically match patterns in real-world data, analyzed using similar inductive techniques, then support is lent to the theoretical processes used in the simulation model. This approach is suggested by Parker et al. (2001). Judd (1997) discusses the possibility of using regression analysis to understand the results of computational simulations in a theoretical context.

The question of how ABM/LUCC relate to statistical models of land-use and land-cover change is often posed. The question of which modeling technique may have greater explanatory power often implicitly underlies this discussion. There is not yet one definite answer, although there are some concrete ways in which these models can be and have been related. Natural complementarities arise between ABM/LUCC and statistical models that parallel the general relationship between mathematical and statistical models. Statistical models can be used to identify empirical regularities of interest, and mathematical models can be used to explore hypothetical causal mechanisms that may generate these empirical regularities. Statistical models also may be used to identify factors that appear to significantly impact the system under study, motivating the inclusion of these factors in the ABM/LUCC. Further, ABM/LUCC can be seen as a complex implementation of mathematical programming models, in the sense that ABM/LUCC provide a parameterized dynamic simulation of a real-world system. As has historically been the case, the parameters of such models may be obtained through econometric estimation. In this complementary role, the explanatory power of each modeling type cannot be directly compared, since the explanatory power of the ABM/LUCC would depend both on the quality of econometric estimates and on the validity of the structural representation of system dynamics. (See section 2.4 for a discussion of structural validity.)

However, one potential advantage that ABM/LUCC may have over pure statistical models lies in their ability to represent structural dynamics. Because of requirements for statistical identification of estimated parameters, statistical models are often estimated as a reduced form, rather than as a structural representation of system dynamics. Therefore, they are not well suited to extrapolation or prediction outside the range of the dynamic state under which they were estimated. Even when structural statistical models are estimated, parameters are estimated under assumptions of temporal and spatial stationary. Once again, the ability of statistical models to represent dynamics outside the range of the data may be limited. Therefore, in direct performance comparisons for extrapolation and projection, ABM/LUCC might potentially dominate statistical models in cases where dynamic processes have an important impact on outcomes. The potential for ABM/LUCC as tools for extrapolation and projection was seen as a major conceptual advantage by many participants, although participants emphasized a scenario analysis or prospective role, rather than a prediction role. Because extrapolation and projection are important priorities for the LUCC community, exploration of potential complementarities between statistical models and ABM/LUCC with respect to development of projective models is an important area for further research. Lessons may be drawn from previous research using parameterized, spatially explicit models such as CA, Markov models, and mathematical programming models.

1.3.2. Specific Roles for ABM/LUCC

Workshop participants identified a variety of conceptual roles for which ABM/LUCC may hold advantages over other modeling techniques. While some of these roles fit into a specific cell in the characterization of the four model classes discussed by Couclelis in section 1.1, others apply broadly to all agent-based LUCC models.

Computational Laboratory

Several participants have used ABM/LUCC in a deductive style to methodically explore human-environmental interactions. As such, ABM/LUCC serve as computational laboratories that allow for thought experiments and may structure the exploration of dynamic interactions. These stylized models are potentially useful for exploring links between micro-level interactions and macro-outcomes, creating long-range theoretical models of the underlying driving forces of global phenomena, exploring systems dynamics and the implications of interactions, and examining the implications of heterogeneity among decision makers and their environment. A powerful role for such models may be to demonstrate a counterintuitive result that runs contrary to established theory and intuition.

Integrated Modeling of Human-Environment Systems

Many participants stressed the potential of ABM/LUCC to represent the co-evolution of human/environmental systems. Because models of human decision making with models of biophysical processes can be linked through a common spatial identifier, ABM/LUCC are seen to hold substantial promise for interdisciplinary modeling. This advantage comes in large part through flexibility in scale of representation on both the agent decision and biophysical modeling side. Unlike analytical models that often rely on aggregation assumptions for mathematical tractability, ABM/LUCC can be constructed to operate at the spatial scale relevant for biophysical process models. This fine-scale representation may offer statistical advantages, since spatial aggregation of data generally implies a loss of statistical information. In general, the workshop participants expect increased exploratory power for environmental models when the influence of human decision makers is included.

Representing Complexity, Emergence, and Cross-Scale Dynamics

Representing complexity is seen as a major strength of ABM/LUCC. Extensive discussions among participants occurred around the concept of "emergence," including its definition and the possible role that emergent phenomena may play in LUCC research. The notion of emergence is a central tenet of agent-based modeling, and the search for emergence is mentioned explicitly by several of the modeling efforts noted in this volume. The term emergent refers to a system having qualities that are not analytically tractable from the attributes of internal components (Baas and Emmeche 1997). Emergent phenomena exhibit structures that are not explained by lower-level dynamics and typically persist beyond the average lifetimes of entities upon which they are built (Crutchfield 1994). More intuitively, an emergent property may be defined as a macroscopic outcome resulting from synergies and interdependencies between lower-level system components.

The concept of emergence and the concept of scale are potentially related. Hierarchy theory helps define emergence by positing that processes are bounded by envelopes of time, space, or causality. Scales are best considered relative to one another and connected through measures common to different levels (Allen and Hoekstra 1992). Levels can influence one another through shared variables, as perturbations in one level affect processes, and this cross-level interaction may affect the functioning of processes in both (Holling 1995). As Parker et al. (in press) argue, these interactions imply that an individual agent or parcel is likely influenced by, and in turn influences, processes operating at multiple spatial scales. In the case of human agents, for example, family members interact to form a household, which may then interact with other households of the same village so that institutional changes at the community level occur, which in turn set new constraints for the resource use of each family member.

Identifying emergence, therefore, may require understanding important cross-scale interactions and deliberately building in interactions across levels, rather than limiting modeling and analysis to a single scale. Related to this theme, the group discussed the concept that emergent properties from one level of interaction may define the units of interaction at the next highest level. For example, urban models such as those of Torrens (section 3.9), Brown et al. (appendix 2), and Irwin (appendix 5) focus on the emergence of patterns of land-use and economic activity within cities, whereas models in the "new economic geography" (Krugman 1995) focus on the determinants of the distribution of population and economic activity between cities. In this system, the form of the city as defined by micro-scale urban models can be seen as defining attributes of cities at the macroscale, which influence location decisions between cities. In turn, population shifts between cities may feed back to the microlevel through impacts on demand for residential housing and subsequent impacts on patterns of land use. While the group concluded that ABM/LUCC have potential to explicitly represent cross-scale interactions and feedbacks, both bottom-up and top-down, concrete results in this area are not yet available, as discussed further in section 4.1.

Among participants, some debate centered on the question of whether emergence was a property of a real-world system or simply a property of a modeled system. Further debate centered on whether or not an emergent property must be "surprising" by definition. 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, surprise is a fundamentally subjective concept. 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. The concept of surprise, though, may provide a counterfactual way of defining emergence: a pattern whose appearance is an obvious consequence of the properties of the underlying components may not be regarded as emergent. Additional discussion of emergence and cross-scale hierarchies is provided by Parker et al. (2001).

It was suggested that emergent properties might be recognized through the language used to describe them—if new language and/or definitions are needed to describe macro-outcomes, they are potentially emergent. Auyang (1998) discusses emergent phenomena in related terms. The group agreed that for LUCC modeling, it would be useful to focus on emergent properties that are explicitly spatial and result from human-environment interactions. Examples discussed included suburban sprawl, ecosystem functions, social norms, and paths of technology diffusion. Such emergent properties may provide targets for model validation and assessment.

Conducting Interactive Experiments

Another role identified by participants for ABM/LUCC is as a tool for conducting controlled experiments with human decision makers. Multiple goals were identified, including assessing the impacts of hypothetical institutional structures on humans' decisions and subsequent land-use change, informing construction of the agent–decision-making specifications of LUCC models, providing an interactive decision-support tool for policy makers, and promoting discussion between stakeholders that may lead to awareness of the views of other co-users of the land and facilitate group decision making.

Scenario Analysis

Participants suggested that scenario development and analysis using ABM/LUCC could supplement findings from existing LUCC research. An ABM that contains a detailed structural representation of the system under study could be used to analyze alternative scenarios that frame the range of plausible driving forces of land-use change. As outlined in Lambin et al. (1999: 81), different types of scenarios could be developed: normative, reference, predictive, and responsive.

1.3.3. Specific Research Questions

Participants compiled a tentative list of specific proposed research topics that could be addressed with ABM/LUCC:

- Temporal and spatial diffusion of technological innovations
- Modeling the impacts of transportation and communication networks
- Scenario analysis for land-use policy and planning
- Understanding structural adjustment in agriculture in response to shifts in policy incentives
- Modeling firm location decisions, impacts on demand for public services, and subsequent feedbacks among levels of spatial organization
- Examining the sustainability of human-environment systems
- Assessing the impacts of global change on land and water resources as well as possible human adaptations

Many of these suggested topics involve understanding the spatial structures that result from existing theoretical models of human decision making. Does this mean, then, that ABM/LUCC are seen primarily as a means of implementing existing knowledge, rather than a means to knowledge discovery? Of these two possible roles, is one more useful for a model in general, and for ABM/LUCC in particular? We argue that both roles are important to the iterative process of development and testing of theories, and we argue that ABM/LUCC can serve both as a means of knowledge discovery and knowledge implementation. By linking processes previously modeled as independent, ABM/LUCC may provide valuable insights into previously poorly understood human/environment dynamics. By testing outcomes of these simulation models against empirical data, ABM/LUCC can lend support to or refute the theoretical models that form their building blocks. By implementing these processes in integrated policy simulation models, ABM/LUCC offer a means to use this knowledge to shed light on important policy debates.

Part 2 Methodological Considerations for Agent-Based Modeling of Land-Use and Land-Cover Change

2.1. INTRODUCTION: SPATIAL ANALYSIS, SOFTWARE, AND VALIDATION
Steven M. Manson

Workshop participants consistently identified three areas of concern that need to be addressed to improve agent-based modeling of land-use and land-cover change: spatially explicit analysis, object-oriented software, and issues of verification and validation. The importance of these topics is evident in how they are revisited throughout the examples of current research presented in sections 3.1–3.9. The following sections provide overviews of these areas, highlight challenges for ABM/LUCC, and offer some potential solutions.

Section 2.2 reviews why agent-based models of land-use and land-cover change are almost necessarily spatially explicit. It considers what makes a model spatially explicit and offers arguments why spatially explicit modeling is important. It also introduces some general tools necessary for spatially explicit modeling. It concludes by considering broader issues of importance to spatially explicit approaches, such as ontology and the role of validation.

Section 2.3 takes a deeper look at object-oriented programming (OOP), a technique particularly valuable for agent-based modeling. It uses the example of a hypothetical land market to illustrate the processes of designing and implementing ABM/LUCC software. In particular, it explores the advantages afforded by object-oriented programming, such as ease of organization and technical characteristics almost critical to the creation of agents. Section 2.3 concludes with a review of existing simulation packages designed for agent-based modeling.

Section 2.4 examines calibration, verification, and validation of agent-based models. While it provides a general overview, its main task is to examine a number of issues raised by workshop participants. It examines the relationship between calibration, verification, and validation in terms of data and model fitting. Closely related are challenges to tests of model sensitivity raised by system complexity and agent interaction. There is also a host of issues concerning the role of theory and empirical research in structural and outcome validation. Finally, section 2.4 considers the use of spatiotemporal statistics in an agent-based model setting and related issues of scale, aggregation, and representation.

2.2. ISSUES IN SPATIALLY EXPLICIT MODELING
Michael Goodchild

Although everything that happens on the Earth's surface is framed in space and time, it is not obvious that models of LUCC need to consider space explicitly. Many processes occur uniformly everywhere on the Earth's surface, without respect to location, and disciplines such as physics, chemistry, or biology rarely need to consider the location at which a process occurs, or to question whether location has a significant impact on a process. Social processes are similar in many respects, and human behavior is therefore often analyzed with the expectation that the underlying processes are constant in space and time.

Much attention has been paid to the roles of physical separation and intervening distance on social processes. People widely separated by space are less likely to interact, other things being equal; markets distributed over wide areas may operate imperfectly if communication is imperfect; and the costs of transporting goods clearly impact industrial processes. But here again an explicit recognition of location is rarely necessary, since location and distance are surrogates for lack of communication, or transportation cost, rather than actual causal factors.

This section reviews some of the arguments for explicit recognition of space in agent-based modeling of LUCC, and summarizes the issues, many of them raised by participants at the workshop. The next section addresses the precise meaning of spatially explicit. This is followed by a section summarizing arguments supporting spatially explicit modeling, first in general and then in the specific context of LUCC. The third section provides a brief summary of the available tools for spatially explicit modeling. The fourth and final section reviews issues that are endemic to a spatially explicit approach, including the key issue of alternative ontologies, and the role of space in model validation.

2.2.1. What does it mean to be spatially explicit?

Many disciplines use the term *spatially explicit*, but in different ways. An ecologist or economist might call a model spatially explicit if it recognizes two markets or habitats separated by a partial communication barrier, whereas a geographer is more likely to reject such gross lumping, and to insist that a spatially explicit model be constructed in a continuous spatial frame. Nevertheless, there seem to be some simple tests that one can apply to determine if a model is spatially explicit, or if an area of investigation demands spatially explicit modeling. Four such tests were discussed at the workshop:

1. The *invariance* test: A model is spatially explicit if its results are not invariant under relocation of the objects of study. In other words, a model is spatially explicit if its workings are affected by randomly moving the objects that participate in the model.
2. The *representation* test: A model is spatially explicit if location is included in the representation of the system being modeled, in the form of coordinates or derivative spatial properties such as distances.
3. The *formulation* test: A model is spatially explicit if spatial concepts such as location or distance appear directly in the model, in algebraic expressions or behavioral rules.
4. The *outcome* test: A model is spatially explicit if the spatial forms of inputs and outputs are different. In other words, a spatially explicit model modifies the landscape on which it operates.

Any one of these tests might be sufficient to determine whether a model is spatially explicit, and a given model might satisfy any combination of the tests.

2.2.2. Why be spatially explicit in modeling LUCC?

Agent-based models of LUCC are complex, representing many distinct processes. For many of these processes, space is clearly irrelevant. For example, models of the individual choices made by actors on the landscape may be essentially invariant under relocation, such that the rules governing the behavior of a decision maker are identical wherever that decision maker is located. In other cases, actions may be determined to some degree by spatial context, or by the distance separating the decision maker from key inputs to the decision.

But the most important reason for LUCC modeling to be spatially explicit may be related to model outputs, and thus to the outcome test outlined above. The processes of LUCC modify landscapes, producing fragmentation, regionalization, and other types of patterns—and these patterns are of very significant interest to policy makers. Many of our research questions in LUCC modeling are related to the spatial structures of outcomes, in part because of the importance of spatial structure in other processes for which land use is an input, such as biological conservation. A LUCC model is likely to be assessed, at least in part, through the spatial patterns that it produces, and their agreement with observed spatial patterns. It follows that LUCC models must be spatially explicit.

2.2.3. The Toolkit for Spatially Explicit Modeling

In recent years, there has been a dramatic improvement in the availability of tools for spatially explicit modeling; so much so that this alone may account for much of the recent growth of interest in modeling LUCC, which previously had to rely almost entirely on laborious coding in source programming languages. Geographic information systems (GIS) are perhaps the most conspicuous of the new range of tools. They can be defined as systems for input, management, analysis, and output of spatially referenced information—in fact, for the support of virtually any form of systematic operation on such information (Longley et al. 2001). GIS software provides the foundation for representation and handling of spatially explicit information, and makes it very easy to add a wide range of analytic, modeling, and related functions. Thus much recent work in spatially explicit modeling has used GIS, sometimes coupling with other forms of software more directly related to modeling. PCRaster is an instance of a GIS designed specifically for dynamic modeling—it was developed at the University of Utrecht and is downloadable over the Internet. But more generally, commercially available GIS software tends to have been designed for comparatively static applications and is not easily used as the basis for dynamic models. More work is clearly needed at a technical level in integrating agent-based modeling capabilities with GIS, an area recently reviewed by Gimblett (2002).

Cellular automata software provides another, somewhat more restricted environment for spatially explicit modeling. CA are typically restricted to models that can be expressed as simple rules applied to cells in a *raster*, modifying the state of one cell based on its prior state and the prior states of its immediate neighbors. SpaceStat (www.spacestat.com) supports the analysis of spatially explicit models defined over more general, irregular geometries, with spatial lags that are the two-dimensional equivalent of temporal lags.

Finally, much effort in recent years has gone into the development of appropriate metrics of landscape fragmentation and related properties. Fragmentation statistics can now be readily evaluated in a GIS environment and used to test LUCC models against patterns of fragmentation on real landscapes. Participants also discussed the role of geostatistics, the branch of statistics based on the theory of spatially regionalized or autocorrelated variables (see, for example, Isaaks and Srivastava 1989, Burrough and McDonnell 1998), and its specific tools, such as kriging and co-kriging. These and many other forms of analysis might be used to compare model outputs to geographic reality, and thus to approach the validation of LUCC models (as discussed in section 2.4).

2.2.4. Challenges in Spatially Explicit Modeling

Participants in the workshop identified several issues that are of critical importance in spatially explicit modeling. Some of these will be familiar to anyone who has worked with spatial data, while others are related to the specific context of LUCC modeling.

Scale is important in two distinct ways in LUCC modeling: in the form of extent, or the area covered by the model, and in the form of resolution, or the level of detail inherent in the model. Extent is important because of the general property of spatial heterogeneity, or the tendency for geographic context to vary slowly but consistently across the surface of the planet. It follows that the results of any analysis or modeling will depend explicitly on the choice of study area, and that it is virtually impossible to select any area to be typical or representative of the Earth's surface as a whole, or any substantial part of it. Generalization from a single case study over a limited area is necessarily difficult. Resolution is critical because of the role it plays in determining whether a model of LUCC can be successful. Any spatially explicit process has an inherent scale, and attempts to model the process at levels of resolution coarser than the inherent scale will inevitably fail, because details that are important to the process will be missed by the model.

GIS software tends to be complex and difficult to learn and use, at least in part because of the many distinct ways in which spatial variation can be represented in digital form. Choices exist in levels of detail, the objects chosen to be represented in the database, whether or not to represent the third spatial dimension, whether to recognize change through time , whether to implement models using raster or *vector* representations of spatial variation, and in many other aspects. We recognize these choices in the form of alternative data models and structures, and data modeling has emerged as one of the most important areas of GIS research. In its most general form, data modeling is the study of ontology, a branch of science concerned with the process of description. One of the most fundamental distinctions in spatially explicit ontology is between fields—descriptions that conceptualize the Earth's surface in terms of the continuous variations of measurable quantities such as elevation or temperature—and discrete objects that litter an otherwise empty space and can be counted and manipulated. Examples of the latter include biological organisms, landscape features such as lakes or habitat patches, and human constructions such as buildings.

Ontology is critical because it ultimately affects the types of models that can be built. Human agents might be conceptualized as discrete objects, moving around in space, but influenced in their behaviors by continuously varying fields capturing such properties as population density (and hence crowding), agricultural suitability, land rent, or climate. In turn, these discrete objects and fields would be represented in digital form using appropriate GIS representations, at levels of detail that are appropriate to the processes being modeled. The combination of mobile objects and spatial fields which are dynamically updated in response to human actions was recognized by participants as defining one of the major challenges for development of ABM/LUCC.

2.3. SOFTWARE TOOLS AND COMMUNICATION ISSUES

Robert Najlis, Marco A. Janssen, and Dawn C. Parker

2.3.1. Introduction

In this section, an example of a hypothetical land market is used to outline issues related to the design and implementation of ABM/LUCC in computer code. The land market example will be used to demonstrate some advantages of OOP and provide a framework for discussing important programming issues. In addition, the perspectives of workshop participants will be included throughout. The section concludes with a review of existing simulation packages designed for agent-based modeling.

The land market to be used as an example in this section is as simple as possible in order to focus on elucidating programming concepts. The land market can be conceptualized as shown in Figure 2.

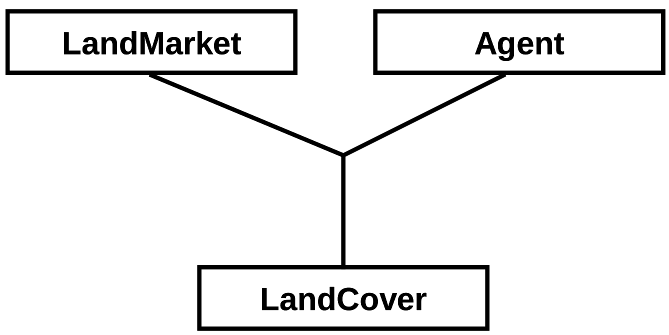

Figure 2. A Simple Land Market

Thus, we are concerned with three main elements: the land market itself, the agents that will interact in the land market, and the land cover of the land in the land market. Before we actually look at the whole land market example, we will discuss how to represent elements of the land market in an object-oriented computer program. Then, we will look at the whole land market from the perspective of an object-oriented computer program. We also will do some comparison with procedural programming in order to understand the differences between procedural and OOP methods.

2.3.2. OOP As an Organizing Technique

One important consideration in programming is that the programmer be able to focus on only one aspect of the whole program at a time. Thus, if we were writing code about how an agent makes decisions, we wouldn't want to concern ourselves with how trees grow on the landscape. Furthermore, it makes programming easier if the code can be broken down in into small pieces. Again, when programming an agent, we wouldn't want to have to write code about every aspect of the agent at once. It would be easier to write a small piece of code describing how an agent moves, and another describing how an agent interacts with other agents. These code elements could be made to interact with each other: for example, move until finding another agent, interact, then move again. By keeping pieces small, not only does it make it easier to focus on a particular piece, it also makes changes easier to implement. If we were to change how agents interact, perhaps by adding different pieces of code for different types of interactions, we could make this code communicate with other code describing how agents move without having to change the original code for agent movement.

OOP was developed subsequent to procedural languages such as C, Pascal, and FORTRAN. Object-oriented languages were developed as a means to organize code into separate concerns and manageable units. Thus OOP languages aim to optimize the speed with which the programmer is able to work, rather than execution speed of the program. Although there is an overhead, and thus a speed cost in running an object-oriented program, the time to actually write and verify such a program is considerably shortened in comparison to procedural languages. There is not too much that can be done uniquely in either OOP or procedural programming. Clearly, very complicated work can be done in procedural programming, as many operating systems (most notably UNIX) are written in C. However, OOP is easier to work with, as it provides more tools for organizing code into discrete units. A good, but technical, reference on OOP is Booch (1994), and a less technical reference is Taylor (1998).

2.3.3. Classes and Class Hierarchies

In procedural programming languages, functions and data are separate. There is no link between the two. Of course, functions can act upon the data, but a programmer must be very explicit in telling the function what data to use, and each function must know what the data means. In contrast, OOP works to organize code by encapsulating both data and the functions that act upon that data into one unit (a class). By encapsulating data and functions in a class, every instantiation of the class has both its own data and functions associated with it (Figure 3). Contrast this with procedural languages in which data may be bound together but functions are left separate (Figure 4).

The distinction between OOP and procedural programming, while subtle, is important. In OOP, each function in the class knows about its associated data, as they are bound together into the same unit. For example, each function inside ClassA is programmed with information about the data in ClassA and how to access it. Thus, any other functions outside ClassA do not need to know how data within ClassA are stored. Other functions only need to call ClassA's functions to get the data from ClassA. In contrast, given encapsulation of only data, as in procedural programming, any function that needs to access data from DataA would need to identify DataA as the source and understand the format of the data. Thus, the work of identifying and accessing data in OOP has been localized into the class. While this difference may seem small, it is in fact what gives OOP much of its power. The knowledge of data and functions that a class has allows work to be done in clear and well-organized ways.

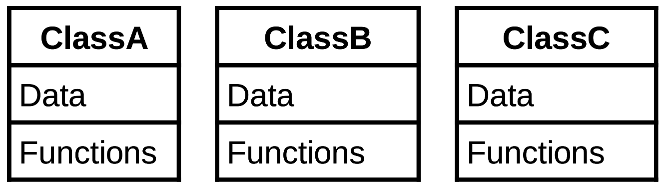

Figure 3. Organization of Object-Oriented Programming (OOP)

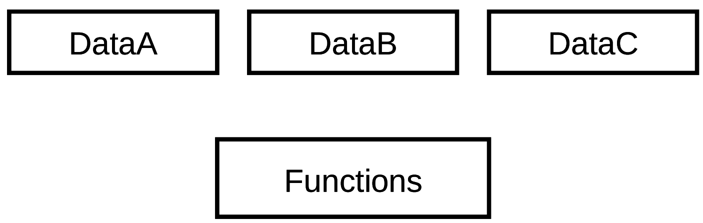

Figure 4. Organization of Procedural Programming

As an example of a simple class, we might choose to represent a Tree class as shown in Figure 5. This class incorporates data (type, height, age), with functions (grow, reseed). Any work that needs to be done on either the data or functions related to trees need only be done in that one class. This can be important in a few ways. If a function needs to be used in many places, that function need not be repeated in separate places throughout the program. This lack of repetition is most important when updating or verifying the actions of said function. If the function is spread out through the code, it can be very difficult to assure that the function has the same code in every place.

Of course this is a very simple class, only meant for demonstration purposes. We might want to have different types of trees. Starting simply, we might want to consider coniferous and deciduous trees as shown in Figure 6, which demonstrates an example of inheritance. A coniferous tree is a tree, and so is a deciduous tree. In general, a class is a superclass of any class that inherits from it: thus the Tree class is the superclass of the ConiferousTree and the DeciduousTree classes. Similarly, a class is a subclass of any class from which it inherits, thus ConiferousTree and DeciduousTree are both subclasses of the Tree class. The inheritance hierarchy can be further extended. For example, a LandCover class could be created as a superclass of the Tree class. Furthermore, a PineTree class could be created as a subclass of the

ConiferousTree class. An important property of inheritance is that it allows sharing of code. Both the ConiferousTree class and the DeciduousTree class have all of the data and functions of the Tree class.

If it is necessary for one of the subclasses to define extra data or functions, the definition can be implemented easily. For example, the DeciduousTree class has a defined function called dropLeaves. The ConiferousTree class would not require such a function, so it would not be defined in the Tree class, as not all of the Tree subclasses need to share this code. Furthermore, one of the subclasses might want to override a function defined in the superclass. For example, the ConiferousTree class defines a growth function that is different from that of the Tree superclass. In sum, we have a class hierarchy, which can be extended to include LandCover as a superclass of Tree or to specify WhitePineTree as a subclass of ConiferousTree.

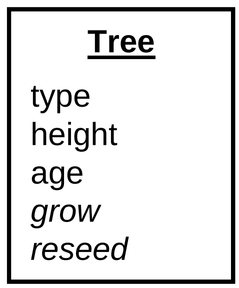

Figure 5. A Simple Tree Class in Object-Oriented Programming (OOP)

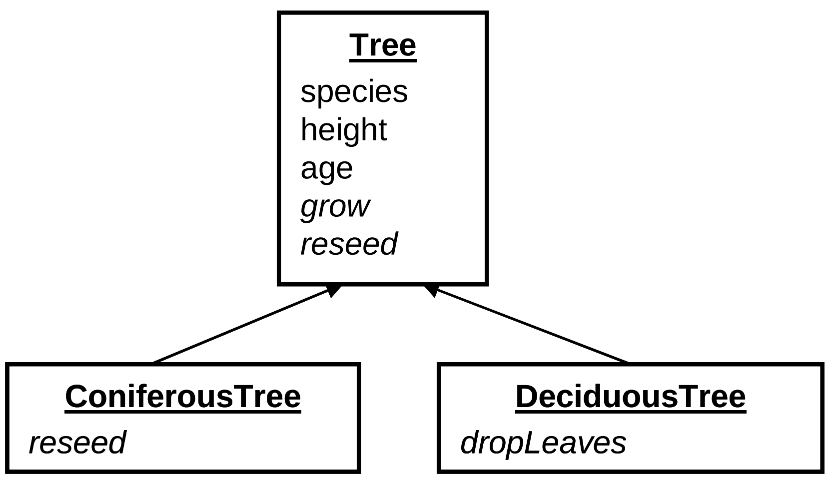

Figure 6. Inheritance among Classes in Object-Oriented Programming (OOP)

2.3.4. Composition

Classes also can be arranged through the concept of composition. That is, one class contains or has an instance or instances of another class. For example, an agent class might have an agent decision module (see Figure 7). Composition is useful when one class frequently makes use of some code but wants to keep that code separate for some reason. In the case of the Agent and AgentDecision classes, this separation is important, as it allows for the use of polymorphism, as will be seen next.

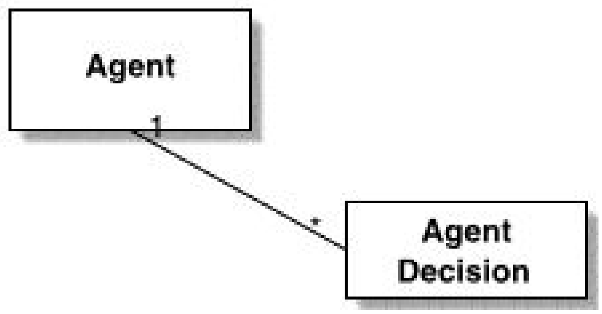

Figure 7. Simple Composition in Object-Oriented Programming (OOP)

2.3.5. Polymorphism

There is another aspect of OOP that is often, though not exclusively, accomplished through inheritance: polymorphism. The fact that the superclass and all subclasses define data and functions that serve the same roles allows the classes to be used interchangeably. That is, no matter whether we use the superclass or one of the subclasses, the same data and functions will be available for use. The functions and data will have the same names, will be called in the same way, and will return the same type of information (though of course they may return different values). If we look back at the Agent and AgentDecision classes, we will quickly realize that there are many different possible types of AgentDecision classes. Furthermore, it is quite likely that in a heterogeneous environment, we would want different agents to have different decision-making mechanisms, so we would want the Agent classes to use different AgentDecision subclasses. By subclassing AgentDecision, we can create as many different decision classes as we need.

In Figure 8, each of the AgentDecisionA–C subclasses inherits important basic functions of the AgentDecision class. Since each of the AgentDecisionA–C subclasses is an AgentDecision class, any one of them can serve as the Agent's AgentDecision class. Each of the AgentDecisionA-C subclasses defines a different decision-making *algorithm*, such as *Bayesian learning*, Q-learning, and *genetic algorithm*, as seen in Figure 8. Thus, the particular AgentDecisionA-C subclass used will affect how the Agent class makes decisions. Although the algorithms defined in each subclass are different, they are used in the same way. Therefore, any one of the AgentDecisionA-

C subclasses can be used by the Agent class as its AgentDecision class. Thus an Agent class can have any AgentDecision A–C subclass as its AgentDecision class. Thus, the Agent class does not need to do any extra work to find out which AgentDecisionA–C subclass it is using, or to understand how to use it.

