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A Review and Assessment of Land-Use Change Models

Dynamics of Space, Time, and Human Choice

by

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1. INTRODUCTION

The Significance of Land-Use Change

Land-use change is a locally pervasive and globally significant ecological trend. Vitousek (1994) notes that "three of the well-documented global changes are increasing concentrations of carbon dioxide in the atmosphere; alterations in the biochemistry of the global nitrogen cycle; and on-going land-use/land-cover change." In the case of the United States for example, 121,000 km^2 of non-federal lands were converted to urban developments over the 15-year interval between 1982 and 1997 (NRCS/USDA 1999). On a global scale and over a longer time period, nearly 1.2 million km^2 of forest and woodland and 5.6 million km^2 of grassland and pasture have been converted to other uses during the last three centuries, according to Ramankutty and Foley (1999). During this same time period, cropland has increased by 12 million km^2. Currently, humans have transformed significant portions of the Earth's land surface: 10–15 percent is dominated by agricultural rowcrop or urban-industrial areas, and 6–8 percent is pasture (Vitousek et al. 1997).

The Need for Land-Use Models

These changes in land use have important implications for future changes in the Earth's climate and, in return, great implications for subsequent land-use change. Thus, a critical element of the U.S. Global Change Program of the Department of Agriculture's Forest Service (FSGRCP) is to understand the interactions between human activities and natural resources. In particular, FSGRCP has identified three critical actions for this program element:

1. In response to global climate change, identify and assess the likely effects of changes in forest ecosystem structure and function on human communities and society;
2. In order to mitigate and adapt to the effects of global climate change, identify and evaluate potential policy options for rural and urban forestry; and
3. In order to integrate risks associated with global climate change, identify and evaluate potential rural and urban forest management activities.

In addition to the action items listed above, significant attention has focused on land-use change models. All land-use models need to be built on good science and based on good data. Research models should exhibit a high degree of scientific rigor and contribute some original theoretical insights or technical innovations. In contrast, originality is less of an issue in policy models and sometimes it is more desirable for a model to be considered "tried and true." Also important to policy models is whether the model is transparent, flexible, and includes key "policy variables." This is not to say that research models might not have significant policy implications (as is the case with global climate models developed during the past decade) nor is it to say that policy models might not make original contributions to the science of environmental modeling.

Because of the applied mission of the FSGRCP, we propose that the FSGRCP will need to focus on land-use models that are relevant to policy. This does not mean that we expect these land-use models to be "answer machines." Rather, we expect that land-use change models will be good enough to be taken seriously in the policy process. King and Kraemer (1993:356) list three roles a model must play in a policy context: A model should clarify the issues in the debate; it must be able to enforce a discipline of analysis and discourse among stakeholders; and it must provide an interesting form of “advice,” primarily in the form of what *not* to do—since a politician is unlikely to simply do what a model suggests. Further, the necessary properties for a good policy model have been known since Lee (1973) wrote his “requiem” to large-scale models: (1) transparency, (2) robustness, (3) reasonable data needs, (4) appropriate spatio-temporal resolution, and (5) inclusion of enough key policy variables to allow for likely and significant policy questions to be explored.

Global Change Research and Assessments and Land-Use Change Models

In response to the FSGRCP’s action priorities and associated interest in land-use modeling, the Forest Service’s Northern and Southern Global Change Programs decided, through the National Integrated Ecosystem Modeling Project (NIEMP:Eastwide), to

1. Inventory existing land-use change models through a review of literature, websites, and professional contacts; and
2. Evaluate the theoretical, empirical, and technical linkages within and among land-use change models.

The goal of this report is to contribute to the NIEMP:Eastwide modeling framework by identifying appropriate models or proposing new modeling requirements and directions for estimating spatial and temporal variations in land-cover (vegetation cover) and forest-management practices (i.e. biomass removal or revegetation through forestry, agriculture, and fire, and nutrient inputs through fertilizer practices) in terms of extent and distribution of land-cover and land-management practices and historic, current, and potential future scenarios of land-cover and land-management practices.