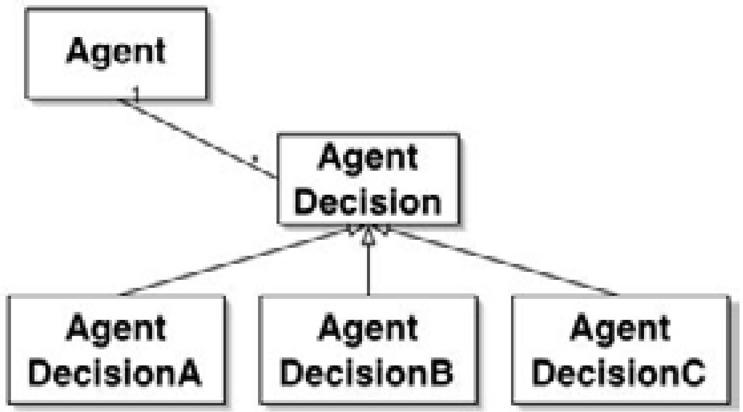

Figure 8. Polymorphism in Object-Oriented Programming (OOP)

2.3.6. Loose Coupling

By combining all of the needed data and functions into one class, OOP means to provide fairly self-sufficient units. That is, each unit has what it needs, and that is the only place one would need to look for that information. Furthermore, each unit should not be too tightly integrated with others—classes should not need to know about the inner working of other classes, and they should not be dependent upon too many other classes. Such loosely coupled classes can then work with different classes without difficulty. If the classes were tightly coupled, they could only work with a given set of classes, and the program could not be extended to provide other interactions. This is because the classes would be dependent on how other classes worked. A change in one would mean a change in many, and could easily end up breaking the system. The advantage of loose coupling is illustrated in the ability to provide an Agent with different AgentDecision classes without altering any of the code in the Agent class or any of the classes associated with the Agent class. This concept applies to many areas, including data. For example, loosely coupled data are easier to share between programs. Data can be coupled loosely by having a format available to all programs, rather than internal to only one. In Extensible Markup Language (XML), for example, it is possible to define data formats that can be used by any program, thus keeping the data loosely coupled instead of dependent upon one or another program.

2.3.7. The Land Market – An Example

Now we can look at a fuller example of the land market, which incorporates elements of OOP. Specifically, we will look at a simple model of the process of putting a piece of land up for lease. The example in Figure 9 demonstrates the use of inheritance and composition. Additionally, there is a class in the center of the diagram called the Mediator class. This class is not a part of modeling the land market per se; rather, it is used as an organizational class. In order to ease communication between classes, this class mediates between them. Without the Mediator class, all classes would have to be directly linked to every other class with which it might want to communicate. In this particular model, a lot of interdependencies would result, and we would lose the idea of loose coupling. This organizational structure is an example of the Mediator pattern. There are many useful patterns that can be used to design OOP. A good, though perhaps advanced, resource on this topic is Gamma et al. (1995).

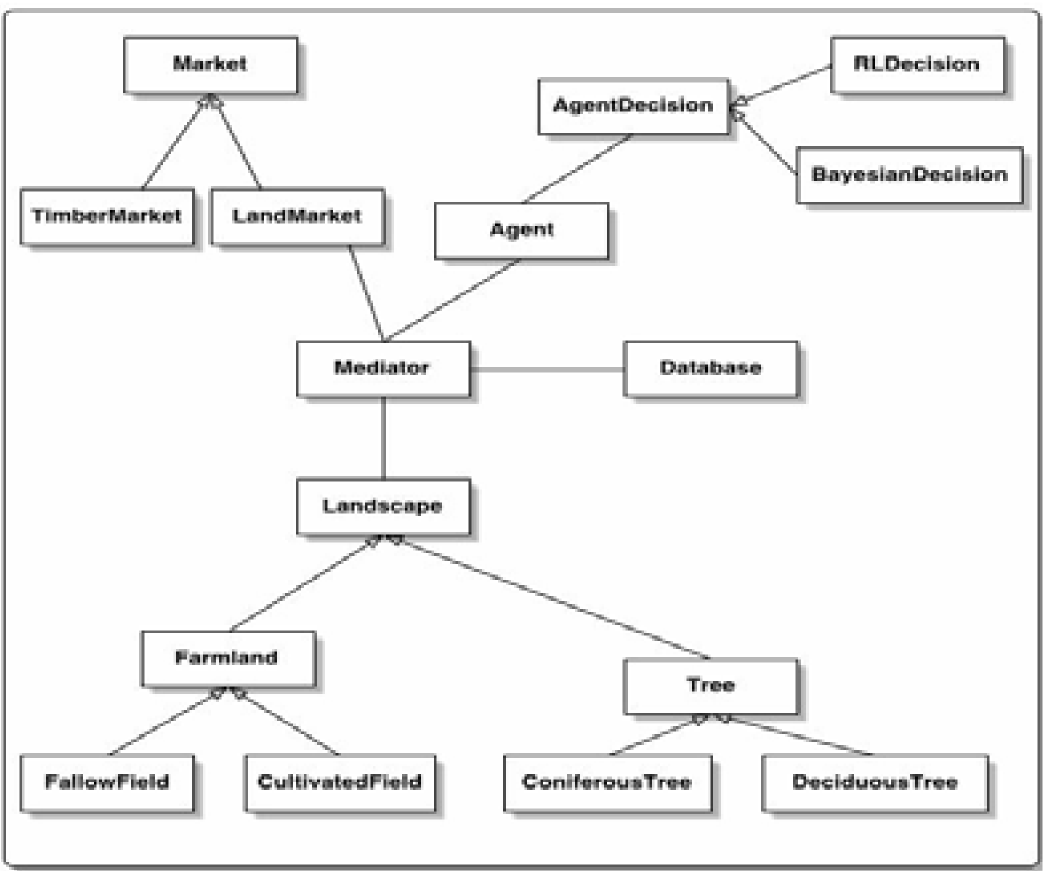

Figure 9. Land Market Example Demonstrating Composition and Inheritance in a Mediator Pattern

We will consider only three steps of agent interaction in a land market: (1) put a land parcel on market; (2) get bids; and (3) decide to accept a bid or take the land parcel off the market. In the model, this process would be accomplished as follows (note that <name> indicates a class name):

1. <Agent> puts parcel up for bidding and sends to <Mediator>.
2. <Mediator> sends parcel to <LandMarket>.
3. <LandMarket> requests information on land parcel from <Mediator>.
4. <Mediator> gathers information on parcel from <Landscape> and <Database>.
5. <Mediator> gives information to <LandMarket>.
6. <LandMarket> determines a bid. (This also requires getting input from other agents.)
7. <LandMarket> gives the bid to <Mediator>.
8. <Mediator> gives the bid to <Agent>.
9. <Agent> decides to accept or decline the bid using a decision determined with the help of its <AgentDecision> module.

In the example, there are a number of instances of both inheritance and composition. For instance, the Landcover class has instances of the Tree class, as well as the Farmland class. Similarly, the Agent has an AgentDecision class. As noted earlier, there are subclasses of the AgentDecision class. The Agent class does not need to know ahead of time whether it will use Bayesian learning, *reinforcement learning*, or some other type of learning, so long as each of these learning strategies are all properly defined subclasses of the AgentDecision class. In this case, the mediator only has one agent to which it must give the bid information. However, one could certainly imagine a case where there might be multiple agents who would be interested in such information. In such a case, the mediator, perhaps with the assistance of information from other classes, would give the appropriate information to the relevant agents.

2.3.8. Event Sequencing: Synchronous, Asynchronous, and Event Driven

Workshop participants discussed event sequencing in models. Event sequencing relates to the scheduling of agent decisions and interactions. Two general approaches are possible: predetermined (synchronous or asynchronous) or event driven. In a synchronous or asynchronous program, agents act in a predetermined manner, even if that might be randomized, as in some asynchronous programs. In an event-driven program the interaction of agents depends on actions (events) of other agents or of the rest of the computer environment. For example, an agent might react to another agent’s decision to sell some timber. Alternatively, an agent might react to an event such as a sudden storm that floods its fields. The main difference between these two approaches is that in event-driven programs, agents’ actions follow directly from events in the environment, rather than having each agent action selected in some predetermined manner on each time step.

2.3.9. Why OOP?

As noted earlier, OOP languages were developed to make programming easier. There is an overhead in using them in terms of processing speed. Instead of just being able to call a function, now a class has to be called which will in turn call that function. While it is true that OOP languages do tend to be slower than procedural languages such as C, with the continuing speed increases in computer hardware, those differences are not as great as they once were, and for many purposes, are relatively inconsequential.

As an example of the differences between OOP and procedural programming, consider again the agent with multiple decision-making algorithms. In OOP, the Agent class can handle any of the AgentDecisionA–C subclasses as its AgentDecision class without any difficulty. Since the AgentDecisionA–C subclasses all define the same data and functions, the Agent class can call any of the functions. Whichever AgentDecisionA–C subclass the Agent class happens to be using will use its own data and functions. This also could be accomplished in procedural programming, but we would find even this relatively simple task to be quite a bit more complex. For example, a procedural program may define a data type such as a vector or list to hold all of the data for agents. One data slot would need to represent the agent decision-making algorithm that is being used. We may start out with two decision algorithms: Bayesian, and reinforcement learning. This information could be coded into the agent's data slot. Every function that the agent's decision function calls would then need either to get the information telling which algorithm is in use or to access directly that aspect of the agent's data, extracting the relevant number. This would involve a clause in each function calling the agent's decision function to check which decision algorithm is being used.

At some point, we probably would want to add more decision-making functions. For example, instead of just reinforcement learning, we might want to specify two types of reinforcement learning: Q-learning and a genetic algorithm. At this point, the code for every function that does something based on the decision would need to be updated to check and respond properly to the algorithm in use. It is also possible that different algorithms might need to access different data. This access would need to be handled properly in every associated function as well. While it is possible to achieve the same results in a procedural program, the code would be much more spread out and would contain a great deal of redundancy. Aside from making the work more difficult, this design also opens the door for bugs to creep into the code. From this relatively simple example, we can see that OOP languages achieve their goal of organizing code into localized and manageable units, and this organization has advantages over procedural approaches.

2.3.10. Combining Pieces

Participants also discussed the need for ABM modules to interface with other software tools, GIS in particular. For some simple models, communication with a GIS may not be needed, if the model can be parameterized with an initial landscape and then simply export a final landscape back to GIS when the model run is complete. However, some cases were identified in which sequential communication between the ABM and GIS might be needed: feedbacks between human actions and the natural environment that relied on GIS modeling (for instance, a vector hydrologic model) and spatial network interactions, especially transportation networks. (For a more detailed discussion of the issue of connecting a GIS and ABM, see Westervelt 2002.) Participants also agreed that integration with a good database program and tools for visual output and display are needed. In principle, a GIS could meet these needs. Finally, in reference to needs for verification and validation, participants stressed the need for either built-in statistical modeling functionality, or seamless linkages with statistical analysis software. In particular, it may be very useful to have standard techniques for validation of landscape models built in to ABM/LUCC tools, as well as a range of nonparametric statistical analysis techniques. There also may be a need for statistical modules that spatially extrapolate aggregate socioeconomic data using standard functions. Access to operations research tools for optimization and analysis of complex systems also may be useful.

While combining software tools and programming languages is not always simple, it generally can be accomplished. Most software packages have mechanisms by which they can be called from other programs. For example, Swarm, an agent-modeling toolkit can be called from any C or Objective-C program. Furthermore, Swarm has a toolkit for interacting with a GIS environment. Since different pieces of software might require different programming languages to call them, it might be necessary to have a programming language that can work to tie all of the pieces together. OOP can help this process by encapsulating the code for interacting with an external element in one class. For example, in the land market example presented in section 2.3.7, one might want to use a GIS. Furthermore, one might want to use different GIS depending on the platform the code is running on, or the types of spatial operations needed in a particular run. This goal could be accomplished by creating a GIS interface class, and then subclassing it with interfaces for specific GIS software. Then the appropriate interface could be chosen polymorphically at run time (with no need to recompile the program). The key to accomplishing such flexibility is loose coupling. By keeping other classes only loosely coupled to the GIS, the class that accesses the GIS can be changed to access a different GIS without affecting other parts of the program.

In general, there are different ways to call external programs. Sometimes the software package or programming language being used provides a facility for calling other programs. Sometimes one might want to depend on tools within the operating system. UNIX, for example provides many such tools. Many languages can serve to link one program to another. The only requirement is that the language be able to call both programs. Many languages are likely candidates, including Perl, C/C++/Objective-C, and Java. Other useful tools for linking languages and software are CORBA, which can act as a middle layer, and XML, which is gaining in popularity. In XML is possible to define data formats that can be used by any program, thus keeping the data loosely coupled instead of dependent on one or another program.

To make it easier for one’s own programs to communicate with other software, it is important to write a good interface. This is not an interface that a user interacts with; instead, it is a way for code between different programs to communicate. Your own program should be able to call other programs through this interface. An interface also may allow other programs to call your program. Once again, the key to such an interface is loose coupling. This way, as your program changes, the interface need not. The link between your programs and external programs will remain intact even as your program is updated.

2.3.11. Communication and Model Comparisons

Workshop participants noted the need to have mechanisms to communicate the structure, processes, and rules that drive model outcomes. The presentation of a fairly simple model in

Figure 9 reveals that communication can be quite difficult due to the complex nature of most ABM/LUCC programs. There are, however, tools that can help with this difficult task. The Unified Modeling Language (UML), demonstrated in part through the diagrams presented in this section, is commonly used to model computer programs. Not only can it show the structure of the code; it also can be used to show interactions between parts of the code, concerns that a particular part of the code might have, the sequencing of events, and more. UML is most commonly used in conjunction with OOP languages, as the two tools were developed concurrently with the express purpose of developing efficient programming practices. A good resource on UML is Fowler and Scott (1999).

Participants identified a set of key model features that should be communicated as part of dissemination of research results, potentially as part of a standardized "model metadata" format. These factors include but are not limited to the number of agents, agent architecture, agent communication, human-biological interactions, the spatial and temporal scales at which the model operates, sequencing and/or event scheduling mechanisms, frequency and type of updates, etc. The possibility of posting model metadata on an ABM/LUCC research website also was discussed.

Participants discussed the role of comparisons between software models as a part of code verification. One proposed strategy for model comparison would be to have a standardized dataset that a variety of models in different packages are constructed to run against. An alternative strategy would be to have what should be the same process or problem modeled in several languages/platforms. Differences between model outcomes would reveal artifacts.

2.3.12. Object-Based Simulation Platforms

Many specific ABM software platforms were discussed by workshop participants, with an underlying question being whether it would be useful for the community to move to or develop a single, standardized platform that would be widely used for ABM/LUCC. A variety of criteria across which software models could be evaluated were discussed, including:

- The model's ability to represent space (discrete, continuous, raster, vector) and topological relationships
- Mechanisms for scheduling and sequencing of events
- Interoperability with other programs as well as with the Internet
- Distributed processing capabilities (for speed)
- Ease of programming and/or using the package
- Size of the community using that platform
- Size of programming community familiar with the language in which the package is implemented
- Ability to represent multiple organizational/hierarchical levels, or scales

One of the major concerns with regard to all types of object-based models is that the results of simulations based on them are difficult to verify. It is difficult to determine if the performance of the computational model is as intended, or if it is due to programming errors or other encoding mistakes. This is discussed in section 2.4. Although it is feasible, the process of error detection is, of course, time consuming and difficult. Thus, to bypass some of these difficulties, and to avoid the need for modelers to keep reinventing the wheel, several groups have developed simulation platforms in which object-based computational models can be implemented. The four described in detail here, SWARM, RePast, Ascape, and CORMAS, are all written in object-oriented programming languages. The review is based on both documentation from the official websites and an informal survey conducted among the developers of the platforms in November 2001.

The SWARM simulation system was originally developed at the Santa Fe institute and is now maintained by the SWARM Development Group (www.swarm.org). SWARM is a set of software tools written in Objective-C, an object-oriented language based on C which uses the Smalltalk model of OOP (as opposed to C++, which also is based on C but uses a different model of OOP). Recently it became possible to use Java to call upon the facilities offered by the SWARM libraries. SWARM includes libraries of standard object design and creation routines, analysis tools, and a simulation kernel that supports hierarchical and parallel processing. It is specifically geared toward the simulation of agent-based models composed of large numbers of objects. The sequence in which actions of agents are executed can be sequential, asequential, or event-driven. Event-driven actions indicate that agents react to observed changes rather than just acting at specified times. SWARM is not focused on a particular application, but the large number of users cover many application fields, including geography. SWARM has been a source of inspiration for other ABM platforms like RePast and Ascape, which are more focused on social science applications.

The first version of RePast is mainly based on SWARM but is written entirely in Java. The goal of RePast is to move the representation of agents as discrete, self-contained entities toward a view of social actors as permeable, interleaved, and mutually defining, with cascading and recombinant motives. One of the highlights of RePast is the strong support for network models. As with Swarm, agent actions can be sequential, asequential, or event-driven.

Ascape is being developed at Brookings Institute, the home of the Sugarscape model (Epstein and Axtell 1996), to support the development, visualization, and exploration of agent-based models. It also is written entirely in Java and is designed to be flexible and easy to use. A high-level framework supports complex model designs, while end-user tools make it possible to explore existing models easily. An important difference between SWARM and Ascape is that the latter is simpler to use and has a very complete user interface. Unlike SWARM and RePast, Ascape is not event driven. In each time step, the agents execute their actions either sequentially or asequentially; Ascape does not allow for event-driven scheduling.

CORMAS (Common-Pool Resources Multi-Agent System) is a programming environment dedicated to the creation of multi-agent systems, with a focus on the domain of natural resources management. CORMAS is being developed at CIRAD (http://cormas.cirad.fr/indexeng.htm) in Montpellier, France, and is based on the objective-oriented language Smalltalk. CORMAS provides a framework for developing simulation models of coordination modes between individuals and groups that jointly exploit common-pool resources.

SWARM is the most powerful and comprehensive multi-agent package. A drawback is the steep learning curve since strong programming skills are required. Since SWARM is used in many disciplines, the standard version is not focused on a specific field of application. The other three platforms have shorter histories, and they are more focused on social science applications. Not all tools available in SWARM, such as statistical libraries and GIS connections, are available in RePast, Ascape, and CORMAS. However, these three platforms require fewer programming skills. Each platform has its own focus, which can be characterized as follows: RePast focuses on network dynamics and more comprehensive agents, Ascape concentrates on the ability to create simple models easily, and CORMAS emphasizes the development of applications for common-pool resources together with local stakeholders. A summary of the four platforms is given in Table 1.

Table 1. Object-Oriented Packages for Agent-Based Modeling

	SWARM	RePast	Ascape	CORMAS
Developers	Santa Fe Institute/ SWARM Development Group	University of Chicago	Brookings Institute, Washington, D.C.	CIRAD, Montpelier, France
Start development	Early 1990s	Early 1999	1997	1996
Website	http://www.swarm.org	http://repast.sourceforge.net/	http://www.brook.edu/es/dynamics/models/ascape	http://cormas.cirad.fr
Language	Objective C/Java	Java	Java	Smalltalk
Operating system	Unix/Linux, Mac OSX, Windows	Windows, Unix/Linux, Mac OSX	Windows, Unix/Linux, Mac OSX	Windows, Unix/Linux, Mac
Required experience	Strong skills	Some Java programming	No experience of running existing models, basic skill for changing models, and strong skills to make major extensions	None, if attending the training courses, basic skills in programming otherwise
Event driven?	Yes	Yes	No	No
GIS connection	Kenge/GIS library: http://www.gis.usu.edu/swarm/	In development	Beta version	Generic methods to import/export maps from/to MapInfo, both for vector and raster formats. With ArcView, a dynamic link via Access has been successfully tested by using ODBC and DDE
Spreadsheet connection	No	Yes	Yes	Yes
Statistics of runs	The statistical package R, and Splus clone, handles the statistics	User can calculate statistics, the Colt library that comes with RePast provides some statistical functions, and RePast itself can calculate some simple network statistics	Many, like average and variance, Gini . . .	User can define which data to store
Main focus of applications	Natural and social sciences, military and commercial applications	Social science	Social and economic systems	Economic and ecological simulation, and natural resource management
Available demo-models	On the SWARM website there are only a few demo-models, but there are many journal publications, and a few books with SWARM applications	Six demo-models	About 20–30 demo-models	Numerous models are described on website, with papers and electronic addresses of the authors
Documentation	Yes	Yes	Yes	Yes
Tutorial	Yes	Yes	Rudimentary	Yes
Training courses	No	There have been courses in the past	No	Various courses are given each year

2.4. CALIBRATION, VERIFICATION, AND VALIDATION

Steven M. Manson

2.4.1. What makes a model correct?

Workshop participants noted that as agent-based modeling becomes more common for exploring land-use and land-cover change, they must pay more attention to the challenges of verification and validation. Verification refers to the how well model software works, and validation concerns how well a model characterizes the system it is meant to represent. Calibration is similar to validation but refers to fitting the model to data before running the model, while validation involves comparing model outcomes to data. Most ABM/LUCC research endeavors have an underlying conceptual model that is instantiated as an agent-based model. This model represents a target system that concerns land-use and land-cover change. The model is verified by ensuring the proper functioning of its underlying programming. The model is then subject to structural validation (how well the software model represents the conceptual model) and outcome validation (how well model outcomes characterize the target system). Evidence of mounting interest in verification and validation is exemplified by a recent special issue of *Agriculture, Ecosystems and Environment* (Veldkamp and Lambin 2001).

While this section touches on general aspects of calibration, verification, and validation, it is concerned more with issues raised by workshop participants about a number of tasks: (1) the potentially problematic relationship between calibration, verification, and validation in terms of data and model fitting; (2) challenges raised by model sensitivity, complexity, and agent interaction; (3) issues surrounding balancing the role of theory and empirical research in structural and outcome validation; (4) problems raised by using spatiotemporal statistics in an agent-based model setting; and (5) the challenges posed by scale, aggregation, and representation.

2.4.2. Data and Model Fitting

Potentially problematic relationships exist among calibration, verification, and validation. All three activities are similar since they involve fitting a model to data and theory. A researcher creates a model structure, verifies this structure, *calibrates* or parameterizes it, and uses it to create outcomes. Data are used throughout this process and are drawn from sources that range from observations of the target system to the products of other models judged to adequately characterize the target system. Participants noted that surveys, role-playing games, interviews, censuses, and remote sensing are particularly valuable data sources for land-use and land-cover change research.

Important "data" also are provided by theory or other models, since they can provide synthetic information such as prototypical agent behavior or plausible landscape patterning. While not realistic in the sense of being empirically observed, these synthetic data address many aspects of land-use and land-cover change that are not readily measured. The Anasazi project noted in appendix 3, for instance, faces a situation where calibration and validation data must be carefully pieced together by combining empirical and theoretical studies. The use of theory in validation is explored more fully below.

Given the variety of tasks to which data are applied—calibration, verification, and validation—participants noted that it is important to recognize that data used for one purpose should be kept separate from those used for others. Some data should not be used for model estimation or calibration, for instance, if a model is intended to project future land-use and land-cover change trends. These held-back data are retained for outcome validation. Admittedly, the workshop participants, like other land-use and land-cover change researchers, rarely have data for more than two or three periods, given the expense of data acquisition. As a result, there is an understandable desire to use all available data for model construction and calibration. This conflicts with the need to hold back data for validation. There is less need to reserve validation data when the model's structure itself is the "outcome" of interest, as is the case when all available data are used for estimation of regression-based models (e.g., Mertens and Lambin 2000). In this case, the regression equation is simultaneously the model and the model outcome, and therefore the model is subject only to verification and structural validation. If this regression equation is then used to create a spatial image of land-use and land-cover change with new inputs, the resultant image could be the subject of spatial outcome validation.

2.4.3. Sensitivity, Complexity, and Interaction

The simplest form of model verification lies in forcing the mathematical and computational components of a model to fail by varying model configurations and inputs. This kind of verification involves debugging a program to find programming flaws that cause the model software to cease functioning. Another kind of verification involves looking for subtle programming artifacts caused by slight, cumulative errors being introduced into a model from seemingly well-established tools, such as random number generators or the precision with which numbers are stored in computer memory (Stroustrup 1997). Error propagation can be estimated from the kinds of operations performed on data (Alonso 1968) or considered in terms of uncertainty within a Monte Carlo framework, whereby repeated model runs shed light on how random changes in inputs affect model operation (Heuvelink and Burrough 1993). Another kind of error likely to occur in agent-based models, given interaction between agents, is the potential for spatiotemporal ordering of model events to create artifacts (Ruxton and Saravia 1998). Much of the research described in section 3 has free-moving agents placed on a grid. The locations at which these agents begin their activities could conceivably influence the outcomes of the activities (see also Otter et al. 2001).

Sensitivity testing is another form of verifying an agent-based model commonly practiced by workshop participants. In sensitivity testing, parameters are varied across model runs and resultant changes in model performance are noted, particularly those that demonstrate the spatial or temporal limits of a model's applicability (Klepper 1997). This form of verification shares assumptions with many statistical and mathematical methods such as statistical normality and that outcomes should change roughly in proportion to changes in input. These assumptions allow verification techniques to accommodate the vagaries of measurement error, sampling regimes, observer bias, statistical stationarity, and data availability. Verification also helps address any differences between random "white" noise and others such as "black" and "pink" noises that are characterized by power density functions. The latter indicate the presence of seemingly random signals from the environment that may indicate an environmental phenomenon requiring further investigation.

Unfortunately, these assumptions may pose problems for researchers because agent-based models join a host of other research efforts that are designed to accommodate complex behaviors caused by sources such as sensitivity to initial conditions, self-organized criticality, or nonlinearities (for a review, see Manson 2001). Agent-based modelers often seek realistic portrayal of agent interaction, for instance, which creates the potential for sudden shifts in model behavior. These shifts occur due to processes such as disequilibria, positive feedback, and path dependency. The potential for complex behavior is an important reason to use agent-based models, but it complicates verification and validation. There is therefore a need 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 sensitivity testing (Miller 1998). Since agent-based models are often meant to simulate complex systems where variables interact in complex ways, these models may not be amenable to traditional testing methods that modify one parameter at a time. This complexity suggests special caution regarding structural verification, as researchers must be sure that complex outcomes result from underlying structural dynamics, rather than simply being the result of model artifacts.

2.4.4. Validity and Theory

Workshop participants noted that a completely inductive model could produce seemingly valid outcomes under a given set of circumstances. If these circumstances change, however, it is likely that causal mechanisms will not be adequately represented by the model and its outcomes will not remain valid. A structurally invalid model is likely to be overtailored to a particular time, place, or set of circumstances. As a result, the model is less able to speak to circumstances outside those used to calibrate the model.

A model is more likely to be structurally valid when it ties closely to a conceptual framework. As noted in section 2.3, use of OOP and ABM allows the modeler to express concepts in a number of ways that make it easier to see how the model encodes agent behavior. Researchers have traditionally represented pedestrian movement with equations based on assumptions of how people act in aggregate. In an agent-based framework, the modeler can invest each agent in a group of agents with different abilities and motivations that govern movement in a manner that is more closely tied to theories of individual decision making. This difference in how agent movement is represented impinges on a model’s structural validity and can lead to fundamentally different model outcomes (Kerridge et al. 2001).

In addition to providing the backbone for structural validity, theory can be necessary to outcome validation when, as noted above, theory becomes a source of validation data. Agent-based models are often concerned with outcomes that are imputed or abstract, such as trust or learning. Validating abstract outcomes is difficult since they are hard to define and measure. Aggregate characteristics of modeled outcomes may have to be compared to idealized characteristics of the real-world target system. Several projects described in this volume demonstrate how models recreate processes such as firm specialization or household income stratification. Even when little empirical data are available for validation purposes, experience and expert opinions can be combined with theory to provide validation. A number of projects described in these proceedings validate abstract and emergent model outcomes through expert and stakeholder interviews that provide a sense of how model outcomes relate to the target system.

Theory can be problematic, however, when applied to outcome validation. Several authors described in this volume, for instance, explore how institutions and common-pool resource issues relate to land-use and land-cover change. Modelers can draw on common-pool resource theory to identify prototypical outcomes that can be compared to model outcomes. The authors note, however, that there is growing experimental evidence suggesting that instances exist in which the theory is incorrect. Indeed, one key reason to use agent-based models is the potential to create results that appear to be counterintuitive or at odds with theory. The lesson learned is that use of theory for validation must be balanced by consideration of empirical data and model outcomes.

2.4.5. Statistics, Space, and Time

The complexity of land-use and land-cover change and agent-based modeling demands spatiotemporal tests of outcomes (Turner et al. 1989). This need is evidenced by a variety of agent-based model applications described in this volume that use spatial statistical approaches to compare modeled outcomes to validation data. Workshop participants use a variety of metrics: indexing systems such as quad trees; cross-scale metrics such as rank-size relationships and distance-decay functions; landscape metrics such as fragmentation; and geostatistical and mathematical measures provided by techniques such as variograms or Fourier analysis.

Use of seemingly simple spatiotemporal validation techniques raises a number of issues. The simplest spatial method for comparing model outcomes to real data is error matrix analysis of categorical map layers. With this technique, the spatial location and kind of land use or land cover in the model outcome is compared to that in the validation data. Error matrix analysis is useful yet does not readily account for the effects of unequal quantities of each category of land use or land cover. The kappa statistic accounts for this problem, but Pontius (2000) notes that it does not recognize when model outcomes have accurately determined the relative quantities of each cell state, necessitating a measure that differentiates between location and quantity (see also Pontius and Schneider 2001).

The dynamic between quantity and location is complicated by considerations of location versus pattern. As some workshop participants noted, in many situations it is critical to estimate the timing and location of land-use and land-cover change. The pinnacle of modeling land-use and land-cover change would be the ability to predict exactly where and when a given transition occurs. Other workshop participants note that this task is difficult, and perhaps impossible, and modelers therefore assume a higher burden of proof when they promise such specificity.

Seen in another way, location-specific estimates may not be as useful as having model outcomes reproduce realistic pattern and texture metrics such as dominance, patch size variance, fractal dimension, nearest-neighbor probabilities, contagion, and adjacency (Giles and Trani 1999). These metrics can be more useful when looking at the effects of land-use and land-cover change on ecological characteristics such as biotic diversity. As with location-based statistics, however, their use is not without problems. Fractal dimension, for example, may be used to validate model outcomes but must be applied with care, given the degree of uncertainty about the linkage between fractal metrics and ecological processes (Li 2000).

2.4.6. Scale and Aggregation

There are scale-related problems held in common by validation, verification, and calibration. A host of statistical issues surrounds the scale at which land-use and land-cover change is observed and modeled (Nelson 2001). Change analysis, for instance, is affected by changing resolution (Lam and Quattrochi 1992) and extent (Saura and Millan 2001) of spatial data. Researchers have known for some time that an ecological fallacy occurs when the characteristics of an individual agent are incorrectly inferred from the characteristics of the population from which it is drawn (Robinson 1950). Similarly, the modifiable areal unit problem makes itself felt through an aggregation effect, when larger spatial groupings of data create better correlations, and a zoning effect, whereby an area can be subdivided into an almost infinite array of configurations that share a common statistic, such as area or shape, yet differ in others (Openshaw 1977).

Both the modifiable areal unit problem and the ecological fallacy can be statistically causal, since variables differentially co-vary as a function of the scale at which they are measured. In other words, scale can be an independent variable (Bian 1997). Although agent-based modeling is in many respects a new methodology, it is still affected by scale-related problems of causality. Research in land-use and land-cover change is rife with examples of how spatial data resolution can affect the apparent magnitude and direction of relationships among causal factors (Kummer and Sham 1994). Remedies to scale effects include inductive search techniques (Openshaw et al. 1987), use of fractal measures (Lam and Quattrochi 1992), and geostatistics (Chou 1993).

Validation, verification, and calibration are also complicated by the scalar effects of aggregation. *Pixels* or individuals are routinely combined into larger units such as grid cells or households. The import of finer-grained units is often assumed to be encapsulated by that of more coarse units. We also may treat these collections as mere simplifications of the lower-level objects and not as entities that can have their own behaviors (Kimble 1951). When spatial data are partitioned into exclusive categories, spatial processes may be separated from those not related to these categories. Aggregation issues are especially germane when we want agent-based models to portray emergent behavior. (See section 1.3 for more on emergence.) Emergence may be at odds with the assumption that larger units are representative of smaller units. In this case, as with many other aspects of validation and verification, there are no hard and fast rules, so the best advice is: “forewarned is forearmed.” There was little doubt on the part of the workshop participants that verification and validation over multiple scales is possible despite the challenges posed by scale.

2.4.7. Conclusion

Verification and validation require use of multiple, complementary methods to identify shortfalls in data, theory, and methodology. Some workshop participants call this triangulation, the general form of which is the mainstay of qualitative research. Simply put, rarely is one source of information or kind of technique adequate to address the complexity of situations common to land-use and land-cover change. Instead, researchers must bring multiple techniques and viewpoints to bear on a problem in order to distinguish legitimate model outcomes from model artifacts. Verification and validation of agent-based models will be aided by better communication of model design. The growing adoption of common languages noted in section 2.3 should lead to common validation and verification tools. Much work remains to be done, however, in terms of linking this agent-based modeling software to other software used in land-use and land-cover change research (e.g., GIS, statistical packages). Validation and verification should become easier as more attention is paid to theory development and data provision for land-use and land-cover change research.

Part 3 Examples of Specific Research

3.1. INTRODUCTION

Thomas Berger and Dawn C. Parker

3.1.1. A Comparative Framework

In order to structure the discussion of the workshop presentations in this section, we employ a simple classification building on Couclelis's essay in the first section. We will distinguish four classes of ABMs applied to the question of land-use and land-cover change. The four model classes are organized in the form of a matrix defined by two characteristics (Table 2). The first distinguishes between agents and their environment, the latter broadly conceived of as any medium shared by the former, as defined in section 1.1. The second organizing characteristic considers modeling as a form of experimentation, whereby model components—agents or environment—are either designed or analyzed. Designed agents are not directly inferred from empirical data. Analyzed agents, in contrast, are directly grounded in empirical data or ad hoc values that are realistic substitutes for observed data. The analyzed agents may be actual decision makers in experimental or decision support setting. By the same token, a designed environment is one without empirical parameterization (first row), whereas an analyzed environment relies directly on empirical measurements (second row). We also include in the second row those models in which direct empirical measurements are not yet employed but are potentially feasible. As with many classification schemes, the boundary between designed and analyzed is not always easy to draw, especially when ad hoc data are employed.

Table 2. Matrix Classification of ABM/LUCC Models

		Agents	
		Designed	***Analyzed***
Environment	***Designed***	Cell #1: Abstract Balmann *Appendix 1* Polhill et al. – FEARLUS *Section 3.2* Torrens – SprawlSim *Section 3.9*	Cell #2: Experimental d'Aquino et al. – SelfCormas *Section 3.8* Opaluch et al. *Appendix 8*
	Analyzed	Cell #3: Historical Gumerman and Kohler *Appendix 3*	Cell #4: Empirical Berger *Section 3.4* Deadman et al. – LUCITA *Section 3.6* Huigen – MameLuke *Section 3.3* Manson – SYPR *Section 3.5* Parker et al. – LUCIM *Section 3.7*

Table 2 arranges the workshop contributions according to the agent/environment and designed/analyzed distinctions. Cells are numbered consecutively from 1 to 4, starting with the cells in the first row. Again, this classification is subjective, and several models also might fit in other categories. For example, Polhill et al.(see section 3.2), whose FEARLUS model is in cell #1, adopt a strategy of developing first a model of designed agents and environments that will be enriched with empirical data step by step and will therefore move gradually toward cell #4. The same applies for Balmann (see appendix 1), who started with a model of designed agents and environments and now employs more empirical data for the agents. In the models of d'Aquino et al. (see section 3.8), stakeholders participate in empirical parameterization of agent decision models, and thus, their work also moves toward cell #4. Numbering from 1 to 4 does not imply any ranking among the models or indicate a model development path. Each cell of the matrix addresses different research questions and implies different modeling philosophies.

Table 3 illustrates different purposes and modeling philosophies of the workshop participants. For the models in cell #1 (in which both agents and environment are designed), parsimonious construction is more important than a realistic representation of real-world agents and environments. The more parsimonious the model, the better suited it is to discovering and understanding subtle effects of its hypothesized mechanisms. Axelrod (1997) identifies simulation in which both agents and environment are designed as a third way of doing social science that complements induction and deduction. Computer simulations serve as thought experiments that lead to new hypotheses about relationships between humans and their environment. Balmann (1997), for instance, demonstrates with designed agents/environments that the decline in the number of farms in agriculture is related to the spatial distribution of farm assets and of land use. This simulation-based research suggests the existence of path dependence in the evolution of land use that calls for rethinking some elements of current agricultural policy.

Table 3. Purpose/Intent of ABM/LUCC Models in Matrix Classification

		Agents	
		Designed	***Analyzed***
Environment	***Designed***	Cell #1: Abstract Discovery of new relationships Existence proof	Cell #2: Experimental Role-playing games among stakeholders Laboratory experiments
	Analyzed	Cell #3: Historical Explanation	Cell #4: Empirical Explanation Projection Scenario analysis

In contrast, the models in cell #2 (agents analyzed, environment designed), involve computer experiments that establish artificial environments that interact directly with human actors whose behavior is then analyzed. Opaluch et al. (see appendix 8) conduct controlled experiments with real people in designed environments to gain insights into human decision making. Their experiments also can provide information that is difficult to estimate from field data, and they can therefore supplement other empirical studies of land-use and land-cover change. D'Aquino et al. (see section 3.8) use their ABM to accompany and support group decision making by structuring, and being structured by, role-playing games. Their model contains designed environments and computer agents that behave according to the rules that the real actors establish through repeated, iterative interviews. Group members establish rules that govern agents' behavior in the model, examine how their computational analogs play out in the computational results of the role game, and then can subsequently alter their decision rules. In addition to the group affecting the simulation, repeated simulation runs can in turn induce new directions in the group decision-making process that can lead to improved LUCC strategies.

The third class of models is intended to improve our understanding of long-term land-use changes that occurred in the past. Gumerman and Kohler (see appendix 3) employ time series of environmental data and design computer agents whose actions fit the available archaeological data. The models in cell #4, in contrast, use empirical data for the environment as well as for agents to a much larger extent. LUCITA (Land-Use Change in the Amazon, see section 3.6) and LUCIM (Land-use Changes in the Midwest, see section 3.7) aim at explaining land-use and land-cover change in a forest region for the past seventy and thirty years, respectively, whereas SYPR (southern Yucatan peninsular region, see section 3.5) focuses on the projection of future land-use and land-cover changes. Berger (see section 3.4) uses his model for the analysis of policy and environmental scenarios. All models in cell #4 are fully parameterized with empirical data or employ ad hoc yet realistic values that will be measured in follow-up studies. This summary of model purposes complements the more extensive discussion of the potential roles for ABM/LUCC provided in section 1.3.

Table 4 demonstrates how the different categories of models have different needs and strategies for model verification and validation. Clearly, the rather stylized models of cell #1 are difficult to validate in many traditional respects since they lack an empirical context. This poses a particular challenge for the model builder to avoid artifacts—results that stem from the program structure or built-in model failures. The validation strategy is often, therefore, to compare the results to other theoretical findings or the outcomes of other, different analytical or computer models. The results of cell #2 models are also difficult to validate as such since they are in essence laboratory exercises. As with other kinds of experiments, however, they may be repeated to minimize the measurement error. In addition, the modeler must ensure that the experimental design is adequate and that the agents actually play the game the modeler intends. When stakeholders are direct participants in model construction and validation, such concerns may diminish. Cell #3 models allow for validation of the results by comparing them to empirical data. The data set for validation is of course much more limited than in cell #4, where extensive statistical tests may be conducted against more readily available empirical data. The adjectives "qualitative" and "quantitative" in cells #3 and #4 emphasize this difference in validation due to availability of empirical data. Verification and validation issues are discussed in detail in section 2.4.

Table 4. Verification and Validation Strategies for ABM/LUCC Models in Matrix Classification

		Agents	
		Designed	***Analyzed***
Environment	***Designed***	Cell #1: Abstract Theoretical comparisons Replication	Cell #2: Experimental Repetitions Adequacy of design
	Analyzed	Cell #3: Historical Qualitative “goodness of fit”	Cell #4: Empirical Quantitative “goodness of fit”

Model purpose and data availability also have direct implications for the choice of software or programming language, as illustrated by Table 5. Models in cell #1, for example, usually can be implemented within existing simulation platforms for agent-based modeling such as SWARM, RePast or Ascape (see section 2.3.12). Using these widely tested platforms provides a certain guarantee for minimizing model failures due to programming errors. They cannot, however, prevent artifacts arising from ill-defined model structures. Since cell #2 models are employed for games with real persons, a certain degree of minimum flexibility and a well-developed graphical user interface (GUI) may be required, and here a package such as CORMAS may be preferable. The choice of software and tools for cells #3 and #4 depends on the amount of data that has to be manipulated. Advanced simulation platforms such as SWARM may work fine in both cases, but they have disadvantages in terms of providing run-time links to other kinds of software such as hydrological models or GIS. Established agent-based models also may not yet be sufficiently tailored to the specific needs of implementing full-fledged empirical models. It is for these reasons that Manson (see section 3.5) and Berger (see section 3.4) use the OOP language C++ to build their models from scratch. An extensive discussion on software aspects is provided in section 2.3.

Table 5. Appropriate Software Tools for ABM/LUCC Models in Matrix Classification

		Agents	
		Designed	***Analyzed***
Environment	***Designed***	Cell #1: Abstract Easy-to-implement simulation packages	Cell #2: Experimental Flexible simulation packages with well-developed user interfaces
	Analyzed	Cell #3: Historical Advanced simulation packages interfaced with geographical information systems	Cell #4: Empirical Low-level programming languages

3.1.2. Explanation of Standardized Project Descriptions

In the remainder of this section, the workshop participants provide more detailed information about their specific modeling efforts. Most projects are works in progress, though in some cases theoretical and empirical results are already available (see reference section). To facilitate a direct comparison between the models, the participants were requested to address in their short presentations the questions listed below. Table 6 summarizes the main model characteristics and provides a structured overview.

Problem and Research Question

- What are the specific hypotheses and/or broad research questions addressed by your project?

Methodological Pre-Considerations

- Why have you chosen an ABM approach over other land-use modeling techniques? What lessons have you drawn from the experience of broader communities such as LUCC modeling and agent-based modeling?
- What role(s) does or will your model play? How has this choice affected the level of abstraction and complexity present in your model?
- What will be endogenous and exogenous to your model? How has your particular research question influenced this choice?

System under Study

- What area/region/zone/location is being modeled, including an estimate of its size, both in terms of area and people?
- What temporal period is being modeled?
- What types of land-use and/or land-cover modifications are being modeled?
- What real-world agents are being modeled, including typology with basic agent characteristics?

Model Implementation

- At what spatial and temporal scales does your model operate? How have you identified the appropriate scales for your model?
- How many functional types of agents are modeled? Do any agent types represent non-human entities? What factors are included that are thought to affect agent decision making? How do agents interact?
- What ecological processes are included? What types of ecological and biophysical feedbacks does your model account for?
- How does your model deal with space? Which types of environmental and human spatial interactions are considered?
- Do you model sociopolitical phenomena such as endogenous rule formation, group decision making, institutions, etc.? If so, how?
- How do you model land allocation?

- What types of heterogeneity, interdependencies, and nested hierarchies are present in your model? (special emphasis placed on spatial aspects)

Verification and Validation

- What are your strategies for understanding model behavior (validation methods)
- What are your sources of data? How have you integrated data across spatial and temporal scales?
- Do you anticipate / Have you identified "emergent properties" of your model?

Technical Aspects

- What software tools are you using? Why have you chosen these tools?

Documentation/Publication

- What is the time line of your project?
- Do you have a website and/or publications related to the project?
- What are your strategies, if any, for model communication and dissemination?

Several project descriptions of ongoing research are included in the appendices. While these authors were not able to provide the format and level of detail required for inclusion in this section, their contributions reflect promising research in progress.

Table 6. Comparison of ABM/LUCC Projects in Progress

	FEARLUS (§3.2, Polhill et al.)	**MameLuke (§3.3, Huigen)**	**Multiple-agent modeling applied to agroecological development (§3.4, Berger)**	**SYPR (§3.5, Manson)**	**LUCITA (§3.6, Deadman et al.)**	**LUCIM (§3.7, Parker et al.)**	**The SelfCormas Experiment (§3.8, d'Aquino et al.)**	**SprawlSim (§3.9, Torrens)**
Research questions	Creating a framework, more than an actual model: What can ABM tell us about LUCC that other techniques cannot?	Proximate causes influencing the land-use dynamics; impact of various policies including the implementation of a national park	Diffusion of water-saving irrigation methods; effects of innovation on farm structure; impacts of possible government interventions; land and water markets	Development of scenario-driven integrated model to project trends in tropical deforestation and cultivation and their effect on carbon sequestration	Human model: modified classifier system	How individual decisions of land-owning households influenced by biophysical heterogeneity impact patterns of land-cover change	How can we help actors to govern themselves instead of propose pretentious technical solutions?	Developing geographical automata tools for testing ideas and hypotheses relating to the study of the mechanisms driving suburban sprawl in North American cities and the spatial patterns that sprawl generates
Purpose of model (refer to Table 1)	Exploratory modeling of land-use change scenarios	Replicating and thus understanding the land-use dynamics in the watershed area	Analysis of technological, environmental, and policy scenarios (land-use dynamics)	Projection of tropical deforestation and cultivation and their effect on carbon sequestration	Development of prototype simulation that integrates models of ecological processes and human systems	Exploring the impact of rural household decisions on observed patterns of land-cover change	Aiding policy and land-use management by linking role-playing games, GIS, and ABM	Advancing urban simulation technology; testing ideas and hypotheses relating to the processes driving urban growth, its geography, and its sustainability
Study area	Scotland	1. San Mariano watershed, Philippines 2. Settlements/ villages in San Mariano watershed	Melado River catchment, Chile	Yucatan peninsula – Quintana Roo and Campeche states, Mexico	Brazilian Amazon, Altamira, Brazil	Three townships in Monroe County, Indiana, USA	Three villages located on the Senegal River delta	Midwestern Megalopolis, USA (Milwaukee, Chicago, South Bend)
Spatial extent	$1km^2$–$1000km^2$	1. Watershed: 400 km^2 2. Village: 50 km^2	670 km^2	18,000 km^2	2,360 km^2	42 km^2	2,500 km^2	52,125 km^2
Spatial resolution	$150m^2$–$1000m^2$	1. Watershed: 100 m^2 or 30 m^2 based on Landsat and aerial photographs 2. Village: 10 m^2	158 m^2	$900m^2$; $10{,}000m^2$ or 1,000,000 m^2	100 m^2	$50m^2$–200 m^2	6,250,000 m^2	180,093 m^2
Population	30–500 farms	1. Watershed: approx. 37,500 people 2. Village: approx. 1000–2000 people	5,400 farm-households	> 30,000 people	236 farm-households	117,000 people	40,000 people	millions
Temporal extent	50-year projection	60 years (1960–2010)	19 years (1997–2016)	40 years	40 years	65 years (1939–current)	one year	200 years
Temporal resolution	annual	1. Watershed: 1 and 10 year(s) 2. Village: seasonal and monthly	Monthly	Annual	Annual	Annual	Monthly	Annual; three months
Types of land-use modifications	Crop choice (agricultural land use)	Crop choice (land use) and forest use/extraction	Detailed land-use systems (including forest)	Land use (crop and forest types)	Crop choice (agricultural land use)	Land use (forestry, agriculture, residence)	Crop choice (agricultural land use)	Residential use, tenure, property type, population density, land value
Number of agents included in the model	30–500 farm agents	1. Watershed: between 1 and 2000 2. Village: between 1 and 2000	5,400 farm agents	150 agents or 4,800 agents	236 farm agents	330 agents		
Types of agents	Land managers	1. Tribal community; household units, grid cell (= locations), markets, roads, and others 2. Farmers, family, Barangay captains, farmer cooperation, government officials, traders, and many others	Family farm-households, commercial farm holdings, non-agricultural landowners	Typical household or disaggregated households	Farm-households	Residential landowner	Farmers	Developer agents and residential agents
Model of human decision making (rational choice, bounded rationality, simple heuristics)	Simple heuristics	Bounded rationality derived from action in context research; starting point: rational actor models	Bounded rationality; special case: rational choice	Bounded rationality	Heuristics (modified classifier system)	Homo economicus and bounded rationality	Heuristics	Utility calculations, economic calculations, demographic motivation, life-cycle motivations, spatial behaviors
Agent-agent interactions (markets, imitation, . . .)	Imitation, exchange of land parcels	Markets for seedling, machinery, crops; group/cooperation effects on individual decision making, actor imitation strategies; tribal attraction; knowledge/memes exchange	Land and water markets; communication networks	Trading land-use strategies and competition for land	None	None	None	Residential location and competition, sociospatial biases
Ecological processes included (crop growth, water flow, erosion, nutrient leaching, . . .)	Currently none	Yield/crop growth, soil nutrient leaching, soil compaction, deforestation, typhoons	Crop growth, run-off flows	Secondary succession and pest invasions	Changes in soil conditions and crop yields	Forest growth	Vegetation regrowth	Overcrowding
Agent-environment interactions (crop-water production functions, . . .)	None besides choice of land use and receipt of yield	Soil-specific crop-water production functions	Soil-specific crop-water production functions	Cellular model environment reacts to agents' land-use decisions, and agents incorporate environmental factors in land-use decisions	Soil-specific crop-production function	Soil degradation, tree harvesting		Land development
Factors included for agent decision making	May include history of land use, climate, and economy; neighboring land uses, biophysical properties of the land parcel, and preference of the land manager	Education, tribal agricultural knowledge, infrastructure, policy, yield potential, market prices, group/cooperation influences, tribal crop preferences, etc.	Farm assets (including labor, water, and land), prices, thresholds to adoption (adoption costs), thresholds to migration	Household characteristics (e.g., labor, food needs), institutional factors (e.g., land tenure), and environmental influences (e.g., soil, precipitation)	Existing labor and capital supplies	Biophysical characteristics, socioeconomic and cultural factors	Reactive factors (until an agent reaches a satisfactory threshold, it will continue to perform a given activity according to some basic searching mechanism)	Sociodemographic, socioeconomic, spatial, microscopic, mesoscopic, macroscopic

3.2. MODELING LAND-USE CHANGE USING AGENTS IN THE FEARLUS PROJECT

J. Gary Polhill, Nick M. Gotts, and Alistair N. R. Law

Problem and Research Question

The FEARLUS (Framework for the Evaluation and Assessment of Regional Land Use Scenarios) project started in April 1998, to run initially for five years. It is one of two main approaches to the modeling of land-use change being conducted at the Macaulay Institute, the other being Bayesian modeling of empirical data. The approach used within FEARLUS is to apply agent-based modeling techniques to various contexts in which land use might undergo significant change, such as the introduction of new legislation, globalization of markets for farm produce, or climate change.

The long-term goal of the project is to create a tool that would be useful for providing advice to policy makers on possible land-use outcomes, for various scenarios they might want to explore such as climate change, globalization, or changes to regulation or international agreements. The emphasis is very much on possibilities rather than prediction—the latter, in our opinion, being difficult to achieve with any precision in a domain involving the interactions of a diverse set of complex systems (social, economic, climatic, ecological, biological, cognitive). Such a tool also could be used by historians wishing to explore how a particular situation might have turned out other than it did. There is scope for using FEARLUS to involve stakeholders in land-use planning and management issues. For example, it could be used as an educational tool to increase public awareness of the difficulties faced by land managers, or involve them in the development of legislation.

In the short term, FEARLUS is concerned with proof-of-concept work in agent-based modeling, and the development of methodologies for using agent-based models. We are thus aiming to provide answers to questions such as the following: What can agent-based modeling techniques tell us about land-use change that other modeling techniques cannot? How should agent-based modeling techniques be applied? How should the scope and scale of the model be determined? How should the results of agent-based models be interpreted?

Methodological Pre-Considerations

There are a number of modeling frameworks that have been applied to land-use/land-cover change. Which technique to apply depends entirely on the purpose of the model, or the research question under investigation. Even then it is difficult to provide any rational a priori argument why one particular modeling framework is necessarily superior to another, with the possible exception of Occam's razor (the argument that if two models provide exactly the same behavior then the simpler is to be preferred). However, land-use change involves interactions between ecological and socioeconomic systems. Until recently, these systems tended to be studied separately, with socioeconomic research paying less attention to spatial factors and ecological modeling largely ignoring the human behavioral component of land-use change (Irwin and Geoghegan 2001). A more complete picture of land-use/land-cover change than perhaps is drawn through traditional modeling techniques would therefore seem to involve integrating these two disciplines—spatial and agent-based modeling.

The case for agent-based modeling is reasonably well rehearsed (Axtell 2000, Moss 1999). However, the dangers of dismissing other approaches for reasons such as the complexity of the domain also have been made clear (Balzer et al. 2001). While agent-based modeling is often argued for on the basis that mathematical modeling is intractable, this is not necessarily true for all phenomena. Even when mathematical modeling is feasible, however, agent-based modeling can be used as an inspirational basis for more rigorous results. Much of the analytical work on the Prisoner's Dilemma has been based on results achieved using agent-based models by authors such as Axelrod (Gotts et al. in press).

In FEARLUS, therefore, the approach has been to start with a simple, abstract, agent-based model of land-use change and to conduct a series of experiments exploring the emergent properties of the model to look for interesting effects. These effects are confirmed using non-parametric statistical tests (those that do not assume an underlying normal distribution) over a series of runs with the same parameters but different seeds for the random number generator. Where possible, a mathematical model can be built to describe these effects (such as the superiority of one approach to choosing land use over another in a particular environment), and prove further results. Analytical modeling and simulation are thus seen as complementary tools rather than rival techniques (Gotts et al. 2002).

If we are to achieve our stated aim of providing a modeling tool for policy makers, however, we will need to move away from abstract, generative models of land-use change to more realistic, descriptive models based on real-world data and processes. To this end, future models will be built using a modeling framework—a meta-model whose parameters are the models that will be used to simulate the various components of the system—enabling the user to configure the degree of realism desired in the simulation. The goal of simple explanations still applies, however, and the move to more complex and realistic models of land-use change will be made only on the foundation of a thorough understanding of the behavior of simpler, more abstract models.

The modeling framework will be designed, as far as possible, to allow the inclusion of new modules as the need arises. This enables us to put off the decision about what to include until we need to make it. For example, having studied a model with no simulation of the climate whatsoever, we could then move to a model with an abstract representation of the effects climate might have on the yield from various crops to see if this has any effect on our earlier results. A more sophisticated climate model drawing on real-world data could then be applied to see what effect this has. As the context of the required model changes from scenario to scenario, so will the degree of realism in (or indeed the need for) particular modules vary.

System under Study

Although FEARLUS is an abstract model, it is aimed at illuminating aspects of land-use change in Scotland (population about 5 million; area about 8 million ha) or particular subregions or catchments therein from the present day forward to about 50 years from now. The agents, for now, are land managers, who have to choose among an abstract set of land uses represented using bitstrings (strings of binary digits), though in the future we expect to include agents representing non-governmental organizations (NGOs) that stand for particular stakeholder interests, and local or national governments.

Model Implementation

In determining the structure of the FEARLUS model, we decided to make the spatial unit of resolution the land parcel, with the overall environment consisting of a rectangular grid of land parcels, broadly intended to represent a particular catchment or region. (It could thus be argued that the model satisfies Goodchild's representation test in section 2.2.1.) The abstract nature of FEARLUS means that the correspondence between geographical entities in the model and those in the real world is flexible and open to manipulation. The land parcels in the model could equally stand for entire farms, and the overall environment a small country or island. One of the difficulties with simulating land-use change is that the scales at which various phenomena occur are all different. There is a difference between the scales at which managers interact with their land when making land-use decisions, when buying or selling land, or when harvesting yield. For example, land-use decisions could be made at the field level, whilst exchange of land between managers typically involves a number of fields. When harvesting, however, the yield acquired for a particular crop can vary considerably within a field. FEARLUS does not currently distinguish between these, and other scales of interaction of its component systems, except that the climate and economy are experienced at the environment rather than the land parcel level. We intend to introduce the capability to vary these scales in future developments.

The environment consists of a uniform, two-dimensional grid of cells with each cell representing a land parcel—meaning all land parcels have the same area. Facilities are provided for simulating hexagonal and triangular cells, as well as squares with von Neumann or Moore neighborhoods (rook or queen's contiguity). The grid may be bounded, with edge and corner cells having fewer neighbors than the other cells, or toroidal (wrap-around), in which edge cells have neighbors on the opposite edge. Each land parcel has individual biophysical properties, simulated using a bitstring. These spatially varying biophysical properties remain constant during the course of the simulation. Currently, they are not affected by the land uses or climate, though we have plans to introduce the option for this to happen in the next stage of development. Temporal variation is introduced by the climate and economy, also simulated using bitstrings. They are constant over the space, and we refer to them generically as external conditions because in the model there is no difference in the way they influence yield. A fixed set of land uses is determined at the start of the simulation, and, in principle, all land uses are available for selection by land managers at all times. Land uses also are simulated using bitstrings. The yield from a particular land use is determined by how well its bitstring matches with the conjoined bitstrings of the external conditions and the biophysical properties of the land parcel.

The model simulates a yearly cycle in which land managers choose their land uses, get their wealth updated according to their harvest, and sell off or buy land parcels. (Although the land uses are abstract, they may be different at the start of the model from what they are after a number of yearly cycles are completed. To this extent, the model satisfies Goodchild's outcome test in section 2.2.1.) The justification for this time unit is that land managers would make one land-use decision per year in reality, though there are counterexamples to this. For example, some farmers are able to sow two or more crops on the same parcel of land in the same year, while other land uses, such as forestry, involve a longer-term commitment and thus do not involve a yearly land-use decision process. Since the model is abstract, none of these specific land uses is represented, and thus this is not an issue, though there is the capability, should it be required, to code for strategies that make land-use decisions using different time periods. For example, a land manager could choose a land use every n years, and in the other years just keep the same land use unchanged.

As stated earlier, the only agents currently simulated in FEARLUS are land managers, which, since they have no fixed lifespan, are best conceived of as families or companies rather than individuals. Land managers perform two main functions in the model: determination of land uses for the land parcels and exchange of land parcels among themselves. Of these, the main focus of the model is on the decision-making process used to select land uses for each land parcel. This selection algorithm consists of three strategies, which reflect the context of the decision and behavioral aspects of the land manager: contentment, innovation and imitation. The contentment strategy is used to determine the land use for a land parcel whose yield exceeds the land manager's individual contentment threshold; for example, a habit strategy might be used in this case, which applies the same land use as the previous year. If the yield is less than the contentment threshold, then the land manager will choose a new land use either by imitating neighbors or by innovating, depending on personal preference. The selection algorithm therefore specifies an innovative and an imitative strategy for the land manager to use when the yield is unsatisfactory, together with a probability to determine which of these will be used each time.

Imitative strategies exclusively use information from parcels belonging to the land manager concerned and their neighbors when determining land uses. The set of land uses available for selection therefore consists only of those that appear in the neighborhood; hence, the model meets Goodchild's formulation test in section 2.2.1. For the purposes of imitation, a distinction is made between the social and physical neighborhoods. The physical neighborhood reflects the topological layout of the environment—which land parcels share borders with which other land parcels. Land managers, however, are simulated as exchanging information socially; thus, imitative strategies use information from all land parcels owned by neighboring land managers, rather than just those land parcels that border those of the land manager making the decision. Imitative strategies represent the only form of communication between land managers that is currently simulated in FEARLUS. This kind of interaction between land managers illustrates a significant aspect of spatially explicit simulations that is not present in simulations ignoring space, in that the land can be used as a means by which agents communicate indirectly.

Innovative strategies make no use of neighboring information, but may choose from any of the land uses. An example of an innovative strategy might be to choose a new land use at random—"innovative" for our purposes meaning that a land use may be introduced that is not currently being applied by any land manager in the neighborhood.

Land managers may be grouped into subpopulations according to the land-use selection algorithm they use. This is used to compare various decision algorithms for their competitive advantage in different environments. We usually assess this competitive advantage on the basis of which sub-population owns the greatest number of land parcels at a predetermined time after the beginning of the simulation, though other measures are possible, such as the greatest accumulation of wealth.

Land managers accumulate wealth from the yield generated by their land parcels, less a constant break-even threshold (used to simulate running costs) applied equally to the yield from all land parcels. Land managers with negative accumulated wealth must sell off their land parcels at a fixed, constant price, until their wealth is zero or above. If they lose all of their land parcels in this way, then they disappear from the simulation, taking any surplus wealth (or outstanding debt) with them. Land parcels put up for sale are transferred to other land managers by choosing at random from the set of land managers with sufficient wealth owning land parcels next to the one that is for sale, or to an extra land manager created and introduced to the simulation if chosen. With the exception of the newly created manager, a land manager chosen to receive the land parcel will have his or her wealth reduced by the land parcel price. Land managers have no option to refuse this transfer.

Verification and Validation

Verification of FEARLUS models involves black-box system testing—constructing simple cases whose outcomes can be calculated manually and confirming that the models reproduce the expected outcomes. Validation, such as it is, is achieved through non-parametric statistical tests of results acquired from repeated runs of the model using the same parameters but different random seeds. Some experiments involve paired replicate runs, which enable us to compare such things as the effect of changing environmental settings (such as how much variation there is in the biophysical properties of the land parcels, or how rapidly the climate and economy change) on the competitive performances of two subpopulations of land managers, or to compare two subpopulations' performances against a third. Examples of such experiments can be seen in Polhill et al. (2001).

In terms of comparisons with real-world data, however, until recently the model has been at too early a stage to make the use of data relevant. A project has been set up at the Macaulay Institute to investigate the degree of influence farmers exert on each other, and we hope to be able to compare the results of this survey with our own work on imitation. Real-world data can be used in a confirmatory way to check experimental results acquired within FEARLUS, should this prove necessary or interesting. For example, recent work on land manager strategies has found that in environments with rapidly changing climate and economy, strategies with a contentment threshold below break-even are more successful than those with higher contentment thresholds (Gotts et al. in press). Since, in the experiments conducted, land managers who achieve their aspiration threshold adopted a habitual behavior, confirmation of this result could be found from sociological research investigating whether there was any relationship between volatility of the factors influencing welfare, and the aspiration levels and degree of motivation of people living under these conditions.

Technical Aspects

The FEARLUS model is currently written in Objective C to make use of the SWARM (Minar et al. 1996) library functions. We chose SWARM over other modeling platforms because it provides key tools for setting up agent-based simulation models without prohibitive restrictions on the functionality of the agents or environments. In particular, SWARM provides facilities for random number generation, scheduling, memory management, and commonly used data structures (such as lists and arrays), and has a substantial user community.