Overview of Report

This report is structured in the following way: In the Methods section, we develop a framework for comparing different models of land-use change. In particular, we propose that models of land-use change be compared in terms of scale and complexity, and how well they incorporate space, time, and human decision making (HDM). Subsequently, we describe the methods we used for identifying the models we reviewed, including how we narrowed a list of 250 relevant citations to a set of 136 possible references, and then to a list of 19 land-use models that we found to be the most relevant and representative. In the Findings section, we summarize the 19 models in terms of scale and complexity as well as critical model features, such as whether or not they include time lags and feedback loops. In the Discussion section, we discuss model characteristics in terms of spatial and temporal complexity and which models incorporate higher levels of human decision making. We then examine the social drivers of land-use change and methodological trends exemplified in the models we reviewed. Finally, we conclude with some proposals for future directions in land-use modeling for the NIEMP:Eastwide project.

2. METHODS

Background

Models can be categorized in multiple ways. One may focus on the subject matter of the models, on modeling techniques or methods used (from simple regression to advanced dynamic programming), or on the actual uses of the models. A review of models may focus on techniques in conjunction with assessments of model performance for particular criteria, such as scale (see, for example, the review of deforestation models by Lambin 1994). In the case of FSGRCP, models are evaluated by the following criteria:

1. Identify and assess the likely effects of changes in forest ecosystem structure and function on human communities and society;
2. Evaluate potential policy options for rural and urban forestry; and
3. Evaluate potential rural and urban forest management activities.

While this review does indirectly cover these topics, we developed an alternative analytical framework. As Veldkamp and Fresco (1996a) note, land use "is determined by the interaction in space and time of biophysical factors (constraints) such as soils, climate, topography, etc., and human factors like population, technology, economic conditions, etc." In this review, we utilize all four of the factors that Veldkamp and Fresco (1996a) identify in the construction of a new analytical framework for categorizing and summarizing models of land-use change dynamics.

Framework for Reviewing Human-Environmental Models

To assess land-use change models, we propose a framework based on three critical dimensions for categorizing and summarizing models of human-environmental dynamics. Time and space are the first two dimensions and provide a common setting in which all biophysical and human processes operate. In other words, models of biophysical and/or human processes operate in a temporal context, a spatial context, or both. When models incorporate human processes, our third dimension—referred to as the human decision-making dimension—becomes important as well (Figure 2.1).

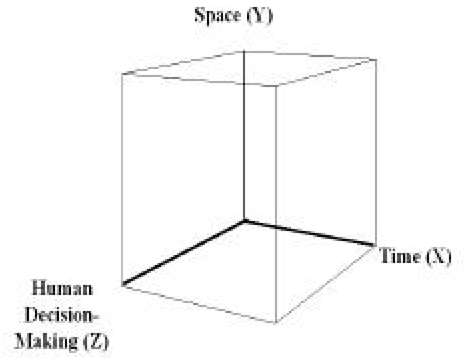

Figure 2.1 Three-Dimensional Framework for Reviewing Land-Use Change Models

In reviewing and comparing land-use change models along these dimensions, there are two distinct and important attributes that must be considered: *model scale* and *model complexity.* We begin with a discussion of scale, since it is a concept that readers will probably find most familiar.

Model Scale

Time Step and Duration

"Real world" processes operate at different scales (Allen and Hoekstra 1992; Ehleringer and Field 1993). When we discuss the temporal scale of models, we can talk in terms of "time step" and "duration." Time step referred to here is the smallest temporal unit of analysis for change to occur for a specific process in a model. For example, in a model of forest dynamics, tree height may change daily. The model would not consider processes which act over shorter temporal units. Duration refers to the length of time that the model is applied. For instance, change in tree height might be modeled daily over the course of its life from seedling to mature tree: a period of 300 years. In this case, time step would be one day, and duration would equal 300 years. When the duration of a model is documented, it might be reported in several ways. In our example, the model duration might be 109,500 daily time steps, a period of 300 years, or calendar range: January 1, 1900, to January 1, 2200.

Resolution and Extent

When we discuss the spatial scale of models, we employ the terms "resolution" and "extent." Resolution refers to the smallest geographic unit of analysis for the model such as the size of a cell in a raster grid system. (Note that each grid cell area is typically uniform across the modeled area, while a vector representation would typically have polygons of varying sizes, although the smallest one may be considered the model's resolution.) Extent describes the total geographic area to which the model is applied. Consider a model of individual trees in a 50-hectare forested area. In this case, an adequate resolution for individual trees might be several meters, and the model extent would equal 50 hectares.

Resolution may be characterized as fine or broad scale. Fine-scale models often depict geographically small units of analysis (and thus are large scale, to use the geographic term), while broad-scale models usually have larger spatial units of analysis (and are thus small scale). Figure 2.2 provides an example of analysis moving from a broad scale (A) to increasingly finer scales (E).

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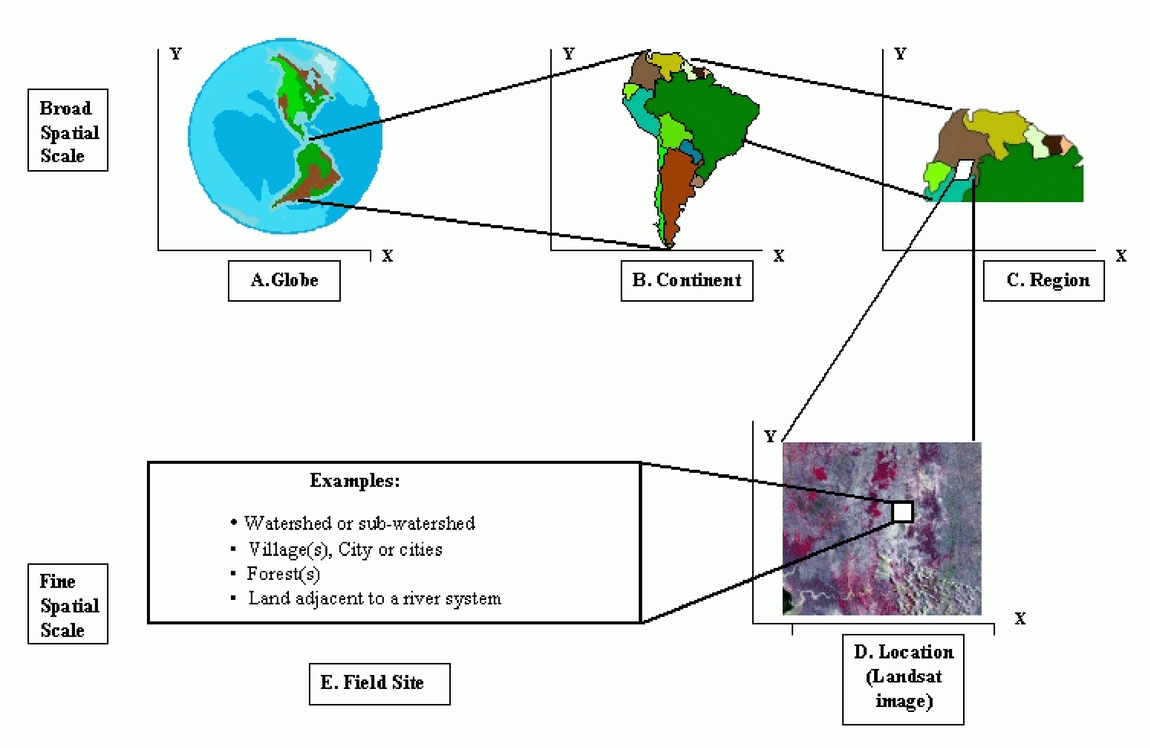