Documentation/Publication

Current funding for the initial FEARLUS project will run out in March 2003, after which we intend to apply for further funds to continue this work. A new project has been set up to integrate FEARLUS with biophysical and socioeconomic models to explore multi-dimensional utility functions in common-pool resource dilemmas with a particular focus on the EU Water Framework Directive. This will run to September 2004. Current publications related to the FEARLUS project include Gotts et al. (2002, in press) and Polhill et al. (2001, 2002). The project website address is http://www.macaulay.ac.uk/fearlus/.

Acknowledgment

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3.3. SPATIALLY EXPLICIT MULTI-AGENT MODELING OF LAND-USE CHANGE IN THE SIERRA MADRE, PHILIPPINES – THE MAMELUKE PROJECT

Marco G. A. Huigen

Problem and Research Question

Land use represents a critical intersection of human activities and the environment. Land use in tropical regions such as the Sierra Madre mountain region in the Philippines is influenced not only by proximate actors such as farmers or loggers, but also by many others, such as government agencies, NGOs, absentee landlords, banks and politicians, who exert numerous influences on the proximate actors and on each other. Land-use and land-cover research has been mainly GIS-based, unable to describe the human dynamics mentioned above. In order to “socialize the pixel,” i.e., to establish the connection between social science and the GIS-based land-use models of geography, the ensemble of these actors is represented in a multi-agent model. (See Geoghegan et al. 1998 for a detailed explanation of “socializing the pixel.”) Thus, decision-making processes of the inhabitants/actors (e.g., an economic analysis) are linked to a spatially heterogeneous landscape that deals with biophysical or biological processes, in which changes in land use are viewed as dependent on how resources are transformed and managed by human activity.

The main objective of the MameLuke[2] project is the design and implementation of a computerized structure, a computarium, that catches the basic processes and causality of LUCC in the Sierra Madre watershed during the past 50 years in a spatially explicit manner, yet remaining sufficiently connected to real-world phenomena and social science theory. This implies that the gap between two kinds of models has to be bridged; on one hand, there is the great modeling power of present-day computer science and, on the other hand, there are the theoretically sound, quantitative models from social sciences such as microeconomics and social psychology. They are as yet not spatially explicit and do not contain the many types of actors interacting in actual land-use changes. The MameLuke project intends to combine these strengths.

The MameLuke project is embedded in a program[3] that also incorporates another project, the CLUE modeling framework (Veldkamp and Fresco 1996, Verburg et al. 1999). The project will exchange important information with the mesoscale project CLUE in terms of the various driving factors that are important for the options and/or motivations (hence the choices) of actors in the multi-agent model. The abstract connection is given in Figure 10. Examples are, among others, shifts in demand and prices, shifts in logging policies, the construction of rural roads, tenure policies that change the motivation of actors to invest in the land they work etc. The causal structure of the model (both the way the agents are modeled and the way they are interconnected) will support the quality of the causal structures as they are modeled at the mesoscale, for instance in the regression analyses.

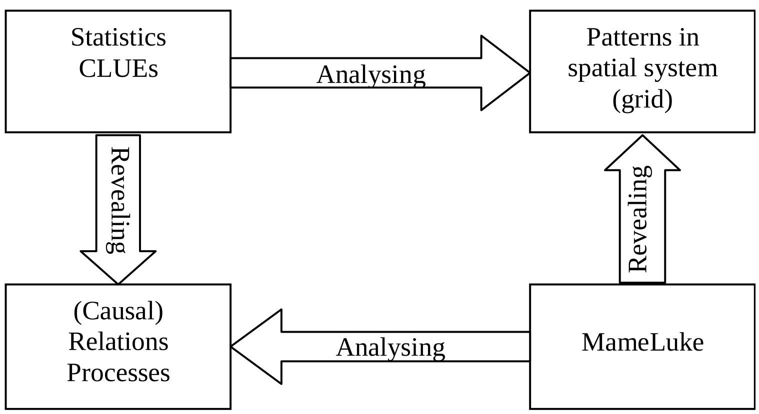

Figure 10. The Relationship between MameLuke and CLUE

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[2] The project name is derived from “Mama, look; I am a ‘MAM in LUCC’ – MameLuke” Mama stands for Mother Nature; MAM and LUCC are abbreviations for multi-agent modeling and land-use cover and change. The Mameluke was a fierce warrior in the ancient Middle East.

[3] Project name: “Integrating macro-modelling and actor-oriented research in studying the dynamics of land use change in North-East Luzon, Philippines,” described on line at http://gissrv.iend.wau.nl/~clue/philippines/intro.htm.

Methodological Pre-Considerations

On Time, Scales, and Levels

In order to deal with multiple scales and levels in the watershed area, two envisioned modeling scales will interact during discrete time steps. One scale, the micro-scale, is at the village level (extent is approximately 50 km^2). The mesoscale is on the complete watershed level (extent is approximately 400 km^2). The resolution or pixel size at the watershed level is approximately 30 m x 30 m up to 100 m x 100 m, while the pixel size on the village level has not yet been established. In Figure 11, a schematic overview of the relevant models and characteristics is given.

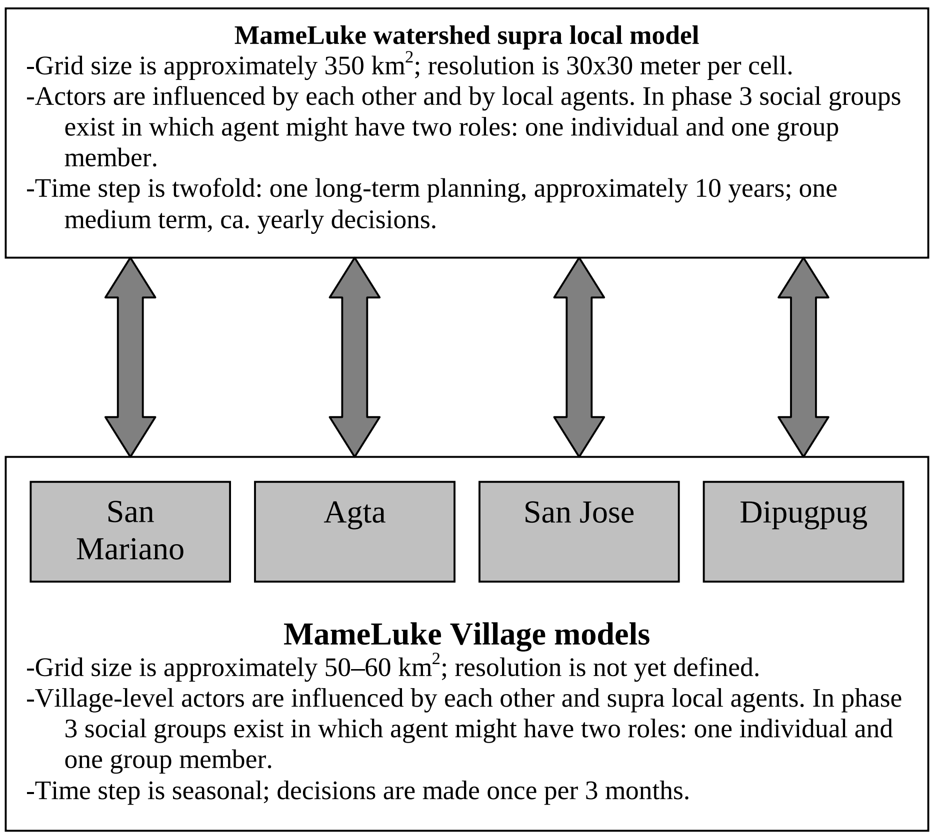

Figure 11. Schematic Overview of the Relevant Models and Characteristics

In addition to the physical, spatial differences in scales, the scale of decision-making processes is different for both models. At the watershed level, the precision of actors on which the decision-making processes are based simplified socioeconomic lines of thought and, by doing so, easily incorporated into GIS-based work. At the watershed level, emphasis is put on the location-based aspects of the area combined with the middle-term and long-term decisions (10 years and more) of the actors. The second step in the project is to dynamically model the village scale. At this scale, the accurateness of the actors' decisions is much higher and based upon household survey data. Also, the higher detail will be included in the temporal (e.g., monthly or seasonal) and spatial scales. During this phase, emphasis also is placed on the multi-level influences. Multiple societal levels will be incorporated at the microscale. In the final phase of the project, I envision four distinct MameLuke-village[4] simulations will "constantly" interact with the mesoscale MameLuke-watershed model. If necessary, the watershed mesoscale will be extended with multiple societal levels.

At the Watershed Scale

As previously indicated, the current theoretical principles that underpin the formation of land-use patterns are the location theory of Von Thünen. However, I do not consider it sufficient to explain the real-world, complex spatial structures encountered. Therefore, I will use these theories as a starting point and create various scenarios that deal with spatial, dynamic heterogeneities (e.g., soil composition, water availability, slopes, erosion, soil fertility decline) and anthropogenic dynamics such as cultural in-migration, road construction, trading, the introduction of fertilizers and the buildup of new markets. In the MameLuke watershed models, the actor relations are included via direct, yet simple, actor interaction (e.g., trading). More relevant at this scale is the communication via the location. Attributes and methods of the location are interpreted by the actor and thus considered a message.

At the Village Scale

When zooming in on the location, the decisional differences of actors become increasingly relevant. In the MameLuke village models, actors and their interactions are shaped according to the action-in-context paradigm by De Groot (1992). The core actor-model describes the causal linkages between actors' behavior (the actions that result from the possible options) and the motivational factors. In this work, various types of actors are related (in the actors field) or linked via so-called power lines. A secondary actor (e.g., a government) influences a primary actor (the actual land user) by setting the rules and regulations under which these farmers have to operate. The secondary actor option is a motivation for the primary actor. In many cases, the primary actors take the actions of the secondary actors as given, at least in the short run. In the long run, the interaction between primary and secondary actors is more complex: through pressure groups, voting and other forms of collective action the farmers do have a certain influence on the actions of secondary actors.

At the Scientific Scale

As mentioned earlier, one of the main objectives is to build a computarium, which is a set of computer models that enables the investigation of various theories delivered by various scientific disciplines. The idea behind this computarium is that students and scholars may experiment with their theoretical considerations. The computarium could induce discussions between various scientific domains and creates a common ground to guide such interactions. Furthermore, effort will be taken to make several models comprehensible for the actors involved. Thus, the models will include local knowledge, symbols, and perception while visually representing certain interventions (e.g., environmental or economic).

[4]These four villages basically represent the four Von Thünen rings. The first village is the market center, the second is located near the market in the intensive agricultural ring, the third is located in the extensive agricultural ring, and the fourth might be found in the "extraction ring."

An important goal is to arrive at a framework that simplifies the understanding of land use and change for various parties involved—scientific domain as well as public domain. The models must be comprehensible for the stakeholders in which various scenarios and their dynamics can be communicated. Another main objective is to reach a certain explanatory power of the spatial land-use dynamics. This explanatory power is mainly measured by comparing simulated land-use patterns with remote sensing data and expert opinions. The MameLuke modeling is not primarily aimed to be quantitatively predictive. Hence, the models enable the exploration of possible future scenarios, but the primary objectives are not aimed at exact predictions.

The beauty of and reason for choosing agent-based modeling is that in such a framework various scientific disciplines may easily be combined. Furthermore, the type of modeling deals with qualitative and quantitative data more easily than equation-based models.[5] Another well-known, appreciated advantage is the multiplicity and heterogeneity of agents in one model.

System under Study

The MameLuke models focus on a watershed area in the Municipality of San Mariano, North East Luzon, the Philippines. The time span under study ranges from the moment that huge logging companies opened up the tropical forests (circa 1950) to the present day. Van den Top's (1998) extensive study reveals that inhabitation of this area follows certain dynamics, influenced by various drivers belonging to such scientific systems as geography, politics, anthropology, economics, and demography. After a logging ban, former logging company employees settled in the area and started a life initially based on subsistence agriculture. Forest patches, cleared by the logging companies were cultivated and became the basis for a rich variety of farming activities.

In the early 1950s, the two rivers in the San Mariano area formed the main means of transportation. Settlers entered the area, while timber concessionaires left. Currently, two paved roads, connecting the three bigger villages, provide an additional entrance to the forest area, used by an even larger number of fortune seekers from all over the Island of Luzon. Traditional rice farmers settle at the hilly or mountainous watershed borders, while other tribal communities cultivate the lesser-sloped hills and floodplains to produce cash crops like corn and bananas. Obviously, in an area with such vast amounts of timber still left and up for the taking, illegal logging activities add to the annual incomes of the population living in the research area.

More and more, NGOs, political players, and policy implementers become aware of the precious situation of this valuable piece of forest that borders a beautiful and valuable national park. All these supra-local actors make up the complex socioeconomic dynamics in the area in which simple agents try to live a farmer's life.

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[5]Agent-based models (ABMs) and equation-based modeling (EBM) differ in two ways (following Van Dyke Parunak et al. 1998): (1) the fundamental relationships among entities they model and (2) the level at which they focus their attention. EBM tends to make extensive use of system-level observables. In contrast, the natural tendency in ABMs is to define agent behaviors in terms of observables accessible to the individual agent, which leads away from reliance on system-level information.

Model Implementation

The World

The world consists of a uniform, two-dimensional grid of cells, with each cell or location representing 1 ha. Each location has biophysical attributes and models (e.g., fertility decline, erosion) that dynamically change during the course of the simulation and, therefore, are affected by the actors' (farmers, traders, and other land users) activities .

The unit of time at the watershed scale is the year, which consists of a number of steps in which many middle- and long-term decision-making processes take place. The actors are involved in a large variety of activities in one time step, depending on many contextual aspects. Farmers settle, choose their land use (which crops they will produce where), sell their yield to traders or middlemen, and thus generate income to buy fertilizers, seeds, and other necessities from the trader, receive credit, and acquire new land locations via slash-and-burn practices.

The village models will initially run on a monthly time step, or a seasonal time step that corresponds to the time scale relevant for household agricultural production decisions. The resolution at which the watershed models operate is 30 m x 30 m. The resolution of the village models depends a lot on the possibilities and results of the planned participatory mapping.

The Agents

The primary actors in both model scales are the farmers and loggers, the direct (proximate) actors in tropical land-use change. Focusing on these actors only, however, does not give insight into the crucial role of numerous other actors who co-determine what farmers and loggers do, such as government agencies, traders, and landlords who are causally linked to each other and to a tertiary layer of actors. The latter, in their turn, may in fact be even more responsible for what actually happens to the forest lands, such as the legislature, manufacturers, or consumers of forest products. Based on previous research in the area (e.g., Van den Top 1998, Huigen 1997, Rombout 1997), candidates for primary and secondary actors are, for instance, corn traders, logging crews, Agta hunter-gatherers, furniture industrialists, the ministry of the environment and forest (DENR), the ministry of agriculture (DA), and local and supra-local politicians. From an ABM point of view, the actors are relatively simple. The decision-making capacities are procedurally and imperatively[6] programmed (see Figure 12).

The actors at the watershed level may have a variety of preferences based on their cultural and social backgrounds that potentially result in a variety of decision-making strategies. Some tribal backgrounds are market oriented, while others are not; some are risk aversive, others are not. Besides the variety of strategies due to agent heterogeneity, different strategies might as well be deducted from approaching the agents as a pure *Homo economicus,* or as a Homo socialis, or with a *bounded rationality*.

[6] In the imperative modeling of agents, the behavior and, thus, the rules are often a behavioral aggregation or process-description. In the declarative modeling, the rules are based on simple behavioral premises.

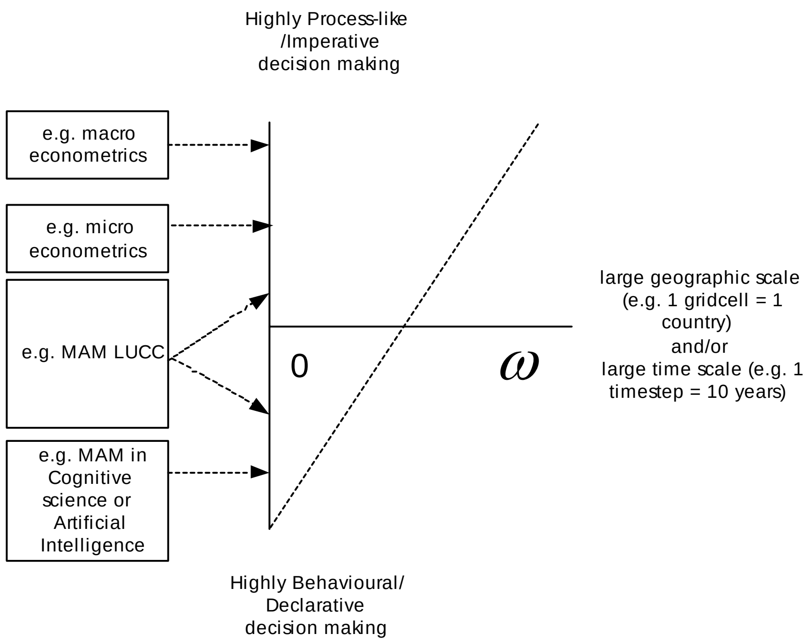

Figure 12: Looking at the Gradient of Possible Agent Implementations in LUCC

At the village level, a more declarative type of actor is foreseen based on a mixture of the actor-in-context structure and a "belief desire intention" agent (Rao and Georgeff 1995). Again, the actors will have pre-defined preference specifications and strategies based on their backgrounds. At this scale, more focus will be put on the actor involvement in many actor-actor and actor-group decision-making processes. The most pertinent type of interaction between agents in the model will follow the principle of the actors field in the action-in-context framework (De Groot 1992). This type of connection is that the options, outcome, or weights on criteria (hence the choices) of the proximate agents (in this case, the farmers) are influenced by the choices of secondary agents, for example, the DENR field officials who may choose to fine small-scale logging activities and confiscate their illegal logs, or traders who may decide to accept a promise to plant corn as a collateral for credit. On top of these vertical interconnections that express the lines of power surrounding local land use, there exists a class of horizontal interconnections between agents of largely the same level (primary, secondary, etc.). Farmer agents, for instance, may learn from each other, imitate each other or coordinate actions. This is the type of interconnection that receives most attention in the majority of current multi-agent models. Hence, computer experiments with learning models (genetic algorithms) and *heuristic* rule-based decision strategies are foreseen.

Verification and Validation

Validation is the process of determining the degree to which a model or simulation is a reliable representation of the target system, or “real world,”[7] from the perspective of the intended uses of that model or simulation. The validation process is the process of comparing the model outcome with its referents[8] and its validation data[9] in order to evaluate the model’s accuracy. Potential referents exist in many forms, varying from subjective and qualitative descriptions to objective and quantitative descriptions:

- Experimental data describing the functionality and performance of a system.
- Empirical data describing the behavior of a system
- Experience, knowledge, and intuition of experts
- Mathematical models of the behavior of a system
- Qualitative descriptions of the behavior of a system
- Combinations of the types described above

The process of checking whether or not a model is consistent with respect to some formalism or theory is known as verification. Verification determines whether the design and implementation of a model or simulation correctly meet the design requirements as best reflected in a validated conceptual model.

Experimental Data Describing the Functionality and Performance of a System

For the simpler models, it is possible to conduct Monte Carlo uncertainty analysis. When constructing such models, but probably also the more complex (many parameters, complicated decision processes with group influences, etc.), the sensitivity of the various aspects and components will be analyzed.

Empirical Data Describing the Behavior of a System

The model will be validated (and calibrated) with:

- GIS maps created and derived from satellite images/remote sensing
- Participatory perceived-value maps derived via interviews
- Available census and socioeconomic data
- Data retrieved via household surveys
- Data retrieved via literature reviews and from archives

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[7] The term “real world” refers to the physical world that currently exists, as well as the one that might exist in the future.

[8] A referent is the best (codified) body of knowledge about what the model-simulation represents.

[9] Validation data are the actual measurements from the real world or best-guess information provided by experts that are used in validation to determine if the results of the simulation are correct enough for the simulation to be useful in the intended purpose. Validation data are the real-world facts used for comparison to validate the results of a simulation.

Backcasting techniques of model simulations for the validation and calibration of the spatial and temporal aspects will be conducted. Hence, the spatial land-use and land-cover maps of the region produced by the framework and its simulations, need to be fairly identical to the remote sensing images at a certain time in history.

The above-mentioned elements for calibration and validation also will be validated themselves through cross-references. Thus, participatory maps (social scientifically obtained) will be compared to quantitative geographic maps, and census data will be compared to actual perceptions of local actors. Furthermore, I foresee that statistical comparisons of the landscape composition and pattern statistics between our simulated and actual landscapes will be conducted (goodness of fit). This may include, among possible others, comparisons on real versus model-expectations of roads, locations of new settlements, locations of and the dynamic shifts of the forest frontier, the real and expected (by the model) economic market locations.

Mathematical Models of the Behavior of a System

It is possible to run a very simple MameLuke watershed model that equals a mathematical, econometric model (e.g., farm household analysis) and see whether results are consistent. Although hard to imagine, one might consider a Markov-chains approach for the simplest of models; however, this will probably be beyond the temporal scope and relevance of this project. Within the project, the CLUE model that predicts land use and cover via multiple regression techniques may function as a validation referent.

Experience, Knowledge, and Intuition of Experts

The project members and the members of the affiliated institutes will have ongoing progress reports and may constantly evaluate and criticize the MameLuke models. The models will be presented at conferences that will be attended by various scholars with diverse scientific backgrounds. Dutch and foreign colleagues and students, again with diversity of scientific backgrounds, related to the project will be given the opportunity to explore and criticize the models. Local Filipino NGOs and governmental officials might attend conferences that are focusing on the MameLuke and CLUE models.

Qualitative Descriptions of the Behavior of a System

During the setup and actual process of role-playing games (Barreteau et al. 2001), well-documented understandings of the model dynamics need to be produced in order to explain it in visual, symbolical, and verbal terms to the local farmers. I will attempt to combine local knowledge and terms/symbols with the scientific discourse in some of the models produced. Besides validation, the aspects of verification also are of major importance in this work. The models will be presented to the local actors and to scientific experts. Besides visual confirmation and verification of the models, artificial actors, during their life, keep track of their decisions, their options, motivations, and intra-actor models via extensive, descriptive logs. These logs need to be logically consistent in the eyes of the represented actors themselves and to various experts. Again, the role-playing game techniques will be used to verify the internal logic and consistence of the decision-making processes and perceived socioeconomic, political, and biophysical processes.

Technical Aspects

The MameLuke models will be built on a framework using Java (based on Ascape and RePast) and a Microsoft SQL server for data storage. I foresee in the future a possible transformation that will reshape the various decision-making processes by the actors, now imperatively rule-based, into a more declarative type (e.g., using SOAR). Furthermore, the software models, written in Java, are linked to several other tools, such as a GIS package (Idrisi) and a smooth user interface in Microsoft Visual Basic and Java.

Documentation/Publication

The project has a four-year time line from May 2001 through May 2005. During this time I expect to publish approximately four papers in representative, relevant journals. The research approach, theoretical considerations, and model implementations also will be presented at relevant conferences. At the end of the four-year period, a dissertation is expected. This work will consist of a website-like structure containing several theoretical and practical chapters that verify and validate my research and ideas. The MameLuke framework will be included, and the models will be interactively available with the description of the MameLuke model code by using UML diagrams (class, sequence, and collaboration). Upon completion of the project, or upon special request, the model code will be available to other researchers.

Acknowledgments

Acknowledgment goes to the editors of this book. The research presented in this section is part of the project "Integrating macro-modeling and actor-oriented research in studying the dynamics of land-use change in North-East Luzon, Philippines," a collaboration between Wageningen University and Leiden University, the Netherlands, funded by the Foundation for the Advancement of Tropical Research of the Netherlands Organization for Scientific Research (NWO-WOTRO).

3.4. MULTI-AGENT MODELING APPLIED TO AGROECOLOGICAL DEVELOPMENT

Thomas Berger

The Center for Development Research (ZEF), Bonn University, carries out several research activities in the field of agroecological development where a multi-agent modeling approach is applied. One of these activities is the LUCC-endorsed GLOWA-Volta project in West Africa that studies interrelated water and land-use changes within the Volta basin in the context of global environmental change (http://www.glowa-volta.de).

This section outlines the prototype for the ongoing research activities at ZEF, a multi-agent model that was applied in 1999 to an agricultural area in Chile. Due to limitation of space, only the main characteristics of this prototype ABM can be described. For empirical results of the Chilean model refer to Berger (2001) and for full model documentation to Berger (2000).

Problem and Research Questions

Agricultural intensification and, in particular, higher levels of efficiency in water and land use are two key elements for improving food security in developing countries. Both generally require some form of innovation, for example, farm investments in superior land-use practices and irrigation methods, agricultural extension, and institutional changes. Several authors argued that viewing land- and water-use improvements as exogenous technical change can yield misleading policy recommendations and certainly to an underemphasis of farm investment as a policy issue. In line with this argument, the Chilean model focused on the diffusion of water-saving irrigation methods in a watershed, the effects of innovation on farm structure, and the impacts of possible government interventions aiming at supporting farmers to improve their resource use efficiency. Various authors also emphasized the role of land and water markets as a prerequisite for a more sustainable resource use and called for institutional reforms. Yet only a few developing countries clearly resolved the intertwined subject of land tenure and water rights. An often quoted positive example is Chile, where water and land rights were plainly decoupled and markets for tradable water rights were established. While Chilean farmers might potentially realize considerable earnings by selling or renting out their water rights, the number and volume of market transactions in most regions was lagging behind the level of theoretical expectations. The multi-agent model also addressed this issue and incorporated land and water markets with the aim of identifying possible bottlenecks.

Methodological Pre-Considerations

Though only a prototype, the Chilean model was in principle designed for providing policy-relevant information, especially regarding the impacts of policy on different farm and resource user groups. Computer simulations should facilitate exploring suitable policy options and forecasting likely land- and water-use changes as the result of technical and structural change in agriculture. This explorative and predictive purpose clearly impacted the level of abstraction and complexity in the representational model. It was structured at a highly detailed level, since the phenomena under study—diffusion of innovations, land and water rental markets, markets for land and water rights, change in farm sizes—required the modeling of heterogeneous farm-households and inter-household linkages. The spatial context was important (e.g., upstream-downstream water uses, local water and land markets), so spatial relationships also had to be included. Accordingly, several socioeconomic and biophysical processes such as decision making and interactions of individual agents, land markets, and alternative land allocation strategies as well as irrigation water flows and agronomic relationships were endogenous to the model. Sociopolitical phenomena, such as rule formation, group decision making, and institutional change, however, were treated exogenously.

System under Study

The model was applied to the Melado River catchment, 300 km south of the capital Santiago de Chile, with a size of about 670 km^2 and 5,400 farm holdings. Irrigation water in this catchment was scarce and only sufficient for extensive cropping and livestock farming. An overall switch of production toward higher-value irrigation systems would have required first the introduction of water-saving irrigation techniques and, second, the reallocation of water rights among farmers (intersectoral water transfers were not relevant in this mainly rural area). Many farmers grew traditional crops such as cereals with relatively inefficient irrigation techniques and made only limited use of their water rights. The situation might, however, change rapidly within the next decade. In 1996, Chile signed an agreement with the South American trade union Mercosur that prescribed reductions of tariffs by 30%, on average, over a period of 17 years. As a consequence, relative prices in agriculture have changed and considerably affected the profitability of different farming practices. The new market environment has created both strong incentives for shifting production systems toward high-value crops irrigated with modern water-saving technologies and disincentives for growing traditional crops with rather inefficient irrigation techniques.

The temporal period being modeled was therefore 19 years, starting in 1997, in order to capture the complete process of sectoral adjustment in agriculture. To model the adjustment process at the farm level, very detailed land-use types in agriculture and forestry were being included: five soil types, three technological levels, and 160 cropping, forestry, and livestock systems. As the catchment's farmers only employed surface water for irrigation, and other water uses were not important, the model concentrated solely on surface water flows in agriculture. The model was limited only to the farm households and non-farm landowners who engage in land and water markets and whose plots belong to different irrigation sections within the Melado water user association. Each household was represented individually; i.e., the model was disaggregated to the farm level. Other real-world agents, such as farm workers and *minifundistas* with farmland of less than 2.5 ha, were not included in the analysis since they actually did not contribute significantly to the resource-use decisions and market dynamics.

Model Implementation

The spatial resolution of the Chilean model was approximately 158 m^2—one grid cell representing 2.5 ha—and the time step was one month. This fine spatiotemporal resolution was chosen because rented farm plots were typically this size, and the hydrology component considered for integration into the model calculated the crop water requirements on a monthly time interval.

The model contained three basic functional types of agents that stood for campesino family farms, commercial farm holdings, and non-agricultural landowners. Based on previous empirical analysis, the two farm-holding types were found to represent two distinct social networks. Within these networks, communication took place, and five subgroups corresponding to the classical adopter categories—innovators, early adopters, early majority, late majority, and laggards—were distinguished. In accordance with theoretical findings (Brandes 1989) and evidence from in-depth interviews in the study region, the model agents were implemented as seeking to maximize expected incomes without exhausting their land and water assets; i.e., they were implemented with a certain preference for staying in the farm sector. In special simulation runs, the model agents' behavior was consistent with standard economic theory; i.e., they had perfect foresight with respect to farm prices and left the farm business whenever their permanent off-farm incomes were higher. The agent's individual decision making was represented by means of *recursive* whole-farm mathematical programming, a technique developed in agricultural economics that is occasionally applied also in land-use modeling (Oglethorpe and

O’Callaghan 1995). Mathematical programming—the maximization of *objective functions* constrained by inequalities or equalities—can mimic the decision-making processes of real farm managers and therefore provides valuable information for policy analysis (Hazell and Norton 1986). In the Chilean model, each farm agent had a separate objective function, had resource constraints, and updated its expectations for prices and water availability. In this respect, this multi-agent model had largely the same characteristics as independent representative farm models (Hanf 1989). There were, however, three important features that distinguished the Chilean model from the conventional independent farm approach:

- One model agent represented exactly one real-world farm household, and there were as many model agents as farm households in the study region.
- The model was spatially explicit and employed a cell-based data representation where each grid cell corresponded to one farm plot held by a single landowner.
- Several types of interactions among agents were explicitly implemented in the model such as communication of information, exchange of land and water resources, and return flows of irrigation water.

Including direct interactions among individual agents broadened the scope of resource-use modeling significantly, because several economic phenomena that standard approaches cannot easily address were explicitly modeled. First, the theoretically well-known effect of internal transport costs from the farmstead to the plot was directly considered. Remote plots might lead to prohibitively high transport costs and, therefore, limit the competition on the land market. Here, the model captured the agents’ location and internal transport costs through a raster-based GIS and incorporated local land markets with endogenous prices. Second, the model reflected a snowball effect that in reality often drives the dynamics of technical change in agriculture and then leads to a cannibalistic process (Cochrane 1979). When farmers differ in their innovative capacities, only the early birds are initially able to adopt a cost-saving technology, and the laggards wait to learn from the early birds’ experiences until they can successfully imitate. Because of their lower adoption costs, the innovative farmers have a competitive advantage over the laggards and may then absorb their land resources over time. The model implemented this snowball effect with the help of adoption constraints and *network thresholds* (Rogers 1995). Again, the model allowed consideration of the standard economic concept of undistorted land markets and so-called *equilibrium diffusion processes* without different adopter categories as special cases (Berger 2001).

In its Chilean version, the model only accounts for hydrologic-agronomic relationships in the form of run-off flows and soil-specific, crop-water production functions. Feedbacks are included in the model, as monthly irrigation return flows affect downstream water availability and may force the model farmers to temporarily undersupply their crops or even to abandon them completely. The spatial interactions of the water resources system were represented at a much coarser scale than the farm plots. Grid cells were grouped to hydrologic units of an average size of about 32 km^2. The model could reflect in different scenarios either a perfect water allocation within the water user association—the farm agents receive the exact quota of their irrigation water—or more realistically, at least in the Chilean context, poorly distributed water rights where parts of the return flows in the irrigation system were uncontrolled. Figure 13 summarizes the spatial data representation together with the heterogeneity, interdependencies and hierarchies of the model. There was spatial heterogeneity (soil quality, irrigation water supplies, ownership of land parcels and water-user rights), technological heterogeneity (farming equipment of different technological levels), and social heterogeneity (different managerial capacity, several social networks). Interdependencies were spatial (return flows, land and water markets) and social (communication networks). Land cover, land use, and water supply of a particular grid cell resulted from the decision-making process at the farm level where technical, financial, and higher-level social constraints were reflected.

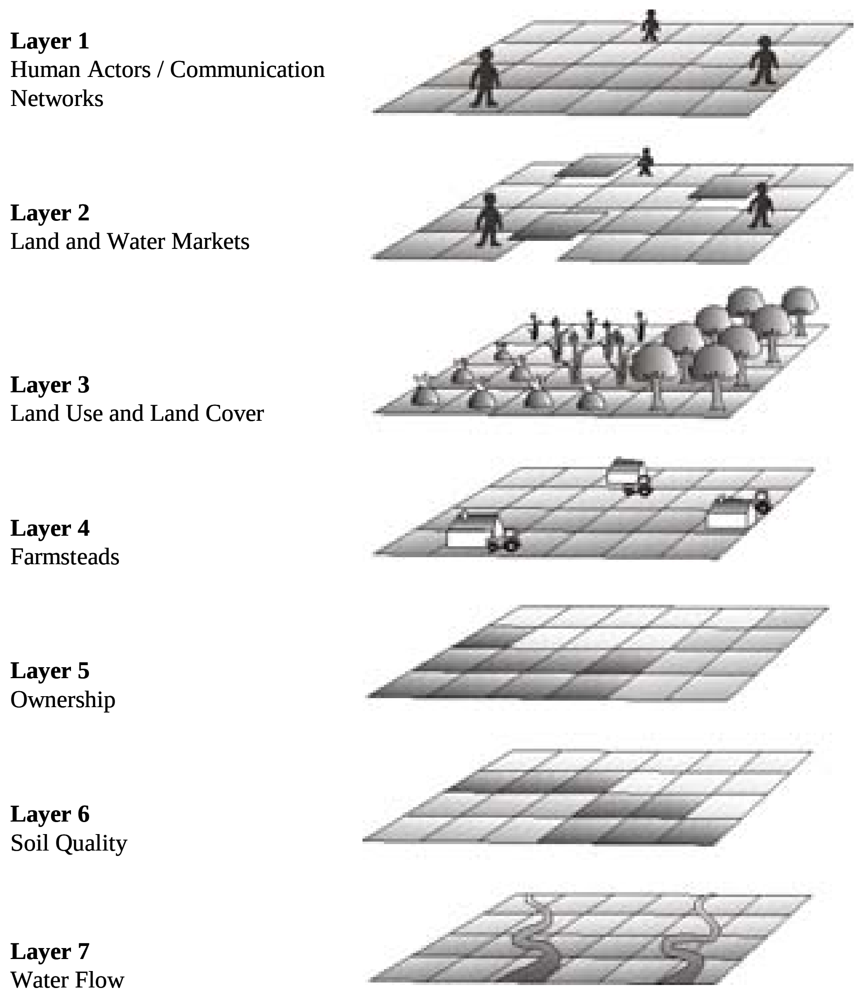


Figure 13. Spatial Data Representation and Interdependencies

Verification and Validation

Having calibrated the model to a base year, standard validation tests of empirical mathematical programming models were performed (Berger 2001). As the model had many degrees of freedom and contained highly recursive dynamics, extensive robustness experiments and Monte Carlo statistical tests also were conducted. Finally, comparisons of its performance with other policy models and field studies in Chile helped to create certain trust in the model's behavior and results.

The often-cited advantage of the mathematical programming approach in merging different data sources was fully exploited (Hazell and Norton 1986). An extensive farm-household survey, in-depth interviews, social network analyses, and results from farm trials were used to derive a consistent farm household dataset. Based on a water engineering study for the Chilean Ministry of Public Works, the hydrologic units, equations, and model parameter were defined. Spatial data at the hydrologic unit level had to be disaggregated to plot level using a random data generator constrained by a priori technical information. The registry of the local water user association was consulted to assign water rights to model agents.

As the model operates on various scales simultaneously—on plot, farm, hydrologic unit, and river catchment level—a previous aggregation of input data to one common level of aggregation was not necessary. This implies, on the other hand, the thorough testing of its ability to approximate real-world observations on the micro-, meso-, and regional level. Only aspatial statistical analyses were conducted that revealed a high goodness of fit. In future model applications with sufficient remote-sensing information, spatial statistical tests also should be employed. Due to incomplete time-series data, change or tracking experiments also remain to be done in a follow-up study, which will collect more field data. Nevertheless, local experts considered the model's predictive capacity to be plausible.

By representing the resource users' decision making in a spatially explicit way, the model generated land- and water-use patterns that might emerge in the next 19 years under different technological, political and environmental scenarios. One important simulation result was that market-driven technological change probably will take considerably more time than Chilean policy makers expected when signing the Mercosur agreement. The model also showed the evolution of farm incomes on marginal lands as compared to the regional average and suggested high levels of out-migration. In other scenarios, the model was used to analyze the effects of different policy programs, such as the one demanded by the Chilean farmers' association. This cost-intensive program, for example, included special credit schemes to facilitate the adoption of water-saving innovations, public investments in irrigation facilities, and fertilizer subsidies, among others. Such favorable conditions could indeed lead to increased employment in agriculture and would even turn a potential sending region into a receiving region; however, the question is whether the net social benefits of this policy program are positive. More details on the policy analysis and especially land/water markets can be found in Berger (2000 and 2001).

Technical Aspects

A custom-made multi-agent software, written in C++, had to be developed because no other software was available that would have been flexible and rich enough to implement the representational model outlined above. The development of the source code benefited substantially from the pioneering experiences of Balmann (1997) with farm-based CA. The new source code has MS Windows 32 bit and UNIX portability. Input and output files are in ASCII text format and can be processed with common spreadsheet and graphics programs. The source code permits modular extensions to include, for example, ecological constraints or to create interfaces with GIS applications.

Documentation/Publication

More information about the Chilean model application and current multi-agent research at the Center for Development Research can be found at the following website: http://www.zef.de/zef_englisch/f_mas.htm.

3.5. INTEGRATED ASSESSMENT AND PROJECTION OF LAND-USE/LAND-COVER CHANGE IN THE SOUTHERN YUCATAN PENINSULAR REGION OF MEXICO

Steven M. Manson

Problem and Research Question

This research develops a scenario-driven integrated model to project trends of tropical deforestation and cultivation and their effect on carbon sequestration in the southern Yucatan peninsular region of Mexico.

Methodological Pre-Considerations

Precursors: The study is conducted as an integrated assessment, defined as policy- relevant global change research that addresses the complex interactions among socioeconomic and biophysical systems. Similarly, the LUCC research literature suggests that two key themes be addressed by the LUCC projective model: (1) the distinct temporal and spatial patterns of deforestation and cultivation and (2) the complexity of and relationships among socioeconomic and environmental factors (Lambin 1994). An agent-based model combined with cellular modeling seemed a good means of addressing these challenges since the former is useful for modeling decision making and the latter has proven applications for environmental modeling (Lambin 1994).

Conceptual framework: The LUCC research community conceptualizes proximate and distal causes of land-use/land-cover change (Turner et al. 1995). Key proximate causes of tropical deforestation and related cultivation in the study site (described below) include logging, farming, cattle rearing, and specialty farms. These proximate activities follow distal infrastructure development, population pressure, market opportunities, resource institutions, and environmental or resource policies. The research proposed here casts these foci as a three-component actor-institution-environment conceptual framework. The first part focuses on the decision making of farming households, or smallholders, who are the proximate actors of change in the southern Yucatan peninsular region (SYPR) and many tropical forests. The second component concerns socioeconomic institutions that affect actor decision making. Both actors and institutions interact with the third component of the conceptual framework, the biophysical environment (Turner et al. 1995).

The agent-based model includes actor processes (e.g., land manager decision-making behavior), and the cellular model is used for environmental functions (e.g., *secondary succession*, pest invasion). An agent-based model also is used to represent institutions, but institutional form and rules (e.g., crop prices) are largely exogenous to the region.

System under Study

The SYPR is an area of 18,300 km^2 in the southern portion of the Mexican states of Quintana Roo and Campeche. Seasonally humid tropical forests dominate the landscape. These states remained largely untouched from the decline of the classic Maya (ca. 1000 AD) until the advent of selective hardwood logging in the mid-twentieth century. Construction of highway 186 through SYPR in 1967 encouraged smallholder agriculture, increased logging, and short-lived mechanized rice projects. As concern over the magnitude of deforestation grew, the federal government created the Calakmul Biosphere Reserve in 1989. The latest large-scale activity, an archaeological ecotourist destination named Mundo Maya, has entailed increased road construction and electrification in the heart of the study area.

Key actors in SYPR engage in swidden cultivation (or milpa), agroforestry, logging, market agriculture (particularly chile and citrus fruit), and trade in non-timber forest products. The study site population grew from under 2,000 people in 1960 to over 30,000 in 1995, largely due to migration from other parts of the country. Critical institutions include state-owned forests, forest concessions, the biosphere reserve, government subsidy programs, NGO initiatives, and ejidos (communal land management councils created about 70 years ago under constitutional reform).

Model Implementation

The spatiotemporal resolution varies; most typical simulation runs are at a spatial resolution of 900 m^2, 10,000 m^2, or 1 km^2. Temporal resolution is generally a one model year iteration, although longer intervals are modeled to reduce computational time and shorter periods are possible.

Agent-based approaches are used to combine empirical and theoretical models of actor behavior in resource-use situations and are used here to embody the actor and institution components of the conceptual framework. Decision-making analogs include simple rules, estimated parameter models such as linear regressions, and genetic program approximations of bounded rationality. Actor interaction is indirect (via land use) and direct through trading of strategies. Land is allocated according to suitability (defined by actor strategies), influenced by institutions (e.g., land tenure) and then partitioned-land allocation problems. Actors are partitioned according to loose spatial boundaries defined by ejidos (or, more to the point, institutions representing ejidos) but otherwise are not organized in hierarchies.

The use of CA in ecological models suggests the use of generalized CA to represent the environment. Cellular automata are two-dimensional grids where cell values, representing land-use/land-cover, change in time according to rules based on the value of adjacent cells. A forest succession model, for instance, could have rules to account for the effect of neighboring timber stands. Actors exist in an artificial world defined by the spatial bounds of the environment and their decision making is influenced by environmental factors. Their actions in turn will impact the environmental grids.

There is a clear distinction between the uses to which agent-based modeling and generalized CA are applied. The former represents actors and institutions and the latter represents the environment. Institution agents interact with actors by changing the resources accessible by actors (represented by actor-agent variables), exogenous variables (global simulation parameters), and spatial data that in turn affects actor decision making. A land tenure institution, for instance, is represented by agent processes that impact land tenure grids stored in the generalized CA. These grids in turn are referred to by actor-agent processes that represent actor decision making. The actor’s decision to use a given plot of land is an agent process that makes a direct change to the CA grid that represents land use. Through shared spatial grids, institution and actor processes interact with generalized CA endogenous transitions that represent ecological phenomena. The plot of land recently cleared by an actor, for instance, is subject to weed invasion and forest regrowth. In software terms, barring continual actor-agent intercession, generalized CA transition rules will move the cells that constitute the plot from a state representing cleared land toward a state of regrowth. As the simulation is iterative, there is a constant interplay between actors and institutions, the effects of actor decision making on the environment, and the effects of environmental transitions on actor decision making.

Verification and Validation

The model is calibrated and validated with remotely sensed imagery and socioeconomic data from household surveys, archival research, and land-use/land-cover and biophysical characteristics derived from satellite imagery and other spatially referenced data. The bulk of these data is from the larger LCLUC-SYPR project of which the author is part. A suite of validation techniques is employed, including the Kappa Index of Agreement, fractal dimension, contagion, a multi-resolution goodness-of-fit metric, and a Monte Carlo uncertainty analysis. Joining this is expert opinion and structural sensitivity analysis.

Technical Aspects

Given the paucity of appropriate model tools when the project was initiated, the model is written in the OOP language C++. This research uses the Idrisi32 GIS application programmers interface for seamless integration. It also relies on the Microsoft Access database software package, chosen for its ubiquity and compatibility with the Idrisi32 database format. Better agent-based modeling packages and options exist now, so it is unclear if improvements in the current package will be pursued.

Documentation/Publication

This is dissertation research expected to be completed during 2002. Otherwise, see www.stevenmanson.com for more details. This research is associated with the NASA-funded LCLUC-SYPR project (http://earth.clarku.edu).

3.6 LUCITA – MULTI-AGENT SIMULATIONS OF LAND-USE CHANGE NEAR ALTAMIRA, BRAZIL

Peter Deadman, Kevin Lim, Derek Robinson, Emilio Moran, Eduardo Brondízio, and Stephen McCracken

Problem and Research Question

Rapid deforestation in the Brazilian Amazon over the past thirty years has raised international concern on a variety of issues, including the loss of biodiversity and the reduction of the region's capacity as a global carbon sink. From an area that in 1975 had less than 1 percent of its forest cover removed, the basin is already 15 percent deforested. This rapid rate of deforestation has driven numerous research efforts to look at the causes of land-use change in this region. Although the large-scale causes of deforestation, such as commercial logging, mining, road construction, and hydroelectric development, are obvious, the processes operating at local scales are often less well understood. The development of an ABM simulation of land-use change in the Altamira region of the Amazon is intended to create a tool for exploring questions related to the effects of different natural, demographic, and institutional factors on land-use change in this region. The overall goal of the project has focused on exploring the utility of an ABM approach for exploring theories of land-use change in the Amazon. To date, the development of LUCITA (Land-Use Change in the Amazon) has been guided by the following objectives:

- Develop a prototype simulation that integrates separate models of ecological processes and human systems through a spatially referenced cellular landscape.
- Evaluate the strengths and weaknesses of the prototype simulation to determine where future research is required.
- Through additional data collection and developments to the simulation explore the effects of changing household characteristics, policies, and environmental conditions on land-use change in the study region.

Progress on the first two objectives has been documented in Lim et al. (2002). Currently, efforts are focused on the third objective. The research associated with the development of the LUCITA simulation system represents a cooperative effort between researchers in the Department of Geography at the University of Waterloo and the Center for the Study of Institutions, Population, and Environmental Change (CIPEC) at Indiana University. This effort is supported by a five-year grant from the National Science Foundation Biocomplexity in the Environment initiative (NSF SES008351).

Methodological Pre-Considerations

The ongoing development of LUCITA is designed to complement other research efforts in the Altamira region, as well as those surrounding the development of LUCIM (see section 3.7). Previous research in the Altamira region has focused on the collection of detailed household information, both during the early years of settlement and more recently between 1997 and 1999 (McCracken et al. 1999). Research also has focused on a detailed analysis of land-use and land-cover change and, more specifically, secondary succession in the 1990s (Moran and Brondízio 1998). Multi-temporal analyses of remotely sensed images has revealed that many once-deforested areas are now undergoing secondary succession, indicating that the rainforest ecosystem may be more resilient than was once thought (Moran et al. 1994). In areas of the rainforest that are characterized by agricultural colonization, such as the area near Altamira, Brazil, research has begun to reveal how patterns of deforestation are affected by a variety of factors operating at local and regional scales. At the local scale, land-use decisions are affected by such factors as household composition, available capital, and soil fertility (McCracken et al. 1999). At regional scales, a number of socioeconomic factors, including local credit policies, market opportunities, and inflation rates also can affect the land-use decisions made by individuals (Moran 1981). Such research has revealed the complexity of the interactions that exist between human and natural systems.

While it has been assumed that deforestation rates are directly tied to population increases, an alternate model proposes that land-use changes in the Altamira region should be understood as a product of the age and gender characteristics of farm households (McCracken et al. 1999). This conceptual model maps out a trajectory for families, which relates the type of agricultural practices pursued to the available capital resources and labor pool within each household. Five temporal stages of household composition are proposed by the conceptual model, with each stage of development characterized by increasing levels of capital and available family and male labor. The evolution of colonist households from one stage to another is associated with a trajectory of land uses. According to this trajectory, young families are typically associated with high levels of deforestation and the growing of annual crops. As families age, land uses progress toward reduced levels of deforestation, increased secondary succession, and the growth of perennial crops (Brondízio et al. in press).

An interest in further exploring the importance of individual household characteristics and land-use decisions to patterns of deforestation in Altamira has led to the adoption of an ABM approach. This approach allows the characteristics and preferences of individual households to be directly expressed in the agents specified for the simulation. The pilot versions of LUCITA have included only a small number of endogenous factors, including soil quality, household size and composition, and household capital. Validation of the early simulation output has focused on observing overall changes in land cover and comparing the trajectory of land-use decisions made by the agents with those outlined in the theoretical model. As development of the model continues, we intend to expand the scope of the simulations to explore the effects of alternate agent decision models and incorporate additional endogenous factors on biophysical, institutional, and socioeconomic themes. Throughout this process, comparisons with LUCIM will be made as they relate to the architecture and behavior of the simulations.

System under Study

For the pilot versions of LUCITA, the raster landscape is representative of the intensive study area documented in the KPROG2 model (Fearnside 1986). The study area is situated in the vicinity of Agrovila Grande Esperança, in the municipality of Prainha, in the state of Pará. The area is approximately 50 km west of Altamira, which lies on the banks of the Xingu River, a tributary of the Amazon. The primary reason for selecting this study area was because of the immediate availability of soils data, such as pH. Subsequent versions of the simulation will reference a study region located just to the west of Altamira. The study site lies along the

Transamazon Highway and includes properties along both the main highway and the side roads spaced symmetrically every 5 km. Farm properties in this region are typically 100 ha in size. Properties that are adjacent to the Transamazon Highway have a lot dimension of 500 m by 2000 m and those located off on feeder roads with lot dimensions of 2,500 m by 400 m. Each raster cell has a grid resolution of 100 m, representing an area of 1 ha. For the purpose of generating a raster landscape, each property lot is assumed to be rectangular in shape. The pilot version of the LUCITA was comprised of 236 farm properties.

Currently, there is only one type of agent in this simulation, representing the households that occupy properties in the study area. Eventually, a heterogeneous collection of agents may be employed, adding agents that represent the actions of local or national government agencies.

Model Implementation

LUCITA is comprised of two separate modeling systems that interact through a raster landscape representing the Altamira study region. One system represents natural processes occurring during the simulation, namely changes in soil quality parameters under different land uses, crop yields under different soil conditions, and stages of secondary succession. Changes in soil conditions and crop yields are calculated using a set of differential equations, originally developed by Fearnside (1986) to calculate the human carrying capacity of the Amazon. These equations determine changes in soil characteristics (N, P, Al, pH, C). Additional equations determine crop yields based on soil conditions and the crop grown in a particular cell. Further, cells that are left fallow undergo secondary succession through a simple series of steps.

Interacting with the natural system through the cellular landscape is a collection of agents, each of which represents a single household. Each agent household is assigned a property of 100 ha. Each agent possesses individual characteristics including household demographic composition, household capital reserves. Once during each round of the simulation, the agents make land-use decisions based on their individual characteristics. The architecture of a household agent is described as an object-oriented class and includes numerous parameters such as demographic characteristics, an internal representation of the environment, and a *classifier system* for adaptive learning and decision-making purposes. The architecture of an agent consists of a set of parameters describing the composition of the household, the monthly available family and male labor, available capital, and a rule base where land-use strategies are represented as genetic algorithm strings. Eight land-use strategies are considered, including the production of rice, beans, manioc, maize, black pepper, and cacao, pasture development, and cattle grazing. The classifier system is used for agent decision making with respect to what land use to implement on a given patch of land, given the resources of the agent and the previous experiences with that particular land use.

For initial simulation efforts, agents simply selected land-use strategies that provided the greatest economic return given their existing labor and capital supplies. This approach proved to be ineffective as an agent's behavior could be predicted in most cases. The approach described here uses a modified classifier system, where land-use strategies (rules) are represented as n-binary bit strings. The *bucket-brigade apportionment* of credit algorithm determines the value or fitness of the land-use strategies, where fitness is primarily a function of the return received by the household for growing that particular crop. With this approach, household agents have adaptive capabilities, adjusting their land-use strategies in response to the returns they receive from specific crops and the demographic and financial characteristics of the household.

The simulation is currently designed to represent a 30-year period starting in 1971. Each round of the simulation corresponds to one year. At the beginning of each round, the frequency of each land cover in the raster landscape is tabulated and land-cover transitions that are not made by household agents, such as the progression of a cell through the stages of secondary succession, are made. The criteria used to determine the transition of one land cover to another is based on the previous land cover of a patch of land and the number of years that patch of land has been in continuous use. For example, a patch of land that has exceeded the maximum number of years of continuous cultivation is processed to a stage of fallow, and a patch of land that is at some stage of secondary succession is shifted to a further advanced stage of secondary succession. Following this step, household agents determine if maintenance is required on any of their patches of land and then commit the necessary labor and capital to perform that maintenance. Any new land-use strategies are not considered until after this maintenance event is processed.

For each individual household, providing labor and capital resources are still available, an event is scheduled for the clearing and burning of one patch of land. Those with available resources will clear a cell of land and implement an agricultural land use as selected by the agent's classifier system. The labor and capital resources required to perform these tasks are deducted from the agent's available resources. This process of clearing cells and selecting an agricultural land use is iterated for as long as agents have unused available labor and capital resources for that year.

After the process of land-use allocation is complete, an event is scheduled to calculate the soil changes for each patch of land in a given property. Not only do soil changes need to be calculated for patches of land that have been cleared and burned for new agricultural land uses, but also for those patches of land undergoing some stage of secondary succession. For any given patch of land under any land cover, a set of KPROG2 (see Fearnside 1986) multiple regression equations exists to determine the appropriate changes in soil parameters. Using these changes in soil parameters, an event is initiated to calculate crop yields for each and every patch of land in agricultural use. The crop yield for each land-use strategy is evaluated against the expected crop yield for the number of patches used for production to determine the effectiveness of that particular land-use strategy. For any given land-use strategy, providing the expected crop yield is satisfied, a reward is sent to the classifier system to reward that land-use strategy in the rule base.

For any given simulated year in LUCITA, a series of events is scheduled to simulate the actions of a frontier colonist who practices slash-and-burn agriculture and the associated impacts of those practices on an artificial landscape. At this present stage of development two versions of LUCITA exist - the 1-household version and the landscape version. The 1-household version of LUCITA focuses on exploring simulations at a local scale (one property), so as to provide a basic understanding of how an agent makes decisions, how decision making is affected by variability in environmental conditions, what relationships or feedback loops exist between both submodels, etc. In contrast, the landscape version of LUCITA focuses at a regional scale (236 properties), where only the regional land-use trends are of interest. The rationale of this approach is that if the one-household version of LUCITA is explored to a point that local interactions can be explained and understood, than at the regional scale, there is no need to consider local interactions but rather emphasis can be placed on observing the emergence of regional land-use trends. Processes or actions relevant to the KPROG2 submodel and the human-system submodel are scheduled as events. The two versions of LUCITA differ only in the number of agents scheduling events and the number of properties affected by agent actions.

Currently, the agents do not interact directly with one another, although future versions of the simulation will include agent interactions focused on land markets, the distribution of credit and commodities, and the communication of successful land-use strategies with neighbors.

Verification and Validation

We plan to validate the output of the simulation in terms of both the spatial patterns of land use produced at the aggregate level and the patterns of land-use decision making observed in the individual agents. Land-cover data from remotely sensed images will facilitate temporally based comparisons of the aggregate land-cover patterns produced by the simulations. Household survey data from the Altamira region will facilitate evaluations of the individual decision-making patterns of the agents in the simulations. The overall patterns of land use observed are an emergent property of the simulation, as are patterns of interaction between the agents related to land markets and credit distribution.

Technical Aspects

The simulation platform used in this study is the SWARM Simulation System, a multi-agent simulation platform developed at the Santa Fe Institute (Minar et al. 1996). SWARM provides a set of software libraries written in the Objective-C OOP language to help facilitate the modeling and simulation of complex adaptive systems. We are currently considering migrating the simulations to a Java-based platform such as RePast.

Documentation/Publication

We are currently beginning the second year of a five-year project that started in January 2001. Lim et al. (2002) outline much of the work in the pilot simulation.

3.7. LUCIM: AN AGENT-BASED MODEL OF RURAL LANDOWNER DECISION MAKING IN SOUTH-CENTRAL INDIANA

Dawn C. Parker

The work described in this summary is the result of contributions from past and present members of the CIPEC modeling/biocomplexity team, including Jerome Busemeyer, Laura Carlson, Cynthia Croissant, Peter Deadman, Tom P. Evans, Matthew J. Hoffmann, Hugh E. Kelley, Vicky Meretsky, Emilio Moran, Darla Munroe, Tun Myint, Robert Najlis, Elinor Ostrom, Dawn Parker, David Reeths, Jörg Rieskamp, James Walker, and Abigail York. Since January 2001, this team has worked to develop a multi-agent model of rural residential landowner decision making in

Monroe County, Indiana, USA. Development of this ABM/LUCC— LUCIM (Land-use Changes in the Midwest)—is supported by a five-year grant from the U.S. National Science Foundation Biocomplexity in the Environment initiative (NSF SES008351). During our first year, we drafted a template for the ABM/LUCC, started development of strategies for empirical evaluation of model outcomes, and designed preliminary economic experiments that will be used to inform our model of household decision making. The following discussion focuses on these initial efforts. Many challenges remain, however, and our modeling and evaluation strategies will likely evolve as the project continues.

Problem and Research Question

Typical of much of the eastern United States, south-central Indiana experienced massive deforestation during the second half of the nineteenth century, followed by a period of gradual reforestation beginning in the early twentieth century and continuing to the present day. However, while net reforestation has occurred, patterns of land-use change are not uniform, with agricultural abandonment contributing to reforestation in some regions, and urban growth pressure contributing to deforestation in others (Munroe and York 2001). Heterogeneity among both biophysical (topography and soil quality) and socioeconomic (demographic and regional economic growth) factors appears to play an important role in observed patterns of deforestation and reforestation. The goal of our project is to explore, via a multi-agent model of rural residential landowner decision making, how individual decisions of heterogeneous landowner households, influenced by variations in local biophysical conditions, impact observed patterns of land-cover change in the region.

Methodological Pre-Considerations

Prior to development of a pilot ABM, CIPEC researchers explored a variety of land-use modeling techniques: game theoretical analytical models (Ostrom et al. 1994, Ostrom 1998), system dynamic models using Stella (Costanza et al. 2001; Evans, Manire, et al. 2001); and various statistical modeling techniques (Evans, Green, and Carlson 2001). They found each of these techniques to have substantial utility and will continue to use them in various related projects. However, several factors led the group to conclude that ABMs would be the most useful for this research endeavor. The first was a goal of exploring how diverse theories of human behavior embedded within socioeconomic and political structure affected land-use decisions over time. The second concerns several factors that appear to influence patterns of forest cover in south-central Indiana. Substantial heterogeneity exists among local decision makers with respect to goals, attitudes, and socioeconomic characteristics. Biophysical heterogeneity also impacts the potential success of particular land uses. The spatial distributions of both kinds of heterogeneity are distinct and overlapping, creating a potentially diverse spatial mosaic of outcomes as differing decision-making strategies are combined with a diverse mosaic of biophysical conditions. Further, spatial interdependencies, such as diffusion of information about timber prices and soil erosion, likely have a substantial influence on household decision making and subsequent impacts on landscape pattern. This complex combination of heterogeneity and spatial dependencies can be prohibitively difficult to represent using a purely analytical model. Econometric-based statistical models, economic experiments designed to inform our model of individual decision making, and analytical models of specific simple processes will supplement the ABMs.

We see the flexibility of the ABM approach as a major advantage, especially in terms of spatial representation. However, we have observed that comparison of alternative models of agent decision making has been sparse. Thus, we have chosen to make comparisons of alternative decision-making strategies a major focus of our modeling efforts. We have concluded that the majority of agent-based models developed to date lack a strong empirical focus. We feel that development of an agent-based model with a solid empirical grounding, usable for testing hypotheses with real-world data, will be a substantial, cross-disciplinary contribution. Therefore, while we will strive for a parsimonious representation of our system, we also will strive to build a model that appropriately represents southern Indiana, drawing on empirical sources from historical documents, census and survey data, expert interviews, and preceding academic literature. The availability and quality of such data are relatively sparser for frontier times and richer for the more recent past. Therefore, although a prototype model developed by Hoffmann et al. (in press) models the process of deforestation and reforestation that has occurred from the mid-nineteenth century to the present, the model currently under development focuses on the time period from around 1950 to the present.

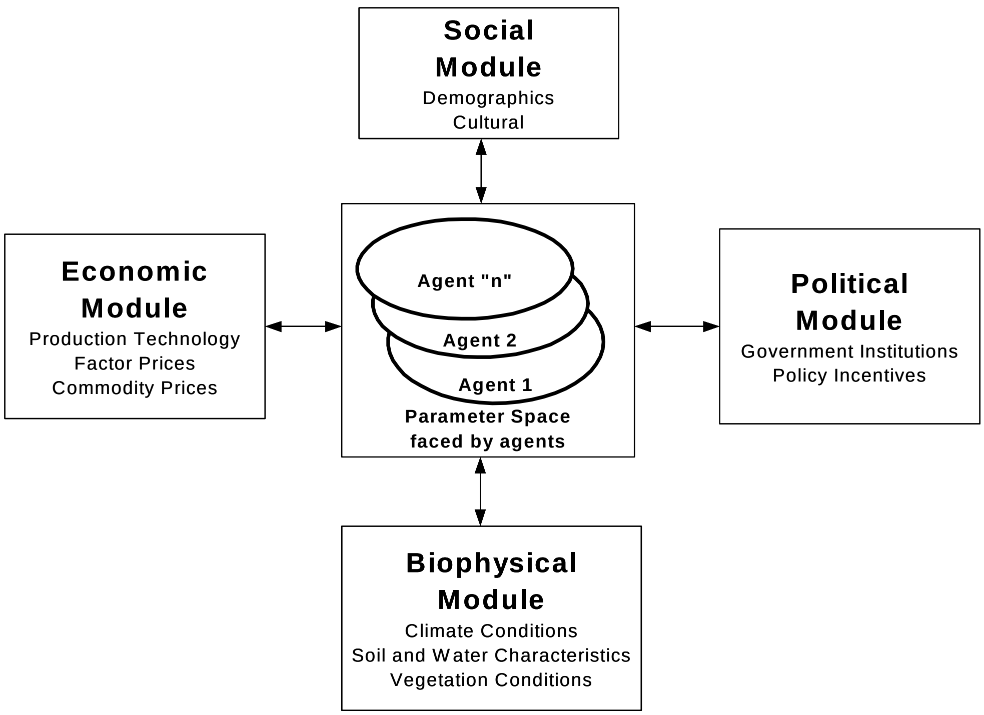
As a complement to this larger model, we also will develop simpler ABMs of specific, stylized processes in order to examine alternative processes that may lead to emergent social phenomena, such as broadly accepted norms or even evolved rule systems (see, for example, Janssen and Ostrom 2001). In such cases, we may not be immediately interested in testing predictions in a specific environment.