Figure 2.2 Hierarchical Spatial Scales in Social-Ecological Contexts

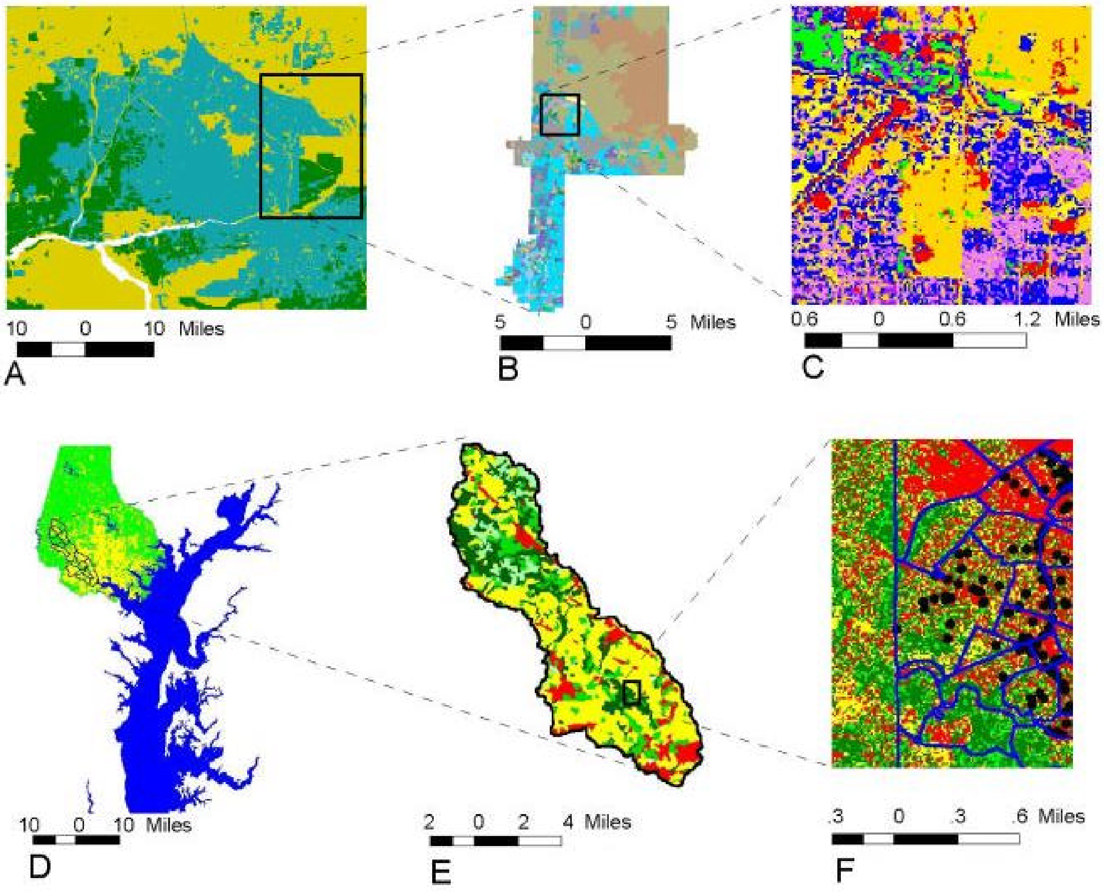
For clarity, we use different terms to characterize temporal and spatial scale. Temporal time step and duration are analogous to spatial resolution and extent. Resolution and extent are often used to describe both temporal and spatial scales; however, we make these distinctions so that readers will not be confused by which scale we are referring to in any particular discussion, and we think these careful distinctions in scale terminology are important for further dialog of land-use/land-cover modeling. We propose a similar approach in describing scale of human decision making.

Agent and Domain

How does one discuss human decision making in terms of scale? To date, the social sciences have not yet described human decision making in terms that are as concise and widely accepted for modeling, as time step/duration or resolution/extent. Like time and space, we propose an analogous approach which can be used to articulate scales of human decision making in similar terms: “agent” and “domain.”

Agent refers to the human actor or actors in the model who are making decisions. The individual human is the smallest single decision-making agent. However, there are many land-use change models that capture decision-making processes at broader scales of social organization, such as household, neighborhood, county, state or province, or nation. All of these can be considered agents in models. Domain, on the other hand, refers to the broadest social organization incorporated in the model. Figure 2.2 illustrates agents (villages) and domain (countries of the western hemisphere) for the study of social ecosystems in a hierarchical approach.

While the agent captures the concept of who makes decisions, the domain describes the specific institutional and geographic context in which the agent acts. Representation of the domain can be facilitated in a geographically explicit model through the use of boundary maps or GIS layers.



Examples of hierarchically nested patch structure at three scales in the Central Arizona–Phoenix (CAP; upper panels) and Baltimore Ecosystem Study (BES; lower panels) regions. At the broadest scale (A, D), patches in the CAP study area include desert (mustard), agriculture (green), and urban (blue); for the BES, patches are rural (green), urban (yellow), and aquatic (blue). B: The municipality of Scottsdale, Ariz., showing major areas of urban-residential development (blue, lower portion) and undeveloped open lands (tan, developable; brown, dedicated). C: Enlargement of rectangle in B showing additional patch structure at a neighborhood scale (green, golf course/park; mustard, undeveloped desert; red, vacant; pink, xeric residential; purple, mesic residential; yellow, asphalt). E: Gwynns Falls watershed, Md., with residential (yellow), commercial/industrial (red), agricultural (light green), institutional (medium green), and forest (dark green) patch types. F: Enlargement of rectangle in E showing additional patch structure at a neighborhood scale (dark green, pervious surface/canopy cover; light green, pervious surface/no canopy cover; yellow, impervious surface/canopy cover; red, impervious surface/no canopy cover; blue, neighborhood boundaries; black circles, abandoned lots). Panel A courtesy of CAP Historic Land Use Project (caplter.asu.edu/elwood.la.asu.edu/grsl/); panels D, E, and F courtesy of USDA Forest Service and BES LTER (http://www.ecostudies.org/bes).

Figure 2.3 Spatial Representation of a Hierarchical Approach to Modeling Urban Systems (Grimm et al. 2000)

For example, in a model of collaborative watershed management by different forest landowners, a multiscale approach would incorporate several levels of linked resolutions and domains. For instance, at a broad scale, the domain would be the collaborative arrangement among owners (coincident with the watershed boundaries), the agent would be the owner and the resolution their associated parcel boundaries (the agent would be the collaborative organization). At a finer scale, the owner would be the domain, and the resolution would be the management units or forest stands within each parcel (the agent being the individual). In this example, we might also model other agents, operating in one of the two domains (e.g., other parcels), such as neighboring landowners whose parcel boundaries would also be depicted by the same domain map. Institutionally, agents may overlap spatially. For example, a landowner might receive financial subsidies for planting trees in riparian buffer areas from an agent of the Forest Service; receive extension advice about wildlife habitat and management from an agent of the Fish & Wildlife Service; and have her lands inspected for non-point-source runoff by an agent from the Environmental Protection Agency.

In our watershed example, also consider the role of other types of forest landowners. For instance, the watershed might include a state forester (agent = state) who writes the forest management plan for the state forest (domain = state boundary) and prescribes how often trees (resolution) in different forest stands (extent) should be harvested (time step) for a specific period of time (duration) within state-owned property. In this case, the human decision-making component of the model might include the behavior of the forester within the organizational context of the state-level natural resource agency.

Model Complexity

A second important and distinct attribute of human-environmental models is the approach used to address the complexity of time, space, and human decision making found in "real world" situations. We propose that the temporal, spatial, or human decision-making (HDM) complexity of any model can each be represented with an index, where low values signify simple components and high values signify more complex behaviors and interactions. Consider an index for *temporal complexity* of models: A model that is low in temporal complexity may be a model that has one time step, or possibly a few, and a short duration. A model with a mid-range value for temporal complexity is one which may use many time steps and a longer duration. Models with a high value for temporal complexity are ones that may incorporate a large number of time steps, a long duration, and the capacity to handle time lags or feedback responses among variables, or have different time steps for different submodels.

Temporal Complexity

There are important interactions possible among temporal complexity and human decision making. For instance, some human decisions are made in very short time intervals. The decision of which road to take on the way to work is made daily (even though many individuals routinize this decision and do not self-consciously examine this decision each day). Other decisions are made over longer time periods, such as once in a single growing season: for instance, which annual crop to plant in a region that has only one growing season per year. Still other decisions may be made for several years at a time, such as investments made in tractors or harvesting equipment. When the domain of a decision maker changes, this change may also affect the temporal dimension of decisions. For example, a forest landowner might make a decision about cutting trees on his or her land each year. If this land were transferred to a State or National Forest, the foresters may harvest only once every ten years.

The decision-making time horizon perceived by an actor could also be divided into a short-run decision-making period, and a long-run time horizon. Thus, to extend the forest example, if a certain tree species covering a 100-hectare area matures in 100 years, there is a need for a harvest plan that incorporates both the maturity period and the extent of forest land that is available. In other words, at least one level of actor needs to have an awareness of both short- and long-time horizons and be able to communicate with other actors operating at shorter time horizons. Institutional memory and culture can often play that role.