In our modular model structure (Figure 14), one-way arrows represent flows of exogenous information, while two-way arrows will represent endogenous interactions. Certain factors, such as climate, will always be taken as exogenous. Initially, political factors and demographic influences will be exogenous. However, we are exploring possible approaches to modeling the endogenous development of institutions. Within the economic module, prices and wages will be modeled as exogenous. However, modeling of endogenous land markets is a high priority. A vegetation growth model will reflect interactions between agent decision making and the biophysical state of the landscape.

System under Study

Our research focuses generally on a nine-county area of south-central Indiana, from frontier times (roughly 1860) to the present day. Frontier settlers relied on their land for subsistence, and incrementally cleared their land of timber in order to plant corn. They also relied on timber for housing, fuel, and building materials (Parker 1991). Much of the region is characterized by non-glaciated, highly sloped land of marginal quality for agricultural production. Thus, these lands were quickly degraded, and, for the most part, agricultural production has been abandoned as the region has become integrated with national markets. However, the region produces high-quality hardwood timber, and non-industrial private forestry remains an important economic activity.

Land use in the region currently consists of a mix of urban/residential, agriculture, and forested land. Few full-time farmers remain in the region, although many landowners practice both part-time farming and forestry. The region has experienced substantial urban growth pressure and conversion of open land to both high- and low-density residential land use. In terms of modeling individual decision making, we have chosen to focus solely on the rural landowner. Therefore we plan to model demand for high-density residential conversion as exogenous.



Models and agents impact each other at a level that is dependent on the degree of complexity being investigated. In the case shown, there is a two-way information and/or impact flow between the decision maker and all modules. Alternative models contain one-way interactions between the agent and some modules, as well as interactions between modules.

Models and agents impact each other at a level that is dependent on the degree of complexity being investigated. In the case shown, there is a two way information and/or impact flow between the decision maker and all modules. Alternative models contain one way interactions between the agent and some modules, as well as interactions between modules.

Source: Hoffmann et al. 2002.

Figure 14. The Modular Decision Setting with Multiple Agents

Model Implementation

Initial model development will focus on a three-township region of Monroe County, Indiana, USA. Each township is approximately 36 square miles. We plan ultimately to model Monroe County in its entirety (2000 population estimated at 120,563 by U.S. Census Bureau). The model will run initially on an annual time step, which corresponds to the time scale relevant for household agricultural production decisions. Currently, three land uses are possible in the model: forestry, agriculture, and pasture. Agents also will have the option to sell their land in future versions.

The model currently runs at a spatial resolution of 30 meters, although we plan to run it at multiple spatial resolutions up to 200 meters. Our determination of appropriate spatial resolution will be reached through further investigation of the minimum-sized areas over which land managers make decisions, the spatial scale at which our biophysical growth model can plausibly operate, an assessment of the scale at which key socioeconomic and biophysical processes are relevant, and the particular methods that we use to evaluate model performance.

Our agents are modeled as striving to increase subjective well-being (“utility”) in a stochastic environment, subject to constraints on monetary and physical resources. Input and output prices, aesthetic values, risk aversion, and income and education levels all impact agent decisions. Agents may vary with respect to their decision technology (e.g., the deductive optimization of the classic Homo Economicus or the inductive optimization of a boundedly rational search algorithm) and with respect to their learning algorithm (e.g., Bayesian, Neural Net, Reinforcement, or Genetic Algorithm). Currently no agent-agent interactions are included, although over time we plan to add interactions through social and information networks and land markets.

A forest-growth model will be an integral part of our model. Given information on soil type, slope, topographic context, and initial vegetation, the model will return an estimate of tree species and height composition (with species in groups by economic value). Growth and natural mortality rates will be modeled using an average for the species group, and a very simple ingrowing algorithm will add young trees over time. Initially, only clear cutting will be modeled; at least two varieties of selective cutting and more realistic in growth will be modeled in later versions. Impacts of climate, fire regime, and grazing also will be modeled in later versions if sufficient data can be compiled.

The model explicitly represents overlapping social and biophysical spatial fields, such as land-use zoning designations and soil classes, and includes a cellular automaton component designed to potentially represent a range of neighborhood influences on a particular cell, such as spatial economies of scale, spatial externalities, information diffusion, and soil erosion. Decision-making agents will not be tied to a particular location, as they can theoretically own parcels in several locations. However, transportation costs as determined by road networks will influence agent decision making. Further, landscape patterns such as parcel size and compactness also may influence agent decision making.

While we are quite interested in the emergence of land-use zoning regulations, since zoning laws (even in their existence) vary considerably within the nine-country region, we do not plan initially to model their formation. However, in later versions, we hope to incorporate endogenous rule and institution formation. Initially, we plan to populate our landscape with a distribution of agents with demographic characteristics consistent with census data. We then plan to allow them to interact via land markets. The details of land market interactions are not yet finalized.

Agents are potentially heterogeneous with respect to abilities, resources, and decision-making strategies. Our model includes many sources of spatial heterogeneity that we believe have an important influence on land use and land cover in the region, including topography, soils, initial land use/land cover, and accessibility. Two sets of interdependencies will play an important role in the model: temporal interdependencies based on interactions between agent decision making and the biophysical growth model, and spatial interdependencies based on the CA/spatial diffusion mechanisms described above.

Verification and Validation

We plan to run extensive simulations that map changes in model parameters against model outcomes. We also plan to run simplified versions of the model for which an analytical solution also can be calculated to ensure that our results are consistent with existing models.

Our work will rely on a variety of data sources for both model parameterization and model validation:

- Land cover from aerial photographs
- Parcel boundaries and ownership information from county assessor's records
- Elevation and soils coverages
- Historical data series on prices, sectoral economic activities, zoning regulations, agricultural subsidies
- Information from a recent survey of local rural landowners
- Data from the U.S. Census Bureau on population and housing and the U.S. Agricultural Census (U.S. Department of Agriculture)
- Results from economic experiments

We will face several challenges regarding data integration. A major challenge relates to the need to spatially disaggregate census data to parameterize a distribution of agent types over space. Since spatial data are available in a variety of formats and resolutions, we will face the challenge of scaling up to determine land cover for particular parcels or contiguous spatial areas over which households make their decisions. Finally, we find that most available forest-growth models operate at a much finer resolution than a reasonable minimum decision-making unit for our behavioral model. We are planning to model a distribution of lumber types for each parcel, creating an additional challenge of developing a price index for the single "harvesting" activity on a given forest parcel.

We have identified a series of macroscopic outcomes to use for aspatial model validation, including on- and off-farm employment, farm income, agricultural production, timber sales, and the distribution of farm sizes at the county level. We plan a strategy of evaluating model performance through comparison of landscape composition and landscape patterns measures, as described in Parker et al. (2001). This strategy includes statistical comparisons of landscape composition and pattern statistics between our simulated and actual landscapes, potentially dividing landscape into non-overlapping regions in order to create a distribution for purposes of hypothesis testing. We plan to compare across multiple spatial scales, controlling for spatial attributes such as topography, soil type, and transport costs. We see our focus on empirical assessment based on landscape pattern as an important innovation. By linking social, economic, and political factors to their potential impact on landscape pattern, we will develop a clearer understanding of the relationship between landscape pattern and socioeconomic function. Further, since landscape pattern is a critical indicator of ecosystem health and function, landscape pattern assessment will allow us to link socioeconomic changes to their ecological impacts.

Our research identifies landscape pattern, measured via landscape metrics, as an important potential emergent property. We hope to explore rules and institutions as emergent phenomena.

Technical Aspects

The current model is implemented in the Matlab package. Several factors motivated the choice to use Matlab. It has several important features useful for large-scale agent-based modeling and testing: optimization routines for parameter estimation, sparse matrix techniques, matrix operators, advanced graphical package, GUI interface development, SIMULINK dynamic systems application package, and interfaces with C and JAVA. Nonlinear optimization routines speed parameter estimation, and sparse matrix functions allow storage and manipulation of large matrices in memory. Matlab has an easy-to-use graphics function and facilities for building GUIs. Finally, Matlab can run on both Unix-based and Windows systems, and it can be compiled in C for faster run time.

Documentation/Publication

The project has a five-year time line, having commenced January 2001. Updated information and a publication list are available at http://www.cipec.org/research/biocomplexity/. We are investigating the possibility of using UML for model development and documentation. Upon completion of our project, we plan to make model code available to other researchers, most likely under an open source licensing protocol.

3.8 THE SELFCORMAS EXPERIMENT: AIDING POLICY AND LAND-USE MANAGEMENT BY LINKING ROLE-PLAYING GAMES, GIS, AND ABM IN THE SENEGAL RIVER VALLEY

Patrick d'Aquino, Christophe Le Page, and François Bousquet

While we focus on one particular study in the following description, it is one of many activities that focus on ABMs and land-use and land-cover change. In addition to using ABMs (Barreteau and Bousquet 2000) and actively developing the CORMAS (Common-Pool Resources Multi-Agent System) simulation platform, our project engages in more traditional modeling and simulation resource-management scenarios (Rouchier and Bousquet 1998; Barreteau and Bousquet 2000; Bousquet, LePage, et al. 2001) and more theory-oriented explorations of artificial societies (Antona et al. 1998, Rouchier and Bousquet 1998, Bonnefoy et al. 2000, Rouchier et al. 2001).

Problem and Research Question

We focus on renewable resource management within the context of nature-society interaction. We are interested in methodological frameworks that both support and are developed from collective decision-making processes. We believe there is an important role for methodology that allows the simulation and analysis of multiple scenarios of important environmental systems. This approach supports a collective, adaptive learning process that directly involves stakeholders in incremental model design, elaboration of scenarios, and running experiments and using their results.

Methodological Pre-Considerations

Agent-based models are more capable of representing system dynamics than GIS, and are better than differential equations for taking into account the heterogeneity of actors, their local interaction, and their learning and adaptation processes. It is also easier to translate what stakeholders believe into digital representations within an agent-based modeling framework, especially when compared to one based on mathematical equations. This ease of representation is crucial to dealing with stakeholders who require readily understandable representations of local situations.

Flexibility is another key benefit of agent-based models. Models must be easily and quickly modified (in a direct, interactive way) to match the suggestions of stakeholders when they are discussing a simulation experiment. This modification is not limited to parameter values, but also extends to model structure, such as adding landscape elements or changing the accessibility of spatial regions to agents. Modeling frameworks also must support easy changes of behavioral rules that govern what agents perceive or how they reason.

We have found collective design exercises and the use of agent-based modeling is not very common in the land-use/land-cover change community. We have therefore drawn lessons from environmental researchers who use role-playing games approaches. We substitute agent-based models for traditional role-playing games because they offer a quicker way of simulating and comparing several scenarios to each other and to reality. The basic role of the model is to stimulate reactions and trigger the proposal of solutions to resource dilemmas. These in turn are repeatedly discussed and retested through simulation.

System under Study

We focus on three villages located on the Senegal River delta in an area of approximately 2,500 km^2 with 40,000 inhabitants.

Model Implementation

We develop three different models based on a common framework of a virtual landscape that is modified by different land-use activities. We consider the structure of the model itself a study result since it reflects the collective agreement of stakeholders on the nature of basic behavioral rules incorporated into the model. At present, we focus on unexpected situations and system properties rather than emergent properties as such due to the simplicity of the model. The project was started in 1997, and we tested the feasibility of the methodology in April 2000. A new set of experiments is scheduled to begin May 2002.

The virtual landscape in the model is a lattice of 400 rectangular cells. Our chief focus is on population living around villages. The temporal period being modeled is one year with a time step of one month. Agent activities begin during the wet season starting in October. This particular model runs at a single spatial and temporal scale but we are moving toward integrating entities defined at several scales.

We consider households that engage in grazing, hunting, fishing, and single- or double-rotation rice cropping. Agents are either settled in one location or they migrate according to specific decision-making rules. Decision making is simple in that agents engage in activities designed to maximize returns as a function of landscape characteristics. Each grid cell has attributes considered pertinent by the stakeholders for each case study, such as distance to water or soil type. Also important is accessibility to cells for each kind of activity as a function of land tenure and time frame. Unless explicitly stated by the stakeholders, each cell is initialized as being accessible for any kind of activity at any time. We use a GIS to initialize the virtual landscape with information provided by the stakeholders, but everything else is considered endogenous in order to avoid a priori assumptions. Stakeholder information is gathered and formalized over two days. Other data include spatial layers, remote sensing, and some other data surveys.

Farmer agents are able to perceive the whole environment. Agents choose locations for their activities on a first-come/first-serve basis. Agents are randomly chosen each time step to avoid bias due to the order in which agents are considered. Sociopolitical phenomena such as endogenous rule formation or institutions are not included in the model. Agent interaction is limited to indirect competition for space.

In terms of ecological modeling, cell-based transition rules account for vegetation succession. Cells with cropping residuals, for instance, are sought after by the farmers for a month after crops are harvested since they are good for pasture. There is also seasonal variation of the quantity of water and its quality due to salt content.

Verification and Validation

We seek to reproduce with the model what has been observed during the role-playing game. We start with sensitivity testing to ensure the model structure is coherent. We then validate the model by asking stakeholders to ensure it is in keeping with their view of the system and that it can usefully support discussion of land-use/land-cover change.

Technical Aspects

CORMAS is developed onsite since intimate knowledge of platform implementation best guarantees the flexibility we require. Development of CORMAS is aided by the fact that we use it in various contexts related to natural resources management. This allows us to incrementally improve it.

Documentation/Publication

The web site for this project and resulting publications is: http://www.cormas.fr. Project-related publications include d'Aquino, Barreteau, et al. (2002); d'Aquino, Le Page, et al. (2002); Lynam et al. (2002); Bousquet, Trébuil, et al. (2001); and Bousquet et al. (in press).

3.9 SPRAWLSIM: MODELING SPRAWLING URBAN GROWTH USING AUTOMATA-BASED MODELS

Paul Torrens

Problem and Research Question

The focus of the SprawlSim project at University College London's Department of Geography and Centre for Advanced Spatial Analysis is on developing models for testing ideas and hypotheses relating to the study of the mechanisms driving suburban sprawl in North American cities and the spatial patterns that sprawl generates, as well as testing potential measures for controlling the phenomenon. The emphasis is on constructing innovative, highly dynamic, interactive, and theoretically informed simulation tools capable of supporting exploration at multiple spatial scales, from the region to individual parcels of land and the individuals who occupy them. The methodology used to develop the simulations relies heavily on automata-based modeling techniques, which have been adapted to make them useful for spatially explicit contexts.

Methodological Pre-Considerations

Traditionally, urban models have been understood to suffer from a variety of flaws, including inadequate flexibility, lack of usability, poor attention to detail, constraining assumptions, and a lack of real dynamics (Lee 1973, Sayer 1979, Torrens 2000b). To a certain degree, the limits of modeling technology for simulating cities have constrained the type of research questions that can be explored through simulation. In recent years, however, several developments in the geographical sciences have enabled the development of a new class of models for urban studies (Benenson and Torrens 2002). In particular, the adoption of the idea of the automaton from computer science, and the adaptation of the concept from non-spatial domains into an explicitly geographical context, has been particularly influential (O'Sullivan and Torrens 2000, Torrens 2002). Those interested in developing models of urban systems now have access to tools for simulating cities at the level of individual units of the built environment and the individuals who occupy them, as well as the dynamic processes that describe the interactions between them (Torrens 2000a). However, the use of automata in urban studies is a relatively new field of academic inquiry and, unlike traditional urban models which have been widely used in practice, the simulation technology has not yet enjoyed much practical application. A number of important questions remain for automata-based modeling (Torrens and O'Sullivan 2001). Nevertheless, research into the field is particularly active, and challenges facing the development of technology for practical application are rapidly being overcome (Torrens and O'Sullivan 2000).

The development of the SprawlSim model is as much an exercise in geographic model building as it is an application of simulation to urban studies. Development of the model has been pursued with attention to addressing some of the weaknesses of automata-based models in spatial simulation: scaling issues, validation, interoperability with conventional urban simulation methodologies, and hybridization of diverse automata-based simulation techniques (Torrens 2001). The model is modular in fashion, with various components devoted to simulating individual subsystems important to the understanding of the geography of sprawl: sociodemographic growth and decline at a regional scale, the allocation of population and opportunities to aggregate levels of geography at an intra-urban level, the formation of new clusters of urban development on the urban fringe, and individual-level models of land development, residential location, and land-use transition (Figure 15).

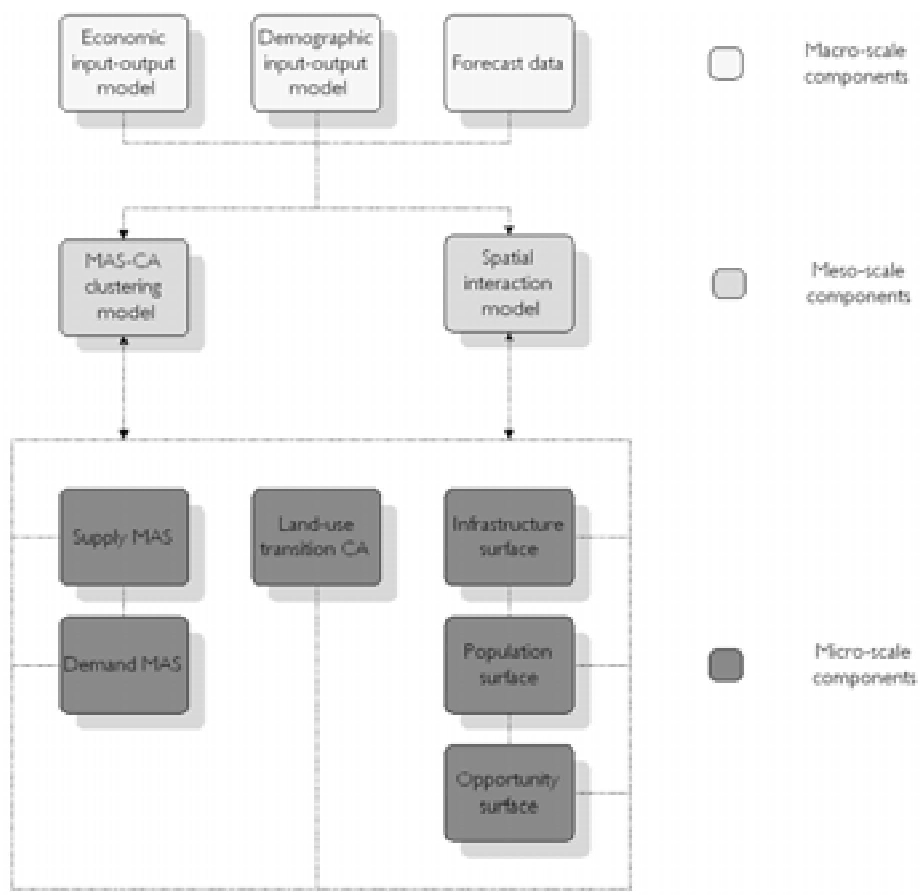


Figure 15. SprawlSim As a Set of Integrated Components Organized by Subsystem and Spatial Scale

The automata used to simulate interactions at micro-scale geographies are composed as a hybrid system: Cellular automata are used to represent the urban infrastructure, and ABMs model the development of land for urban uses and the population that inhabits that infrastructure (Figure 16). Interactions take place between individual cells in the CA and between agents in the ABM. In addition, agents have the capacity to alter state variables in the CA, and in turn be influenced by the dynamics that take place in those models, allowing for exchanges between people and the environments that they inhabit. There is also a set of models that act exogenously from the automata-based models, representing processes that might take place beyond the systems of interest, such as geographical inertia in initial settlement patterns (represented as "seeds": initial starting environments for a model run), and population growth through in-migration and demographic factors (supplied as constraints).

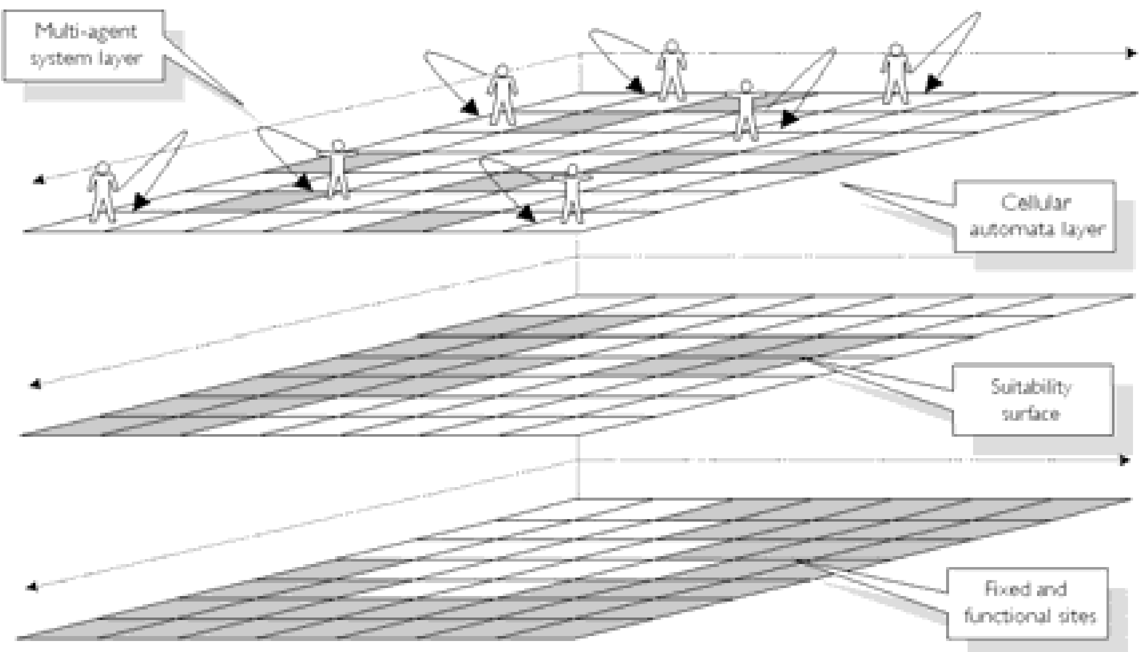


Figure 16. The Hybridization of Cellular Automata and Multi-Agent Systems in SprawlSim

System under Study and Model Implementation

The model is being developed, generically, to represent a "typical" North American city, as the emphasis is on developing a viable and innovative simulation structure and deriving theoretically justifiable rule sets to drive model dynamics. Two modules are reasonably well developed at this stage: a clustering module that operates at macro-level geographies, determining where new urban clusters will be developed at the urban fringe, and a residential location module that operates at micro-level geographies for a hypothetical submarket within a generic city.

Development Module

The clustering component has been tested, in a very general sense, for the Midwestern Megalopolis, encompassing the Milwaukee-Chicago-South Bend urbanized area. It is organized in the following fashion:

External models: Growth rates are derived from census models; likely seed sites for development are coded into the model at the outset of a run.

Agents: developers and resident population

States: (1) developable or not; (2) developed or not; (3) population count (density)

Spatial topology: 484 x 598 square cells (not all active) covering a 300-by-450 mile area

Behaviors: purely spatial

Neighborhoods: CA have nine-cell neighborhoods; agents are free to explore the whole of the model.

Temporal domain: 200 iterations (one year per iteration)

The development module also makes use of suitability surfaces—CA layers that form a landscape of "attraction" for agent-based automata—to supply known conditions: likely seed sites for initial urban growth, as well as fixed (inactive) and functional (active) spaces (White and Engelen 1997). Population growth rates are supplied exogenously, calculated from historical census population data. The transition rules—the formulae that determine how automata should interpret their environments and surroundings—driving model dynamics are formulated in an explicitly spatial manner. The main rule for determining development decisions is formulated as follows:

$$S_{t+1} = f\,(S_t, ßG_c, ßG_a, ßL, ßR_l, ßR_i, ßD),$$

where S is a state descriptor and *ß*-values are weights used to adjust the degree of influence of transition rules.

Agents in the model are programmed in such a way that they represent two groups: developers constructing properties on the land, and a general population of agents that then inhabit those areas. Various rules describe how developer agents should explore the urban infrastructure and develop the CA landscape they encounter: growth and development in a compact manner (G_c), by agglomeration (G_a), or in a fragmented fashion by leapfrogging (L); building roads between existing nodes (R_l) or in a random and irregular fashion (R_i); or even demolishing sites and rendering them vacant (D). We currently are working on an ABM of developer decisions, modeled at more micro-level geographies, to describe the socioeconomic factors that lie behind these development behaviors.

Residential Location Module

The second module handles the simulation of location decisions of households that inhabit the simulated cities. Currently, one such hypothetical residential submarket is simulated. The residential location module is much richer in its description and functionality when compared to the developer module. The purpose of the residential location module is to simulate the decisions that govern households' decisions to leave their homes, seek out new residential locations, and settle on properties within those submarkets, as a function of the geography of a residential submarket, the socioeconomic and sociodemographic profile of households that make up that submarket, and the internal characteristics of the relocating household itself. The idea is to link the residential location component to its developer counterpart in such a way that the model characterizes both the development and redevelopment of new sites, and the dynamics that populate those areas.

The residential location module is organized in the following fashion:

Geography: four scales of geography, including world, submarket, residential unit, and householder

Agents: settled and relocating households

States: variables describing

- submarket properties: number of households, proxy for ethnicity, median income, median age, distance to central business district
- property conditions relevant to sale/rental: sale or rental status, property type, tenure, price, lot size, land-use, number of bedrooms
- life-like attributes of households: type (relocating or settled), household size, household income, median age, number of children, proxy for ethnicity, period of residency

Spatial topology: 250 x 250 square cells for the CA

Behaviors: derived from residential location theory and urban economics

Neighborhoods: cellular automata organized in nine-by-nine cell neighborhoods; agents have full freedom to explore the model "world"

Temporal domain: model iterates through housing search cycles (roughly three months)

Transition rules are based around a series of preference calculations that describe how agents in the model should process the opportunities that are available to them, both at the level of submarket attributes and the characteristics of individual properties: sociospatial and socioeconomic preferences, tenure preferences (rent or own), housing preferences (house or apartment). In addition, there are rules that determine a household's willingness to leave their home and seek a new location, as well as rules that match relocating households' preferences with available opportunities.

Verification and Validation

Verification and validation issues are important considerations in the model development, particularly because the model is going to be tested against some policy scenarios: growth management strategies that operate at macro-scales of geography (urban growth boundaries, green belts) and at individual scales (developer incentives and impact fees, land-use zoning).

Several metrics have been developed to measure the patterns of sprawl produced by the model and to register them against similar patterns discovered in practice (Torrens and Alberti 2000).

These metrics make use of typical geographical descriptors such as population density gradients and surfaces; weighted areal means measurements of fragmentation; fractal dimension; gravity-based (flows between origins and destinations determined by distance and attractiveness) and utility-based (mathematical expressions of the use derived from a given location) measures of accessibility; and isochronic (travel within a given time budget) accessibility measures. In addition, we have been experimenting with the use of techniques from landscape ecology to measure the composition and configuration of sprawled urban areas. However, with the exception of the accessibility measures, each of these metrics is pattern based; we do not yet have a reasonable solution for deriving process-based measurements.

Technical Aspects

Until recently, the model was developed mostly in NetLogo and StarLogoT2001 (Center for Connected Learning and Computer-Based Modeling 2001a, b), outputting model runs as a series of snapshots that are then run through some custom Java code for animation. The StarLogo and NetLogo environments enable the development of CA and ABMs with a relative degree of ease, allowing developers to focus on the derivation of intuitive rules sets and descriptors for their models. However, the environments were not designed for large-scale modeling and soon become unwieldy and cumbersome when confronted with complicated models. Also, the environments are not well disposed to handling real datasets. For this reason, construction of the model has now moved to custom-designed development in Java. Other, more *extensible* systems have been explored, including SWARM (Swarm Development Group 2001) and Ascape (Brookings Institution 2001), but the most promising avenue of exploration for our needs has been RePast (University of Chicago 2001). It is likely that the project will make use of open-source libraries in this package to reduce the overhead of model construction and native Java libraries for distributing processing. There is also the possibility of wrapping individual modules as Java Beans, for integration with existing land-use and transport models, such as UrbanSim (Waddell 2002).

Documentation/Publication

For further details, consult the project website at http://www.geosimulation.com, where the models and technology behind them are discussed in detail; there is also a comprehensive bibliography of papers and presentations related to the project at that URL, and each is available for download. To contact me, send an email to ptorrens@geog.ucl.ac.uk.

Part 4 Synthesis and Discussion

Dawn C. Parker and Thomas Berger

4.1. SYNTHESIS AND DISCUSSION OF ONGOING RESEARCH

This final section is organized as follows. In the remainder of section 4.1, we refer to the list of methodological requirements for LUCC outlined in section 1.2. We proposed at the beginning that ABM/LUCC are promising tools for addressing these methodological challenges. Here we evaluate the extent to which the ongoing research presented in sections 3.2–3.9 is relevant for the proposed methodological challenges and find that the work does substantially address a majority of these challenges. However, some challenges will be identified that still remain to be addressed in more detail. We then summarize a series of open modeling questions discussed during the workshop. Finally we discuss several potential roles for ABM/LUCC beyond those described as needs by McConnell in the preface and Lambin et al. (1999).

Process-Based Explanations

The first of the methodological challenges relevant for LUCC relates to the notion of a process-based explanation. A process-based explanation arises from a structural representation of system dynamics, which can be used to explore, illustrate, and formally test causal relationships between changes in system parameters and endogenous outcomes. The models discussed in sections 3.2–3.9 meet these criteria, as each formally links a flexible model of agent decision making to environmental outcomes. Most models also allow dynamic feedbacks between human decision and the natural environment. These human-environment dynamics are discussed below.

Spatially Explicit Models of Agent Behavior

All of the models presented in sections 3.2–3.9 are spatially explicit according to the criteria outlined by Goodchild in section 2.2.1, although the importance of spatial concepts to model outcomes varies among applications. All models incorporate cellular representation of the landscape on which agents make decisions. Several incorporate distance-dependent spatial interactions: land distribution mechanism in FEARLUS, CA-based ecological process models in SYPR, information flows in LUCIM, distance to water in SelfCormas, and neighborhood land markets in Berger’s model (see section 3.4). Spatial heterogeneity is represented in FEARLUS, LUCIM, LUCITA, Berger’s model, and SprawlSim. Interestingly, few models explicitly include spatial networks. Berger’s hydrology model is an exception (see section 3.4). This omission is surprising, given the demonstrated theoretical and empirical importance of transportation networks and transportation costs on land-use decisions. However, the omission may be due to the difficulty in representing networks outside a GIS environment. Direct integration of ABM software may facilitate inclusion of spatial networks within GIS environments in the future.