Spatial Complexity

An index of *spatial complexity* would represent the extent to which a model is "spatially explicit." There are two general types of spatially explicit models: spatially representative and spatially interactive. A model that is spatially representative can incorporate, produce, or display data in at least two and sometimes three spatial dimensions, such as northing, easting, and elevation, but cannot model topological relationships and interactions among geographic features (cells, points, lines, or polygons). In these cases, the value of each cell may change or remain the same from one point in time to another, but the logic that makes the change is not dependent on neighboring cells. In contrast, a spatially interactive model is one that explicitly defines spatial relationships and their interactions (e.g., among neighboring units) over time. A model with a low value for spatial complexity would be one with little or no capacity to represent data spatially; a model with a medium value for spatial complexity would be able to fully represent data spatially; and a model with a high value would be spatially interactive in two or three dimensions.

The human decision-making sections of models vary in terms of their theoretical precursors and may be simply linked deterministically to a set of socioeconomic or biological drivers, or they may be based on some game theoretic or economic models. Table 2.1 below presents the equivalence among the three parameters, space, time, and human decision making, based on the earlier discussion about resolution and extent.

Table 2.1 Resolution and Extent in the Three Dimensions of Space, Time and Human Decision Making

	Space	**Time**	**Human Decision Making**
Resolution or equivalent	Resolution: smallest spatial unit of analysis	Time step: shortest temporal unit of analysis	Agent and decision-making time horizon
Extent or equivalent	Extent: total relevant geographical area	Duration: total relevant period of time	Jurisdictional domain and decision-making time horizon

Human Decision-Making Complexity

Given the major impact of human actions on land use and land cover, it is essential that models of these processes begin to illuminate the factors that affect human decision making. Many theoretical traditions inform the theories that researchers use when modeling decision making. As discussed below, some researchers are strongly influenced by deterministic theories of decision making and do not attempt to understand how external factors affect the internal calculation of benefits and costs: the "dos" and "don'ts" that affect how individuals make decisions. Others, who are drawing on game theoretical or other theories of reasoning processes, make much more self-conscious choices to model individual (or collective) decisions as the result of various factors which combine to affect the processes and outcomes of human reasoning.

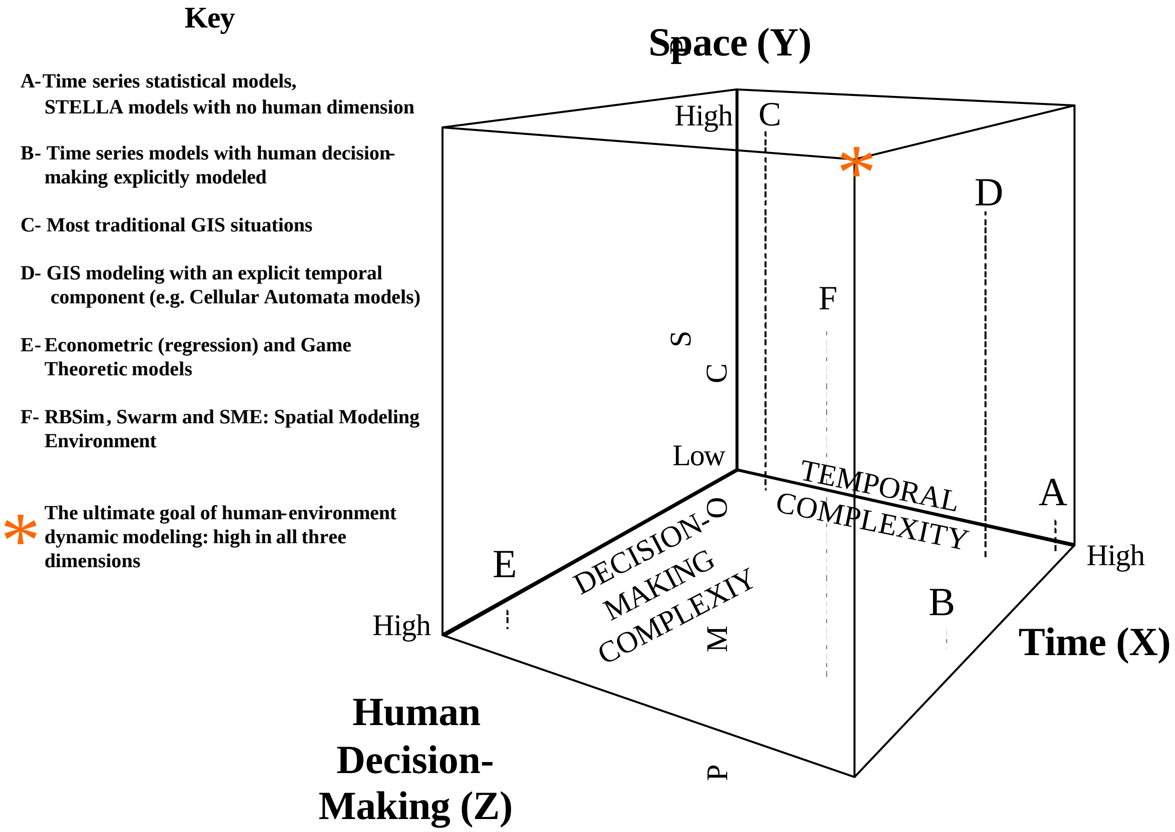
What is an appropriate index to characterize complexity in human decision making? We use the term *HDM complexity* to describe the capacity of a human-environmental model to handle human decision-making processes. In Table 2.2, we present a classification scheme for estimating HDM complexity using an index with values from one to six. A model with a low value (1) for human decision-making complexity is a model that does not include any human decision making. In contrast, a model with a high value (5 or 6) is a model that includes one or more types of actors explicitly or can handle multiple agents interacting across domains like those shown in figures 2.2 and 2.3. In essence, figures 2.2 and 2.3 represent a hierarchical approach to social systems where lower-level agents interact to generate higher-level behaviors and where higher-level domains affect the behavior of lower-level agents (Grimm et al. 2000; Vogt et al. 2000; Grove et al. 2000).