Representation of Socioeconomic-Environmental Linkages

Many of the models explicitly address social-environment interactions by linking a model of agent decision making to models of biophysical processes. Berger links agricultural land use and irrigation technology to crop yield and hydrology. The LUCIM model relates land-use decisions about agriculture, timber harvesting, and recreational/aesthetic use of forest to biological characteristics such as forest size and composition through a forest-growth model. The LUCITA model uses an agroforestry and soil productivity/quality model to determine potential yields from agricultural activities and to calculate the subsequent impacts of agricultural decisions on soil quality. The SYPR model incorporates a generalized CA that determines local vegetation growth and nuisance species populations. The MameLuke model will include soil fertility and erosion models. The SelfCormas model incorporates a simple vegetation regrowth model. Thus, it appears that a healthy exploration of the potential of ABM/LUCC to build interdisciplinary models is underway.

Representation of a Diversity of Human Agent Types

Many researchers both implement heterogeneous representations of particular agent types and represent multiple agent types within their models. The LUCIM model explores the impacts of diversity in preferences, learning strategies, and decision algorithms among rural land managers. The LUCITA model, working from previous field research, explores how differences in household composition and experience impact land management decisions over time. In Berger’s model, heterogeneous thresholds for adoption of new technologies combine with the influence of social networks to determine paths of technology adoption. Berger also develops and applies a method to estimate these behavioral parameters from household survey data. The FEARLUS model implements three separate models of decision making: contentment, innovative, and imitative strategies. The MameLuke model intends to represent several agent types: farmers, loggers, government agents, traders, and landlords. The primary actors differ according to decision strategies, goals, and risk preferences. The SYPR model compares several agent decision strategies, including heuristics, estimated parameter models, and genetic algorithm representations of boundedly rational decision strategies. The SelfCormas model represents decision-maker heterogeneity directly, since local stakeholders interactively determine model rules and structure. SprawlSim relates variations in household size, income, ethnicity, family size and age, and length of residential tenure to residential location decisions. Further, both urban residents and developer agents are implemented. Thus, it is evident that researchers are exploiting the ability to represent heterogeneous decision makers in ABM/LUCC, and that agent heterogeneity can play a central role in the research questions being studied with such models.

Representation of Impacts of Heterogeneous Local Conditions on Human Decisions

As appears to be the case with representation of a diversity of agent types, heterogeneous influences on decision making play an important role in the majority of studies. In LUCIM, agent land-use decisions are influenced by diverse conditions of topography, soil types, accessibility, and land cover. In LUCITA, diverse soil conditions and land cover also play an important role. In Berger’s model, both soil conditions and technology adoption decisions of physical and social neighbors influence cropping and investment decisions. In FEARLUS, on-site biophysical heterogeneity, as well as the influence of physical and social neighbors potentially impact agent decisions. In the MameLuke model, local topography, water availability, and soil fertility will determine payoffs to various land-use choices. In the SelfCormas model, soil conditions, land tenure, and distance to water influence satisfaction thresholds. Once again, the flexibility of ABM/LUCC appears to be heavily exploited. Interestingly, both spatial and aspatial heterogeneity have important influences on model outcomes.

Ability to Analyze the Response of a System to Exogenous Influences, Technological Innovations, Urban-Rural Dynamics, and Policy and Institutional Changes

Many projects are designed specifically to examine the impacts of exogenous factors such as technological innovations, urban-rural dynamics, and policy and institutional changes on land-use. This goal is consistent with the process-based representations possible in these models. The FEARLUS project is designed with the specific goal of analyzing land-use change that may result from new legislation, changes in global markets, and global climate change. The MameLuke model attempts to trace the impacts of shifts in market prices, changes in logging policies, road construction, and changes in land tenure regimes on village-level changes in land use. SYPR can be used to analyze the impact of exogenous economic and institutional changes, such as market prices, government subsidies, and rules concerning land access and use. SprawlSim will be able to track links between population growth rates, decisions of developers, and resulting patterns of urban sprawl. Balmann (see appendix 1) measures the impacts of specific government interventions on the farm sector and calculates the adjustment costs of different environmentally motivated policies. Berger (see section 3.4) assesses the effects of market integration, publicly funded investment and extension programs on land use, technological change, and migration. Thus, these models appear to hold promise as tools for policy analysis.

Integration and Feedbacks across Hierarchical Spatial and Temporal Scales

While participant discussions repeatedly identified cross-scale representation as an important capability of ABM/LUCC, these capabilities have not to date been translated into implementation. While top-down analysis of the impact of exogenous influences could be literally viewed as a representation of cross-scale interactions, we see that such representations are limited to examining the influence of exogenous parameters, such as prices and subsidies, on local decisions. As will be discussed in section 4.2.2., changes in decision making resulting from changes in political or institutional conditions on the whole remain unrepresented. The challenge of representing political and institutional decision making is an obvious explanation for this deficit. One explanation is that formal analytical theories of the influence of economic factors on decision making have a long history, while such formal analytical theories remain less well developed for political and institutional influences. Several research projects propose to implement cross-scale interactions and hierarchical agent representations. Berger and Ringler (2002) propose the integration of mathematical programming approaches into a multi-level multi-agent framework and discuss possible forms of implementation. The MameLuke model plans to implement cross-scale interactions between institutional and policy actors and individual decision makers, drawing on the action-in-context framework (De Groot 1992). Further, direct integration with the meso-scale CLUE model is intended. The SprawlSim model proposes to integrate processes affecting urban development at multiple scales, from local residential location decisions to regional sociodemographic growth and decline.

While cross-scale dynamics clearly play an important role for land-use and land-cover change, it is worth considering whether implementation of cross-scale dynamics within highly empirical models (i.e., cell #4 models in section 3.1) is called for as a next step. It may be important to meet the many open challenges related to building a sound, well-parameterized and well-understood model of processes from the bottom up, before tackling the challenge of cross-scale representation. At the same time, it is worth considering, at a theoretical level, the cases in which a purely bottom-up model may provide misleading answers. We propose that iterative exploration of cross-scale dynamics, drawing on models representing all four cells in our characterization matrix (Table 2), is an important next step.

Improved Means for Projecting and Backcasting Land Uses and Land Covers

Scenario analysis is a stated goal of many of the models presented, including FEARLUS, the Berger model, and MameLuke. SelfCormas states a related goal of “prospective” analysis. The majority of projects, however, specifically reject a predictive or projective goal. Does this mean that such models may not meet one of the stated needs for LUCC for improved means for projecting and backcasting land uses and land covers? There may not be a clear answer to this question, but some further discussion of the capabilities and interpretation of ABM/LUCC may shed light on the question. As discussed by Parker et al. (in press) and by many workshop participants, stochasticity and path dependence often impact outcomes in ABM/LUCC. Further, as discussed in sections 2.3 and 2.4, the sequencing of events in ABM/LUCC may impact final outcomes. Therefore, it is generally appropriate to present a distribution of results, or a set of macroscopic summary measures, rather than a single outcome, particularly a single outcome that demonstrates locations of land uses. An understanding of this need leaves many ABM/LUCC researchers reluctant to promise predictions or forecasts.

Further, one of the great strengths of ABM/LUCC lies in the ability to provide process-based explanations. This strength makes such models particularly appropriate for scenario analysis. Such models can shed light on how human decision makers respond to changing incentives, how these decisions impact their environment, and how changes in the environment subsequently feed back to human decisions. A prediction, in contrast, must assume that the conditions imposed on the model will continue to hold in the future. Given the potential for unforeseen shocks to the system, it is unlikely that these conditions will continue to be in place over the time frame for which the prediction is made. An understanding of process and the dynamics of human responses, therefore, may ultimately be of greater importance to policy makers than a single, static prediction based on current understanding of future conditions. Scenario analysis can frame the possibility space by providing a structured representation of the relationship between possible future conditions and their subsequent outcomes. While scenario analysis may not then directly tell us what will happen, it may at least succeed in revealing what might most likely not occur.

4.2. OPEN METHODOLOGICAL QUESTIONS

While the ABM/LUCC community has begun to address a set of exciting modeling challenges, a series of open questions, around which structured research is required, remain open. Workshop discussions focused on three areas where it was agreed more work is needed: comparative analysis of competing models of individual decision making, modeling the influence of institutional and political factors, and modeling land markets and other land tenure regimes.

4.2.1. Modeling Individual Decision Making

Workshop participants concurred that many potentially competing behavioral models are used to represent individual decision making in ABM/LUCC. The group attempted to compare available theoretical decision models and the specific techniques used to implement these models.

Participants discussed that validation of individual decision-making models poses a substantive challenge, since the underlying dynamics of the decision-making process are fundamentally unobservable. Further, since there is a single observed outcome to the decision process, often the parameters of a decision-making model and the model of the process itself are not identified. Specifically under different parameters, competing decision models might produce the same outcome. The fact that the structure of the decision-making process may itself be complex also was discussed, which may pose a modeling challenge to LUCC researchers who are interested in the emergent outcomes stemming from complex interactions between human decisions and the environment, rather than decision-making itself as an emergent phenomenon. This recognition perhaps suggests that LUCC researchers should strive for the simplest possible representation of human decision making that appropriately captures the human-environment interactions impacting the system under study.

Participants also concurred that different decision models may be appropriate for different circumstances, or it may be appropriate to represent an agent as combining input from a variety of decision-making strategies. An option for this modeling strategy is to construct a flexible agent parameterization that allows for weighted input from multiple strategies. All agreed that much comparative work is needed, especially with the goal of encouraging communication across groups using competing decision models. Beyond creating a well-motivated model of individual decision making, modeling external influences on the decision process is an important open challenge. In many of the projects discussed in section 3, decisions of individual agents are dependent on the actions of other agents. Agent-based modeling has a long history of exploring such intertwined decision problems, beginning with the models of Schelling (1978). Work at the confluence of economics and psychology that provides evidence that agent decisions are interdependent supports these models (Rabin 1998). More research exploring the impacts of such linked decision models on natural resource use is needed, and ABM/LUCC is a natural methodology with which to develop such models.

4.2.2. Modeling Institutional and Political Influences

Several participants emphasized the importance of incorporating social and political influences on individual decision making. Further, the related challenge of modeling group decision making was discussed. Much of this discussion centered on modeling the influence of norms, rules, and institutional structures. As an initial approach, these factors might be modeled as having an exogenous influence on individual decisions. A next step, and one of growing interest to several researchers, would be to construct a model in which norms, rules, and institutions emerge from group interactions. Researchers were interested in a number of specific questions related to this challenge, such as how power differences between agents might impact norms and rules, and how the emergent norm may then impact the system under study. A final option for modeling social and political influences would be to represent a decision-making group, institution, or governing body itself as an agent.

The discussion of modeling social and political influences on decision making revealed some interesting conceptual modeling questions. The first is the relationship between individual decision making, group decision making, and nested hierarchical (and perhaps spatial) structures. The three strategies described above for modeling sociopolitical influences on decision making represent three different modeling treatments of cross-scale interactions. In the first, sociopolitical factors exert a top-down influence on individuals. In the second, these emergent influences define the units of interactions at the next highest level of the system. In the third, both upward and downward linkages are potentially active. Thus, this modeling challenge provides a nice example of the conceptual challenge of modeling complex cross-scale relationships. The second modeling challenge relates to temporal scale. Institutions and rules may evolve over a coarser temporal scale than that at which humans learning and evolution of decision making occurs. Thus, there is a challenge of representing both fast and slow processes and of determining whether individual decision makers perceive rules and institutions as fixed or as evolutionary.

4.2.3. Land Tenure and Land-Use Change

The workshop participants also raised open questions with respect to modeling the relationship between land tenure and land-use change. Land tenure regulates access to land and thus influences the following processes and conditions:

- clearing of forest land for subsistence agriculture
- conversion of agricultural and forest lands into urban lands
- expansion of cultivation into marginal areas with unfavorable agroecological conditions (“fragile lands”)
- intensity of land use; for example, the duration of fallow periods
- use of other natural resources such as ground and surface water
- amount of investments in land conservation or improvement.

There is large agreement in the literature that increased tenure security—which does not necessarily imply formal titling—is a prerequisite for investments related to land conservation and land improvement. There is also evidence that well-functioning mechanisms for transferring land rights provide an additional incentive. In particular, the ability to use land as collateral may lead to long-term investments as equity facilitates the access to formal credit markets.

Participants stressed therefore the need to address tenure systems in the modeling of LUCC. Incorporating agent heterogeneity, land characteristics, transaction mechanisms as well as labor and credit markets would allow for a comprehensive assessment of a given institutional innovation such as the introduction of marketable land rights. Land rental markets may play a very important role for buffering shocks in agriculture and for adjusting the farm size to life-cycle changes. Scenario analyses could then reveal the likely impacts on welfare and land use for different groups of landowners and locations and may help identify suitable policy incentives.

During the discussions, it also became clear that ABM provides a very flexible way of accomplishing this task. Berger (2001), for example, modeled rental markets for land and water in an agricultural region in Chile and was able to replicate observed price levels and numbers of market transactions. He employed an object-oriented implementation of separate local markets for different soil qualities and water availabilities, similar to the one outlined in section 2.3. In Berger's spatially explicit model, distances from the agent's farmstead to a land parcel determine the internal transport costs that accrue to a farm agent who plans to cultivate a specific crop on a specific plot. Due to economic factors such as the level of crop prices, labor costs, and the quality of roads, only a few neighboring agents compete for parcels that are being offered on the land market. This spatially limited competition may then lead to an oligopolistic situation where land prices rise sharply when several model agents with high returns from additional land attempt to expand their acreage. The mediator (see Figure 9) then goes through a sequence of auctions for each plot on the land market and facilitates bilateral trade between the landowner and the agent with the highest bid. The model agents determine their asking prices and maximum bids through economic calculus; i.e., they compute the net increase in income without and with cultivating the parcel under consideration. Once an exchange of the right to this parcel has taken place, the new operator of this parcel might change its land use/cover.

This example of land market implementation shows several advantages that make ABM an interesting tool for the analysis of tenure systems and land-use changes. Agent-based models, in particular, can capture:

- differences in land prices for different soil types and locations that in reality can often be observed;
- impacts of other changing prices (e.g., for crops and fertilizers, on land-use intensity in a spatial context); and
- The structural effects of land markets on the farm sector (e.g., absorption of the land resources of small-scale holdings by large-scale farmers).

The workshop participants also were aware of the remaining challenges for the modeling of land tenure and land-use changes:

- How can the dynamics on the land sales market be captured? Since land has several functions other than serving as a medium for short-term agricultural production—e.g., store of wealth against inflation, source of aesthetic and recreational enjoyment, source of insurance, and speculative value as urban demands rise—agent motivations beyond the directly measurable short-term economic returns gain importance. Estimating model parameters, such as time preference, inflation and price expectations, aesthetic values, and risk preferences, requires empirical data that are difficult to obtain. Frequently, land sales imply considerable transaction costs that also would have to be quantified.

- How can path-dependent processes in land markets, such as timing of agent interactions and access to information, be represented and understood?
- How can the spatial extent of land market participation be empirically estimated, and how can this information be incorporated into the land-market model?
- How can informal non-market tenure systems, such as informal rental contracts, inheritance, assignment by village chief, and common property resources, be represented? Again, many factors other than short-term economic gains may influence these land tenure arrangements. Examples are kin ties, cultural norms and group decision making. (See also section 4.2.2.)

Nevertheless, ABMs are very flexible in their implementation and have therefore a considerable potential to capture these effects.

4.3. ADDITIONAL ROLES FOR AGENT-BASED MODELS APPLIED TO LUCC

In addition to the fields of research defined by Lambin et al. (1999), we see ABM/LUCC as serving some important roles beyond the needs proposed in the LUCC implementation strategy. Recognition of these novel roles brings with it a series of open questions regarding implementation.

Interactive Tools for Integrative Policy Making and Experimentation

We have seen that ABM/LUCC coupled with GIS can be creatively applied to a variety of role-playing games and interactive decision-making settings. These applications move away from pure expert systems, where knowledge is outsourced, toward interactive decision support tools, where existing knowledge can be synthesized and dynamically updated. Especially modelers with a more sociological background advocate the use of ABM/LUCC to promote and support discussions among stakeholders. Collectively creating an artificial world of LUCC within the computer helps stakeholders become aware of the specific views of other land users and might lead to improved decision making.

Further, ABM/LUCC coupled with GIS might serve as a tool for laboratory experiments, raising a series of questions regarding their potential utility. Specifically, how might we systematically analyze role-playing games in order to inform other models of LUCC, including ABM approaches? What insights/generalizable hypotheses can be derived in terms of an integrative theory that would include the process of policy making into the modeling efforts of LUCC?

Integration of Disciplines

Most presentations in this volume have passed through extensive discussion in interdisciplinary groups and provide evidence of the integrative character of ABM/LUCC. We have extensively discussed the capability of ABM/LUCC to create an integrated model of processes combining the social and natural science disciplines. We wish to stress that this potential not only encompasses linking of disciplinary models, which may have been created by independent disciplinary teams, but also encompasses construction of a model which is interdisciplinary at its conception. This approach, while challenging, integrates not only models, but also researchers, across disciplines. We believe that interactions between disciplinary team members at the initial planning stage, while challenging due to the variety of language, models, and priorities among disciplines, will ultimately achieve greater success than attempts to build an integrated model ex-post from separately constructed components.

4.4. FINAL REMARKS AND OUTLOOK

The intended role of this publication is to inform the research community about the ongoing and planned research activities related to agent-based modeling of land-use/land-cover change. Having read the proceedings, readers should have formed an idea of what defines ABM/LUCC, what challenges are involved in their construction, and what is the current state of progress in the field. Again, we would like to state that these proceedings are ABM-focused and workshop-biased. We have enhanced our summary of workshop discussions with the analytical perspective and commentary of the editorial team. The treatment of LUCC-related research issues has therefore not the ambition of a full review, and as such, some relevant references may have been excluded.

A great deal of space is spent in this publication on discussing appropriate roles for these models, spatial issues, verification and validation, and software tools. To recap, the workshop organizers and document editors consider these topics crucial to anyone engaging in ABM/LUCC modeling. This consideration is important for several reasons.

First, each researcher of ABM/LUCC has expertise in one of the many fields that the technique brings together, but may lack awareness of important issues that have a long history of consideration in other fields. For example, some geographers are not familiar with much of the research on modeling human decision making that has been undertaken in the field of economics. Many ABM/LUCC modelers are not aware of advanced verification and validation techniques used by other land-use modelers.

Second, ABM may demand specific methods beyond what has been considered for other LUCC modeling approaches. For example, as discussed in section 2.3, the complex software implementation may require a new protocol for documentation of code and communication of model results. Further, as discussed in section 2.4, the complex nonlinear dynamics may require new techniques for model verification. We devoted the second section to the issues that call for much further research and standardization than has been achieved to date.

Finally, we hope that the workshop and this document will set a standard for identifying important issues for literature in this field. As such, it may provide a guide for a journal reviewer that allows an article to be judged according to some key criteria. For example, is the author clear about the goals of the model? Are those goals appropriate? Has the model appropriately represented relevant spatial processes? Have standard techniques for verification and validation been used? Are the mechanisms of the model clearly communicated to the audience? Have the model mechanisms been appropriately verified? How does the model compare to other ongoing ABM/LUCC work?

Concluding Remarks

Significant progress has been made in the modeling of global environmental change and land-use/land-cover change. However, many challenges remain for forecasting likely human responses at regional and local levels, the environmental consequences of these human responses, and subsequent economic impacts of these environmental feedbacks. Additional challenges arise from the application of the knowledge generated in LUCC models in actual policy-making processes.

The workshop in Irvine illustrated the wide range and structural richness of ongoing ABM research applied to LUCC. ABM/LUCC holds out the promise of being able to successfully address several research questions laid out in the LUCC implementation strategy of 1999. Although only few empirical results are currently available, we believe that greater investment in this new research program will yield useful results for the LUCC community. As ardent believers of a promise yet to be kept, we take a strong stance in this document. Again, these proceedings do reflect the perspective of the ABM/LUCC research group and, most strongly, the three editors.

We also would like to emphasize that we do not propose to solve all LUCC research problems within the framework of ABM. We clearly see ABM as a complement to existing, well-established LUCC approaches, and we encourage comparative analysis between different approaches. We argue that ABM can amplify the range of the LUCC methodology by introducing more human decision making into biophysically inferred land-use modeling. Such models can provide valuable tools for policy analysis related to human-environment interactions. They also might open new, challenging avenues for research into the dynamics of policy-making processes.

Appendices

1. CURRENT RESEARCH RELATED TO AGENT-BASED MODELING AND LAND-USE/LAND-COVER CHANGE

Alfons Balmann

My relation with agent-based modeling started with a spatial-dynamic model of structural change in agriculture that I developed during my dissertation research in the early 1990s at the Department of Agricultural Economics in Göttingen. In the meantime, the modeling approach has been used in subsequent studies with respect to manifold research fields, such as policy analysis, structural change, and land use. In this appendix, I will illustrate the idea of the approach. I continue with present extensions as well as with related research.

Introduction: The Idea

The original inspiration arose from the question whether and under which conditions structural change in agriculture may be path dependent (cf. Balmann 1995, 1999). The idea was to model and to simulate agricultural regions from the bottom up by considering a multitude of individually behaving farms that interact on certain product and factor markets. For instance, it is obvious that farms can increase their acreage only if there is land available in the farms' neighborhood, probably because neighboring farms reduce their acreage. Moreover, if a farm invests, this often has an impact on the farm's production capacities for the lifetime of the asset. The same holds for the capital stock that depends on previous investments as well as on previously gained profits. In such a model, the evolution of every farm depends on its own state and history as well as on the evolution of other farms, particularly the evolution of its neighbors. Once a simulation is started, the evolution of the region and thereby structural change would occur endogenously. Hence, such a model should allow the study of the impacts of sunk costs, factor mobility, and returns to scale on the direction and speed of structural adjustment.

To realize this idea, a spatial model was developed in which farms are located at certain points on a chessboard-like spatial grid. The fields within the grid represent land plots that can be used for agricultural production. The farms compete for the land in repeated, iterative auctions where every farm bids according to its marginal land productivity and its distance to the next available plot. Figure 17 gives a snapshot of a selected simulation run by showing how the land is distributed to different farms after a number of periods. Plots marked with an X represent locations of farms. Plots with the same shading belong to the same farm. Apart from renting and disposing land via central auctions (cf. Balmann 1997), the farms can engage in different agricultural production activities (e.g., dairy, cattle, hogs, sows, arable farming, pasture land) and they can invest in different assets (differently sized buildings for various activities, machinery of different sizes). In addition to the different production and investment activities, the farms can use their labor and capital for off-farm employment as well as to hire additional labor and to make debts. Moreover, farms can give up farming and new farms can be founded. Each of the farms can be understood as an agent that acts autonomously in trying to maximize the individual household income in response to expected market prices and the availability of land. All decision-making routines are based on adaptive expectations. *Mixed integer linear programming* is used to optimize production activities and investment (see Figure 17).

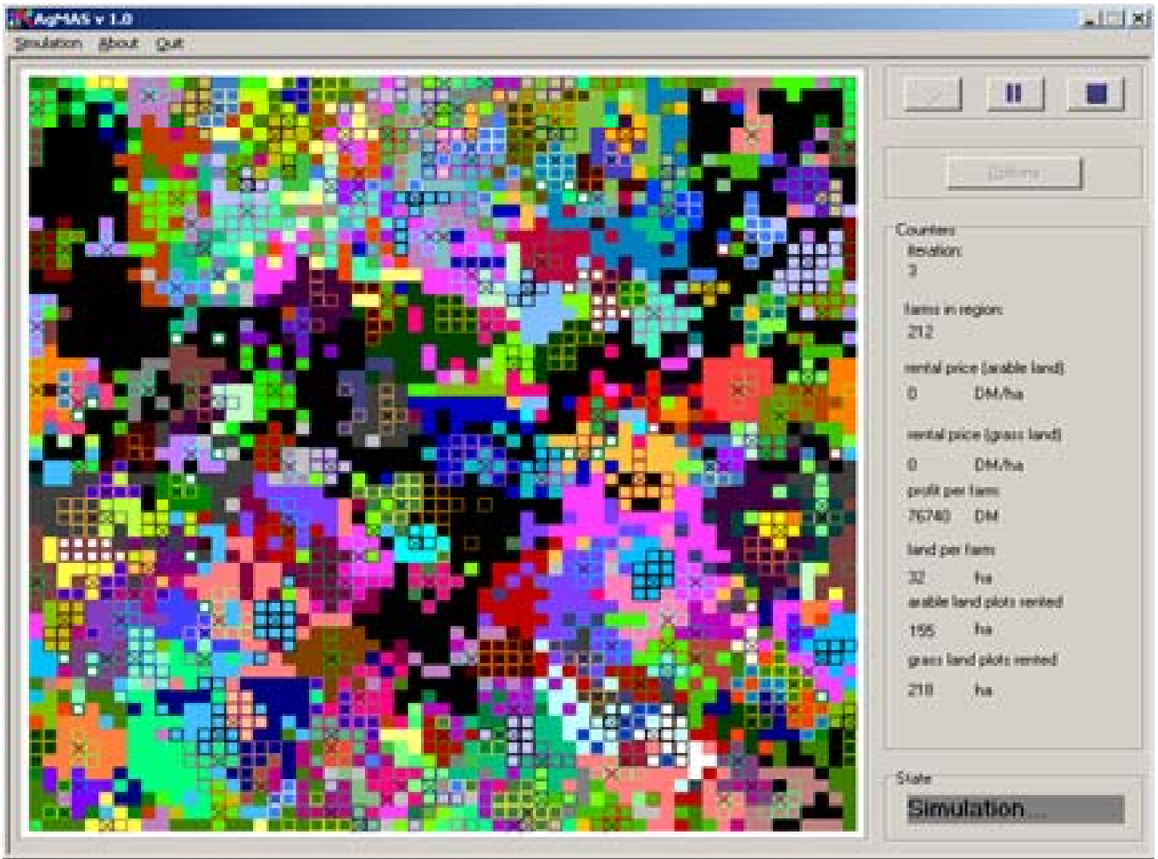


Figure 17. Land Distribution in a Simulation with 1,600 Plots and 110 Farms

Extensions and Related Research

The application of the model led to interesting results and insights regarding the question of path-dependent structural change (Balmann 1995, 1999). This encouraged several subsequent studies:

a) Thomas Berger (2000, 2001) extended and refined the original modeling idea in several significant respects. Berger enabled the farms to follow heterogeneous decision rules, to communicate in information networks, and to exchange land bilaterally. Further extensions included the introduction of heterogeneous land qualities and the integration of regional water resource systems that allow consideration of tradable water rights. Berger completely reprogrammed the model and applied it to a comparatively large agricultural region (with 5,400 farms in a region of 667 km^2) in Chile to study the dynamic impacts of free-trade-oriented policy options with regard to the diffusion of specific innovations and the resulting resource use change.

b) Balmann (2000) presents applications of the original model that focus on the dynamical impacts of selected agricultural policies on structural change, efficiency, land use, and farmers' incomes. The rather explorative simulations show the interrelation of these terms. Particularly, they show how subsidies like direct payments—often considered as non-distorting—may affect the speed and direction of structural change and, thus, they also may affect production and land use. In cooperation with Kathrin Happe (University of Hohenheim) these studies are enhanced and applied to a selected region in the German federal state of Baden-Württemberg. For instance, Balmann et al. (2001) analyze the adjustment costs of a policy switching that aims to reduce per farm animal density in the highly intensive agricultural area of Hohenlohe. The model considers explicitly some 2,500 farms that are derived from a set of 12 real farms from the German farm accountancy data network (FADN) that are considered to be typical for the region. Production coefficients are taken from standard farm data samples. The region's size is about 75,000 ha divided into 30,000 plots. Simulations cover 15 periods of one year each. Land use is considered indirectly. Farms determine their individual production, but the do not allocate land use to certain plots of land.

c) A substantial part of the last-mentioned project with Kathrin Happe is to develop the models to a well-documented, basic model. This is done for two reasons. First, a basic version shall allow third persons in a comparatively easy way to understand its structure and to adapt it for their own projects and to extend it by additional features. Therefore, the actual programming exploits more consequently the object orientation of C++ (cf. Happe 2000). The second reason for a basic, properly documented version may be paraphrased by the term "frankness." For instance, the model developed by Berger (2000: 5–39) contains a source code of 17,000 lines, corresponding to more than 300 pages of text. Such a complexity means that the model is a black box for almost every addressee of the results, and the mediation, particularly of controversial simulation results, is hardly possible. Documentation, standardization, and frankness are seen as means to overcome such problems (cf. Balmann and Happe 2001).

d) An obvious and straightforward extension is the integration of human decision making into such models. Real persons may replace the normative decision routines of individual farmers or of policy makers. This idea is taken up in a joint project with Konrad Kellermann that develops the model's version presented in b above toward an interactive computer game. The game offers several perspectives for future use. The first is to use it for teaching. Students can apply textbook knowledge and can experience the often complex dynamic consequences of strategies. They may either take the role of a farmer who competes with other farms in the region or of a politician who tries to improve efficiency and/or the farmers' incomes. It will even be possible to link different regions via a common market, so that politicians of different regions can interact and compete. A second perspective of the game is to study experimentally the behavior of players that take the role of farmers. It gives, for instance, a kind of benchmark to evaluate how smart a particular computational decision-making routine is. Moreover, it is proposed to identify cognitive deficits of the present computational agents. A third, more visionary perspective is using the interactive model for planning purposes, like the analysis of local policies and dispute resolution, for example, to manage conflicts between farmers and environmental interests. It is quite clear that the model needs to be adjusted to the considered region.

e) Balmann (1998) and Balmann and Happe (2000) investigate whether economic models that are based on artificial, adaptive learning may become a useful alternative to a normative behavioral foundation of the agents' behavior. The studies are based on a simplified comparative-static version of the model, presented above. Again, a number of agents (farms) that are spatially ordered on a grid compete for renting land. But in this model a genetic algorithm (GA) is applied to an agent-specific population of genes representing particular bidding strategies in order to determine the agent's behavior. The GA can be understood as a heuristic optimization technique that breeds solutions by applying operators known from natural evolution, such as selection, recombination (crossover) and mutation. Two principal market constellations are simulated for a variety of parameter constellations. First, a situation of limited market access is defined. A series of simulation experiments shows that for this scenario the model generates results that fit comparative static equilibrium conditions like allocative efficiency and zero profits. Second, a limited market access scenario shows that only under very special conditions does the distributed GA model generate results that indicate oligopolistic behavior. Summarizing, nature-related artificial intelligence methods like GA (and probably artificial neural networks too) seem to be promising alternatives for studying complex spatial processes. These positive experiences of using GAs for analyzing complex microeconomic problems induced further work. In joint work with Oliver Mußhoff, GAs are used to analyze real options problems of single firms as well as of competing firms.