Table 2.2 Six Levels of Human Decision-Making Complexity

Level	
1	No human decision making -- only biophysical variables in the model
2	Human decision making assumed to be determinately related to population size, change, or density
3	Human decision making seen as a probability function depending on socioeconomic and/or biophysical variables beyond population variables **without** feedback from the environment to the choice function
4	Human decision making seen as a probability function depending on socioeconomic and/or biophysical variables beyond population variables **with** feedback from the environment to the choice function
5	One type of agent whose decisions are overtly modeled in regard to choices made about variables that affect other processes and outcomes
6	Multiple types of agents whose decisions are overtly modeled in regard to choices made about variables that affect other processes and outcomes; the model may also be able to handle changes in the shape of domains as time steps are processed or interaction between decision-making agents at multiple human decision-making scales

Application of the Framework

The three dimensions of land-use change models (space, time, and human decision making) and two distinct attributes for each dimension (scale and complexity) provide the foundation for comparing and reviewing land-use change models. Figure 2.4 is an example of the framework with the three dimensions represented together with a few general models, including some types that were reviewed in this study. Various modeling approaches would vary in their placement along these three dimensions of complexity since the location of a land-use change model reflects its technical structure as well as its sophistication and application.


Key

A-Time series statistical models, STELLA models with no human dimension

B- Time series models with human decision-making explicitly modeled

C- Most traditional GIS situations

D- GIS modeling with an explicit temporal component (e.g. Cellular Automata models)

E- Econometric (regression) and Game Theoretic models

F- RBSim, Swarm and SME: Spatial Modeling Environment

*** The ultimate goal of human-environment dynamic modeling: high in all three dimensions**

Figure 2.4 A Three-Dimensional Framework for Reviewing and Assessing Land-Use Change Models

The analysis that follows attempts to characterize existing land-use models on each modeling dimension. Models are assigned a level in the human decision-making dimension, and their ability in the spatial and temporal dimensions are estimated as well. In addition, we document and compare models across several other factors including: the model type, dependent or explanatory variables if any, modules, and independent variables.

Identifying List of Models

Any project that purports to provide an overview of the literature in an area needs to provide the reader with some information regarding how choices were made regarding inclusion in the set to be reviewed. In our case, we undertook literature and web searches as well as consultations with experts.

Literature and Web Searches

We began our search for appropriate land-use/land-cover change models by looking at a variety of databases. Key word searches using *land cover*, *land use*, *change*, *landscape*, *land**, and *model**, where * was a wildcard, generated a large volume of potential articles. The databases that proved to be most productive were Academic Search Elite and Web of Science. Both databases provide abstract and full-text searches. Other databases consulted, but not used as extensively, include Carl Uncover, Worldcat, and IUCAT (the database for Indiana University's library collections). We also searched for information on various web search engines. Some of the appropriate web sites we found included bibliographies with relevant citations.