2. PROJECT SLUCE: SPATIAL LAND-USE CHANGE AND ECOLOGICAL EFFECTS

Daniel G. Brown, Joan I. Nassauer, and Scott E. Page

Project SLUCE (Spatial Land-use Change and Ecological Effects), a new 4.5-year effort (2001–2006) funded under the NSF Biocomplexity and the Environment program, will investigate the dynamics of land-use changes at the urban-rural fringe and their interactions with the natural environment and ecosystem function. The project builds on our separate, ongoing projects on land-use/land-cover change, landscape scenario design and testing, and development and analysis of agent-based and other complex systems models. The model development and data collection efforts will be designed simultaneously to address specific questions about the interactions between land-use decisions; social, cultural, political, and economic structures; specific policy and design interventions, and impacts on ecological landscape patterns and function. Our initial focus will be on the interactions between agricultural and developed land uses. We expect to iteratively develop multiple agent-based models in the course of the project, working initially with Objective C and the SWARM libraries, and to develop several hooks that will link the models with empirical observations.

Identification of specific agent types and behaviors is currently underway and will likely continue for the duration of the project, responding to the needs of the various questions posed. The empirical focus of the project is the Detroit metropolitan area (~5.5 million people). Empirical data will link to the models for the purposes of (1) evaluating model behavior through backcasting exercises, (2) endowing agents with behaviors that are based, to the extent possible, on surveys of actual people, and (3) evaluating historical impacts of land-use change on ecosystem structure through remote sensing. Most work will be done within specific townships, which are selected through stratification of the region according to demographic, economic, and land-use planning characteristics. We are focusing on observations of actual land-use changes that have occurred from approximately 1950 to the present. Data, which include mapped parcel boundaries and owner identifiers together with aerial photography for interpretation of land use, are available on temporal resolutions of approximately one decade each. The model will likely have a finer temporal resolution, and we expect matching model and data resolutions to be an ongoing challenge.

Surveys of landowners, home buyers, developers, and land-use regulators are designed to evaluate the factors that affect residential location decisions, as well as the factors that restrict or affect the supply of land for development. We expect that the surveys will provide information about the relative importance of environmental and social factors for the location decisions. Historical time series of remotely sensed data on landscape structure will be compiled and compared to historical land-use dynamics to begin the process of linking land-use and land-cover dynamics within the modeling framework. These landscape structure descriptions, and their relative degree of ecological impact, are important emergent properties of interest from land-use change dynamics. One of our goals is to use the models we develop to evaluate the potential for specific interventions in the land-use change processes that might lead to more ecological benign and/or beneficial configurations. The kinds of interventions that can be tested include regulation or restriction by governing bodies, incentives of various kinds, educational initiatives, and widespread introduction of alternative landscaping approaches. We intend to use the working models of land-use change to evaluate both the historical dynamics of the region and possible alternative futures that might come about under various scenarios.

3. VIRTUAL ANASAZI: MODELING A SOCIODEMOGRAPHIC SYSTEM OF THE PAST

George J. Gumerman and Tim Kohler

Agent-based computer modeling is now being used to “grow” artificial societies. When compared to prehistoric conditions these models are providing stimulating new insights about how cultures change. Computer programs are used to model actual and systematically altered prehistoric economic, demographic, and settlement behavior in northeastern Arizona and southwestern Colorado. We briefly describe two modeling projects which are described in more detail in Kohler and Gumerman (2000).

Project by George J. Gumerman, Arizona State Museum, University of Arizona

The model is used to predict individual household responses to changes in agricultural productivity in annual increments based on reconstructions of yearly climatic conditions, as well as long-term hydrologic trends, cycles of erosion and deposition, and demographic change. The resolution is one hectare. The performance of the model is evaluated against actual population, settlement, and organizational parameters of the ancient Pueblo peoples—Anasazi. By manipulating numbers and attributes of households, climate patterns, and other environmental variables, it is possible to evaluate the roles of these factors in prehistoric culture change.

The modeled region is semi-arid, averaging 1,524 m in elevation and covering about 270 km^2. The time period extends from A.D. 200 to 1450, and the population ranges from several hundred to about 2,500. Individuals are tracked through the maternal lineage. Much data comes from ethnological references to Pueblo people. Agents have gender, birth, and death rates and caloric needs. They can store resources. Decision making is based on age, resource needs, prediction of resources available, and clan affiliation. The model is compared with the archaeological data on a hectare-by-hectare annual basis. The test is to determine the relative importance of environmental, social, and demographic factors effecting change.

Project by Tim Kohler, Department of Anthropology, Washington State University

The NSF Biocomplexity project entitled "Coupled Human/Ecosystems over Long Periods: Mesa Verde Region Prehispanic Ecodynamics," to be completed in early 2005, builds on an earlier model described in Kohler et al. (2000). The desired end product of anticipated development over the next three years is described below.

This project seeks to understand the long-term interaction of humans, their culture(s), and their environment in southwestern Colorado, USA, from A.D. 600–1300. The research employs agent-based simulation to examine various models for how farmers locate themselves and use resources on this landscape. Further, the simulation will examine the exchange of agricultural goods among households, and whether exchange causes households to aggregate into villages in certain times and places, and disperse into smaller settlements during other times. Finally, the simulation will examine why this area was depopulated in the late A.D. 1200s. Households in this model act in a virtual environment where the elevation, soil type, temperature, vegetation, potential agricultural production, and precipitation vary over an 1800-km^2 study area. The temporal resolution of the model is one year, both in terms of effective agent actions, and in terms of the paleoclimatic reconstruction. The grid size for the agents is 200 m x 200 m, and the area was populated by several thousands of households during portions of the period being modeled. The simulation is possible because high-resolution archaeological and environmental records are available for the study area during this period, including an inventory of thousands of archaeological sites, tree-ring records, and estimates of available surface water and ground water. Estimates of agricultural production change annually according to climatic inputs reconstructed from tree-ring records, and possibly in response to landscape degradation due to farming. Over longer periods, the same factors affect the availability of surface water and ground water, and changes in the location and availability of water also will be incorporated into the simulation.

Population size and the location of settlement on the landscape vary according to the experiences of the households during the period under investigation, and population flows from and to other areas. The simulation will employ cultural algorithms (variants of genetic algorithms) through which households may optimize their landscape and resource use with respect to other households with whom they exchange corn and compete for agricultural land. These algorithms also will be used to simulate selection of farming strategies, including those that use surface water for irrigation. In this way, the simulation will be used to determine how exchange of agricultural goods, competition for land, and changing farming strategies affected household movement and formation of villages. The behavior of households in all variants of the simulation will be compared against a database for archaeological sites in the study area that specifies their location, size, function, and period of occupation, allowing an assessment of how well each variant fits the archaeological record.

This work contributes to understanding changing land-use strategies in small-scale farming societies experiencing significant climate change and population growth. It also contributes to understanding the evolution of economic systems and population aggregation in such societies. In particular, the study will clarify the factors that resulted in village formation and the depopulation in one of the most famous archaeological areas in the world—the Mesa Verde region. In addition, the research will develop tools to make the future examination of such systems more effective. The groundwater model will help to predict what might happen to groundwater supplies in this area as climate changes in the future. Finally, by clarifying the relationships between climate, culture, and behavior this research will be useful in unraveling the complexities of coupled human and natural systems in other areas.

4. THE COMPLEXITY OF POLITICS

Matthew J. Hoffmann

My broad interest in complexity theory and agent-based modeling arose in response to a growing dissatisfaction with the traditional tools of international relations and political science—especially in how my discipline deals with change and evolution. Thus, in graduate school I embarked on a broad research project (one on which I am still working) that explores ways in which the insights and tools of complexity theory can improve upon and complement examinations of world politics.

This broad research interest sparked the specific work of my dissertation, "Going Global: The Complexity of Constructing Global Governance in Environmental Politics." In it, I applied the insights of complex adaptive systems research to the evolution of international negotiations surrounding the ozone-depletion and climate-change issues. I utilized complexity theory to construct an analytic framework useful for structuring case studies in addition to two agent-based models. One of the agent-based models explored the emergence of norms, and the other was a more detailed model that examined bargaining between northern and southern agents over environmental issues. In my more recent work, I have concentrated on the model of norm emergence and evolution. I have improved and extended this model in an attempt to address some fundamental questions about norms that have puzzled both economic and sociological approaches—namely, How do specific norms arise and how do norms change over time?

The other aspect of my modeling work arises from my association with the Center for the Study of Institutions, Population, and Environmental Change (CIPEC). I began working there in fall of 1998 as a visiting scholar. I worked on developing our prototype model with the team that later put together the National Science Foundation grant proposal that was funded under the "Biocomplexity in the Environment" initiative: "Biocomplexity in Linked Bioecological-Human Systems: Agent-Based Models of Land-Use Decisions and Emergent Land-use Patterns in

Forested Regions of the American Midwest and the Brazilian Amazon." (A participants list is available at http://www.cipec.org/research/biocomplexity/participants.html.) In spring of 2000, I continued work on the project as a postdoctoral research fellow and, since January of 2001, I have been a participating scientist on the project. The first paper to detail the prototype model and its results is "Simulating Land-Cover Change in South-Central Indiana: An Agent-Based Model of Deforestation and Afforestation" (Hoffmann et al. in press).

5. RESEARCH ON IDENTIFYING AGENT INTERACTIONS IN MODELS OF LAND-USE CHANGE

Elena Irwin

Research on Agent-Based Interactions

My research focuses on spatially disaggregate, economic models of land-use conversion and household location patterns. My main research interest with respect to agent-based interactions has been on the empirical identification of interactions among landowners who convert their land to development and the role of these spillovers in generating sprawl patterns of development. A secondary research focus has been on the development of a cellular automaton that simulates the net effect of negative endogenous interactions among developed land parcels and the positive, attracting effects of a city center and built infrastructure (e.g., roads). My current research interests include the development of an agent-based model of urbanization in which environmental amenities (such as open space and water quality) are endogenous to household location. In what follows, I elaborate on each of these research areas.

Identification of Interaction Effects among Agents

Manski (1993, 1995), Brock and Durlauf (2001), and Moffitt (1998) have given serious attention to the challenges involved in identifying interaction effects among agents within a regression context. This work discusses three major identification problems that arise in testing for the presence of interactions among agents: the simultaneity problem, the endogenous group formation problem, and the correlated unobservables problem. My research on identifying the spillover effects among developed land parcels has focused on the problem of unobserved spatial correlation in a discrete choice, duration modeling framework. An identification problem arises here because omitted spatial variation leads to correlation between the error and interaction terms, which biases the interaction estimate upward if uncontrolled.[10] As a result, a positive interaction effect may be estimated even in the absence of any such interaction. Solving this problem for cross-sectional models and discrete choice models is difficult. Solutions that have been proposed in the literature include assigning an upper bound to the interaction effect, using instrumental variables or related approach called a partial population identifier, and conditioning out the unobserved component using an analog of a fixed effects approach for discrete choice models. Irwin and Bockstael (2002) use the strategy of bounding the interaction effect to identify negative interactions among developed parcels, which offers one explanation for sprawl

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[10] This same problem arises in the literature on own-state dependence over time, which seeks to separate "true" temporal state dependence (e.g., habitual effects) from "spurious" state dependence (Heckman 1978, 1981).

development. In related research, Irwin and Bockstael (2001) and Irwin (2001) use an instrumental variables and partial population identifier respectively to identify the effects of open space spillovers in a hedonic model of residential property values.

Cellular Automaton Model of Development

Irwin (1998) employs cellular automaton to explore the evolution of regional patterns of development with a negative interaction effect among developed parcels and offsetting positive spillovers from a city center and other built infrastructure, all of which decay over distance. Parcels are represented by cells arranged on a two-dimensional square lattice, and each parcel takes on only one of two states—undeveloped and developed. The growth parameter and unit of time are defined such that one parcel is developed in each time period. Agents form expectations over the returns to converting by considering the location of the parcel relative to exogenous features and the amount of development that surrounds the parcel in the current period. Agents are assumed to be myopic in the sense that they do not attempt to forecast future changes in their neighboring land-use patterns. Once converted, the expected costs from re-converting a parcel back to an undeveloped state are assumed always to exceed the returns of re-conversion, so that development is effectively irreversible. Multiple simulations are performed by altering the distance decay parameters that govern the relative strength of the negative and positive effects. The results demonstrate that varying degrees of clustering and fragmentation emerge, depending on the relative values of the neighborhood interaction and other parameters. In particular, they identify the minimum threshold value required for the negative interactions to generate a sprawl pattern of development. Irwin and Bockstael (2002) use a cellular automaton to predict patterns of land-use change using estimated parameters from an empirical model of land-use conversion to calculate the transition probabilities for yet undeveloped parcels. Because the development spillover is endogenous, these probabilities are then updated with each round of development.

Agent-Based Model of Urbanization with Endogenous Environmental Amenities

The development of this model is still in the very formative stages and is joint work with several others. Initially we are developing a simple model of household location within a region with a given distribution of employment, infrastructure, and environmental resources. Households are differentiated by income and preferences over access to employment and environmental quality. The system evolves with new population being added in each time period and the relocation of existing households, based on utility-maximizing behavior. Environmental quality, which is specified as water quality and surrounding open space, is endogenous and acts as an attractor. A primary goal of this modeling effort is to work with biological and physical modelers to develop an integrated and dynamic model of the human/biological/physical systems associated with Lake Erie. Extensions of this model will include making roads, employment, and public services endogenous to household location, so the entire urban spatial structure of the region can be modeled in a dynamic framework. Ultimately, this modeling effort will seek to explain the endogenous interactions between household location and environmental quality, redistribution of population from a city center to suburbs and exurbs, the formation of edge cities, and the fragmented pattern of exurban residential development within a region.

6. MODELS OF "EDGE-EFFECT EXTERNALITIES": ECONOMIC PROCESSES, LANDSCAPE PATTERN, AND SPATIAL EFFICIENCY

Dawn C. Parker

My interest in spatially explicit agent-based modeling developed as a result of a specific research interest in distance-dependent spatial externalities. An externality in economic jargon is a positive or negative economic impact (1) that results from the actions of a particular economic actor; (2) that has economic impacts on someone other than the actor instigating the impact; and (3) whose external costs are not taken into consideration when the instigating actor makes the decision about the generating activity. My research specifically focused on negative externalities whose impacts decay and may become negligible with distance, such as pesticide drift. Drawing on parallels with ecological edge effects in landscape ecology, I quickly realized that when these externalities are present, some configurations of land use may be more efficient from an economic perspective than others. Further thinking quickly suggested that initial conditions of land use may impact whether an unregulated economy would develop an arrangement of land uses that was economically efficient.

It became apparent that analytical techniques were not well suited to examine this particular research question, due to the high degree of spatial interdependencies and induced spatial heterogeneity that these externalities imply. As a complement to an initial analytical model, I developed a cellular automaton, agent-based model to represent the key components of the system. This model meets the definition of a cellular automaton in the sense that each cell contains a single, identical, immobile decision maker, and the rules available to decision makers are identical. Each agent/cell is potentially impacted by a spatial externality generated by only immediately neighboring cells. However, the model meets the definition of an agent-based model in the sense that the decision rules used by each agent consist of an intelligent decision-making process, whereby agents use a traditional profit maximization algorithm to choose between two possible land uses. A key feature of this model is an endogenous price for the output from one land use (designed to represent a niche market). This endogeneity provides sufficient structure to the model so that both land uses are represented in any economic equilibrium, and the assumption was appropriate for the particular case study for which the model was designed. I have used this model to demonstrate that stable inefficient patterns of land use are possible in an unregulated free-market setting, and that initial conditions influence the final outcome. Further, I have used the model to demonstrate key interactions between transportation costs (an agglomeration mechanism) and negative spatial externalities (a dispersal mechanism). The model and results are described in Parker (1999). The model was created in Mathematica, and the code is available on request. A slightly refined version of this paper, and a discussion of empirical analysis on the locations and patterns of production of certified organic farming operations, are presented in Parker (2000).

Recently, I have used an expanded version of the same model to explore the relationship between economic processes and landscape pattern, with the goal of identifying landscape pattern as a possible emergent outcome in explicitly spatial models of landscape processes. The model has been expanded to include representation of a more flexible range of spatial externalities. In its current form, either of two possible land uses can generate both positive and negative externalities to either or both uses. I also have updated the model to produce a set of landscape metrics that measure pattern outcomes. A paper based on this model (Parker et al. 2001) was presented at the 2001 Society for Computational Economics annual meetings.

7. AGENT-BASED COMPUTATIONAL MODELS FOR THE STUDY OF COMPLEX SOCIAL-ECOLOGICAL SYSTEMS

Marco A. Janssen

My research mainly focuses on methodological aspects of modeling human dimensions of environmental change. These methodological studies are not restricted to LUCC but cover ecosystem management in general. Furthermore, I use different modeling techniques. Next to agent-based computational models I mainly use system dynamics and genetic algorithms for optimization purposes. I require this diverse portfolio of tools to understand how social agents act within systems with complex nonlinear dynamics. I will briefly discuss three areas of my current interest.

Cognitive Strategies

Together with Wander Jager, social psychologist from the University of Groningen in the Netherlands, I have developed the Consumat approach (http://go.to/consumats). This is a multi-agent approach of individual decision making based on a multi-theoretical framework of psychology. One of the main points in our approach is the distinction of different types of cognitive processes based on whether the agent is satisfied or not, and whether the agent feels uncertain or not. We distinguish at the moment four types of cognitive processes: repetition, deliberation, imitation, and social comparison.

The Consumat approach is used to replicate laboratory finding on common dilemmas (Jager and Janssen 2002, Jager et al. in press), explore common dilemmas of more complex artificial social-ecological systems (Jager et al. 2000), and to investigate market dynamics such as fads and fashions (Janssen and Jager 2001). Currently, we focus on diffusion processes of an innovation within a heterogeneous group of agents. This general model is anticipated to be tested on case studies within agriculture, family planning, and marketing.

Self-Organization of Institutions

How to manage common-pool resources is the topic of interest in my work on self-organization of rule systems (Janssen and Stow 2001). The basic question is whether individuals are able to manage a common resource. Empirical research shows that there are conditions that lead to self-organization of formal (law) and informal (social norms) institutions. In Janssen and Ostrom (2001) an agent-based model is presented to test under which circumstances a heterogeneous group of agents build enough mutual trust to support a proposed regulation to avoid a tragedy of the commons. The frequency of interactions affected by environmental conditions can play a crucial role in deriving the critical level of mutual trust. New work is in progress where we look at the evolution of norm to share harvested resources.

Spatial Resilience

Together with colleagues from CSIRO Sustainable Ecosystems in Australia, I look at the interactions of pastoralists and the rangelands. Dependent on the type of management, those rangelands can flip from a desired productive grassland into an undesired, wood-shrub-dominated land. A stylized model was developed to perform bifurcation analysis to assess the resilience of different management strategies (Anderies et al. 2002). Since we did not address space explicitly in our model, we implicitly assumed that the so-called mean field assumptions hold. Another study was performed in which we tackled this assumption by applying a multi-agent model, where sheep were equipped with a number of simple behavioral rules (Janssen et al. in press). Due to the behavior of sheep, like the herding behavior, we found that the tolerated level of grazing pressure is lower compared to a non-spatial version of the model, in order to avoid undesirable flips in the system. This finding will be explored in more detail for rangelands as well as fisheries, which does not always have a well-mixed population as assumed in traditional models.

The challenge is to develop simple stylized models of complex social-ecological systems and confront them with observed behavior. Like the work on self-organization in biological systems (see Camazine et al. 2001), this requires the use of different mathematical tools, as well the interaction between modeling, experimental work, and observations in the field.

8. LINKING AGENT MODELS AND CONTROLLED LABORATORY EXPERIMENTS FOR MANAGING COMMUNITY GROWTH

James J. Opaluch, Peter August, Robert Thompson, Robert Johnston, and Virginia Lee

The increasing concentration of human activity has led to significant impacts to the ecological health, quality of life, and economic vitality of communities. Indeed, in many cases, growth threatens the very amenities that attract people to an area in the first place. The rapid pace of growth is the result of numerous, often small-scale land-use changes occurring over time. The cumulative impact of these diffuse land-use changes can be extremely high when one considers a watershed or landscape scale.

Agent models provide an excellent organizing framework for modeling decisions that determine land-use change in the community. The results of computational models provide insights into the underlying structure of systems, and models are often validated by comparing outcomes of simulated systems to actual outcomes. However, empirical validation of agent models faces the considerable challenge of separating the multitude of endogenous interactions among agents from observationally equivalent exogenous landscape and ecological features that influence development decisions. So there are profound limitations to the use of field data as a basis for analysis and validation of agent models.

Experimental methods are a promising avenue for augmenting field data in validating agent models. In the laboratory, one can combine a known structure with interactions among actual decision makers brought into the lab. In this sense, the experimental environment represents a middle ground between pure computer simulation models and analyses based on field data.

Indeed, use of a controlled laboratory environment allows an entire spectrum of analyses, from fully specified computer-generated structure and parameters to an indirectly observed structure of endogenous interactions among participants, similar to those faced in analyses based on field data. Therefore, augmenting analyses of field data with analyses of data generated under controlled laboratory conditions allows us to better understand the structures underlying decision-making processes and the effectiveness of computational tools to identify underlying structures at varying levels of complexity.

This project links computer simulations of agent behavior with behavior of agents in controlled laboratory experiments. We use CommunityViz® software (www.orton.org), to simulate development under different policy scenarios. CommunityViz® is an extension to ArcView® GIS (www.esri.com), and is made up of three components: Scenario Constructor, Town Builder and Policy Simulator. Scenario Constructor extends the capability of standard GIS software. Town Builder creates three-dimensional renditions that allow interested parties to better visualize growth scenarios. Policy Simulator uses an agent-based model to forecast community growth under alternative policy scenarios.

We propose to augment and calibrate agent models using a controlled laboratory environment using the new Policy Simulation Laboratory (SimLab) developed by the Department of Environmental and Natural Resource Economics at the University of Rhode Island (www.uri.edu/cels/enre/preview/SimLab). The SimLab is a world-class facility for research that integrates science and decision making. It is comprised of computer systems and audio-visual equipment housed in a group of electronically networked rooms. The facility includes a Policy Simulation room, a Presentation Hall, two Group Decision rooms, and a GIS laboratory. The core of the facility is the Policy Simulation room, which contains a network of 26 computer workstations and advanced audio-visual capabilities used to create simulated decision environments. The Presentation Hall is a 125-seat auditorium with in-seat voting capabilities and advanced audio-visual aids. The two Group Decision rooms are conference rooms where participants make decisions while interacting face-to-face, and with notebook computers that are networked with the other facilities. The existing University of Rhode Island Environmental Data Center (EDC), an advanced GIS laboratory, is also networked into the system with a gigabit Ethernet connection.

What makes this facility unique is the close interconnection of the system components, which together comprise an integrated decision research tool. For instance, the Group Decision rooms might each house a team of policymakers designing proposals for community development. The SimLab and GIS computer systems translate the development plans into resultant impacts to the natural and human environment, and create GIS maps indicating consequences of each proposal for water quality and for fragmentation of natural ecosystems. Simultaneously, audio-visual systems are used to present these management plans and their consequences to “voters” in the Presentation Hall, who then vote on the proposals. Policy makers in the Group Decision rooms could then obtain real-time feedback regarding fiscal, social, and environmental implications, as well as voting results, and revise their plans in response.

In the SimLab, real people play the roles of agents by being placed in simulated decision environments, with actual rewards and penalties assessed just as they are in real decision environments. This simulated decision environment represents a middle ground between studies of decision makers in uncontrolled field conditions, and computer simulations that provide complete control over system structure and response. As such, it will provide insights into decision processes whose structure is too complex for estimation with field data, while still including real decision makers making choices in response to incentives and constraints. The system also allows one to assess the performance of institutions that may not exist in the real world, to observe and/or control factors in ways not possible in field analyses and to test the effectiveness of estimation techniques designed for use with field data.

9. THE INTERSECTION OF AGENT-BASED MODELS, LAND USE, AND COMMUNITY MENTAL HEALTH

Keith Warren

I am probably unique among participants in the workshop on ABMs of land-use/land-cover change in that my primary research interest lies in community mental health. Thus, my deepest interest is not so much land use itself as the effects of that use on the human psyche. I am particularly interested in individuals who suffer from chemical dependency and severe and persistent mental illnesses such as schizophrenia and bipolar disorder. However, it is not unreasonable to think that different types of land use might affect the stress level and therefore the mental health of individuals who carry no actual psychiatric diagnosis (Halpern 1995, Ulrich 1993). This abstract will therefore discuss research that would touch on the needs of considerably divergent populations. I should add that I am only in the beginning stages of planning these lines of research.

There is a rich and varied literature that addresses the effect of the built environment of buildings, streets, and landscaped parks on human behavior and mental health (Bechtel 1997, Gifford 1997, Halpern 1995). There is a parallel, and sometimes overlapping, literature that addresses the effect of the unbuilt, “natural” environment on human mental health (Kahn 1999, Kellert 1997, Kellert and Wilson 1993). Much of this latter literature derives from the “biophilia” hypothesis, first stated by Edward O. Wilson, that human beings have an inbred need to affiliate with life and the broader ecological system. However, the built environment is entirely, and the natural environment is largely, the result of human actions and interactions (Meyer and Turner 1994). To look deeper, to understand how the landscapes that affect us arise, we need to understand how these interactions occur. Agent-based models constitute a natural framework for thinking about such interactions.

For instance, the Not In My Backyard (NIMBY) phenomenon, in which homeowners oppose the location of residential facilities for individuals with chronic mental illness in their neighborhood, has blocked construction of as many as half of all planned group homes for people with disabilities in the United States (Tse 1995). NIMBY has probably contributed to the concentration of people with chronic mental illness in relatively impoverished inner-city neighborhoods, whose residents are less likely to be able to organize against residential facilities (Levine and Perkins 1997). Administrators have attempted to alleviate NIMBY by meeting with prospective neighbors of proposed facilities (Zippay 1999), but fundamental questions about NIMBY, such as the motivations of homeowners and how far the effect reaches, remain poorly understood (Colon and Marston 1999, Gilbert 1993, Mangum 1988). Agent-based models incorporating the bounded rationality of homeowners and distance effects could be useful in generating more precise hypotheses than the ones that currently characterize the literature and in thinking about the implications of the somewhat contradictory empirical findings.

There is evidence from both qualitative and quantitative studies that social support can significantly benefit those who suffer from a variety of mental illnesses (Marsh 2000, Paykel 2001). There is also evidence that the built environment heavily influences both the quality and quantity of social support. The conditions for strong social support networks are complex. The opportunity to interact with others is, of course, necessary, but so is the ability to control such interactions. An environment such as a busy street that forces interactions with others actually tends to lead to hostility to neighbors (Halpern 1995). A particularly unpleasant environment can make social interactions far more difficult, while some level of local social heterogeneity appears to foster social networks (Halpern 1995). Agent-based models are natural tools both for studying the way in which different built environments arise and for developing a better and deeper understanding of the effects of those environments on social networks.

Agent-based models of land use also could yield considerable insight into the origin and effects of such environmental stressors as weather, air pollution, noise, and crowding (Halpern 1995). There is evidence that cloudy weather has a negative effect on mental health (Halpern 1995). Cities tend to be more cloudy, more rainy and more foggy than the surrounding countryside (Rogers 1994), and it is possible that this has an adverse effect on the mental health of some urban residents. Levels of environmental noise and crowding are, to a large extent, the straightforward result of urban and suburban development patterns (Halpern 1995). In all of these cases ABMs could be of great value in modeling the interactions that lead to changes in land use, as well as the interactions between those who live in urban and suburban areas, their environments and each other.

There is also evidence that exposure to natural environments improves both mental and physical health (Kahn 1999). Many studies have shown that subjects prefer natural scenes, particularly those that show fairly open landscapes with a scattering of trees and those that include water, to built scenes (Ulrich 1993). There is substantial evidence that many people find that natural settings, whether they are wilderness areas or urban parks, reduce perceived stress (Ulrich 1993). There is even evidence that postoperative hospital patients recover more quickly when they have a window that overlooks a natural scene, when compared to those who have a window that overlooks a brick wall (Ulrich 1993). Human interactions, policies, and land use largely determine where natural environments remain and how easily individuals can gain access to them. All of these, of course, can potentially be modeled through ABMs. Moreover, findings of positive effects of natural environments on mental health would have implications for models of the response of land values to natural amenities, such as Irwin and Bockstael (2001), since they might allow a more accurate quantification of the value of access to those amenities.

There is substantial evidence that both the natural and built environments have significant effects on human mental health. Agent-based models seem likely to be of considerable value both in developing a more detailed theory of those effects and in understanding the human interactions that give rise to much of the world in which we live.

Glossary

algorithm: Recursive computational procedure for solving a problem in a finite number of steps.

Bayesian learning: Using the knowledge of prior events to predict future events; named after Thomas Bayes, an English clergyman and mathematician, who first proposed the probability theorem in the mid-1700s.

bounded rationality: Limited optimization behavior based on inductive reasoning, incomplete information, limited information, or imperfect optimization abilities.

bucket-brigade apportionment: An algorithm that increases the strength of classifiers that effectively match responses to stimuli.

calibrate: Make fine adjustments for optimal functioning, especially with respect to the ability of a parameterized model to replicate observed values of model variables.

cellular automata: Regular spatial lattices of cells, each of which can have any one of a finite number of states, depending on the states of neighboring cells.

classifier system: A collection of if/then statements encoded as bitstrings, which have a strength value dependent on the string's performance. As with a genetic algorithm, better-performing strings have a higher likelihood of reproduction.

differential equations: Equations that express a relationship between functions and their derivatives.

econometrics: Modeling techniques that use parametric statistics to estimate a well-defined mathematical relationship among empirically observed variables.

equilibrium diffusion processes: Disseminating information about new technologies, or innovations in general, among human agents; equilibrium concept postulates a priori complete information set; disequilibrium concept also acknowledges non-technical, psychological factors.

extensible: Of or relating to a programming language or a system that can be modified by changing or adding features.

genetic algorithm: A mathematical or computational analog to Darwin's evolutionary process used for optimization, pattern matching, and curve fitting.

heuristic: Of or relating to a usually speculative formulation serving as a guide in the investigation or solution of a problem.

Homo economicus: A classic economic representation of decision making based on optimization under perfect foresight, information, learning, and computational ability.

Markov model: A probabilistic modeling method where model state outcomes rely strictly on previous model states. With this modeling technique, cell conditional probabilities are used to change cell states through a series of iterative operations.

mathematical programming: Maximization/minimization of an objective function subject to constraints, where the objective function and constraints are often linear.

mixed integer linear programming: Minimization or maximization of a discrete function, subject to constraints.

network thresholds: Relating the behavior of a single human agent to the behavior of other agents who together form a communication network; e.g., an agent who adopts a new behavior before others has a low network threshold.

objective function: A mathematical expression that relates the variables and parameters in the system under study to values that reflect the goals of an agent.

parameter: (1) a constant representing the influence of exogenous elements on a mathematical system; (2) a quantity (as a mean or variance) that describes the distribution of a statistical population.

pixel: The smallest unit of spatial resolution in a photo or remotely sensed image; refers to the area on the ground represented by a digital number; size varies according to the type of sensor used.

raster: A spatial data model in which features are represented by pixels. Each pixel is assigned a value that corresponds to a feature.

recursive: Of, relating to, or constituting a procedure that can repeat itself indefinitely.

reinforcement learning: Learning through stimuli that strengthen or weaken the behavior that produced it.

secondary succession: Regrowth of vegetation following forest clearing.

spatial diffusion models: Refer to the spatial distribution of innovations which is created by diffusion of techniques and ideas through social networks.

state: The level of variable impacted by a dynamic process at a given point in time.

vector: A spatial data model in which features are represented by points, lines, and polygons.

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