All of these searches yielded a total of 250 articles, which were compiled into bibliographic lists. The lists were then examined by looking at titles, key words, and abstracts to identify the articles that appeared relevant for this review. This preliminary examination yielded a master bibliography of 136 articles. They were chosen because they either assessed land-use models directly or they discussed approaches and relevance of models for land-use and land-cover change. The master bibliography is attached for reference (see Appendix 1). We then checked the bibliographies of these articles for other relevant works. Web of Science also allowed us to search for articles cited in other articles.

Twelve models were selected by reading articles identified through this process. The basic selection criteria were relevance and representativeness. A model was relevant if it dealt with land-use issues directly. Thus, models that focused largely on water quality, wildlife management, or urban transportation systems were not reviewed. The other seven models were chosen from recommendations received from colleagues and experts, especially the U.S. Forest Service. These additional models were also reviewed for relevance and representativeness.

The criteria for representativeness included the following:

1. Emphasis on including diverse types of models. Model type was considered in choosing articles for review. If several models of a particular type had already been reviewed, other applications of that model type were excluded in favor of different model types. For example, our search uncovered multiple spatial simulation models, several of which were reviewed.
2. If there were numerous papers on one model (e.g., six on the NELUP model), only the more representative two or three were reviewed.
3. If there were several papers by one author (e.g., Wear) covering two or more models, a subset that looked most relevant was reviewed.

Survey of Experts

Expert opinion helped locate some of the models we reviewed. In addition to our literature and web searches, we consulted with the Program Managers for the USFS Southern and Northern Global Change Programs to identify other significant land-use change models. In addition to the models they identified, the Program Managers also identified science contacts who were working in or familiar with the field of land-use modeling. We followed up with these contacts in order to (1) identify any additional relevant models that we had not identified through our literature and web searches, and (2) evaluate whether or not our literature and web searches were producing a comprehensive list. The evaluation was accomplished by comparing our "contacts' lists" with the land-use model list we had developed through our literature and web searches. Over the course of three months, this follow-up activity provided fewer and fewer "new models," and we shifted our efforts to the documentation and analysis of the models we had already identified.

By the end of the exercise, we had covered a range of model types. They included Markov chain models, logistic function models, regression models, econometric models, dynamic systems models, spatial simulation models, linear planning models, non-linear mathematical planning models, mechanistic GIS models, and cellular automata models. For further discussion, please refer to the subsection on methodological trends in Section 4.[1]

3. FINDINGS

We reviewed 19 land-use models for their spatial, temporal, and human decision-making characteristics using the framework we discussed in the previous section.

Models Surveyed

1. General Ecosystem Model (GEM) (Fitz et al. 1996)
2. Patuxent Landscape Model (PLM) (Voinov et al. 1999)
3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkamp and Fresco 1996a)
4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b)
5. Area base model (Hardie et al. 1997)
6. Univariate spatial models (Mertens et al. 1997)
7. Econometric (multinomial logit) model (Chomitz et al. 1996)
8. Spatial dynamic model (Gilruth et al. 1995)
9. Spatial Markov model (Wood et al. 1997)
10. CUF (California Urban Futures) (Landis 1995, Landis et al. 1998)
11. LUCAS (Land Use Change Analysis System) (Berry et al. 1996)
12. Simple log weights (Wear et al. 1998)
13. Logit model (Wear et al. 1999)
14. Dynamic model (Swallow et al. 1997)

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[1] We have tried to be as thorough as possible in our search for existing land-use/land-cover change models (as of May 2000). However, we certainly would like to know of any important models we may have missed in this review. For this reason, we will be posting the model references to a new web-based database we call the "Open Research System" (at http://www.open-research.org). If you have a reference to a model we missed, we encourage you to visit this site, register with the system, and submit a reference to a model publication using the submit publication form.

15. NELUP (Natural Environment Research Council [NERC]–Economic and Social Research Council [ESRC]: NERC/ESRC Land Use Programme [NELUP]) (O'Callahan 1995)
16. NELUP - Extension, (Oglethorpe et al. 1995)
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998)
19. Cellular automata model (Clarke et al. 1998, Kirtland et al. 2000)

We summarize some key variations in modeling approaches in Table 3.1. All the models were spatially representative. Of the 19 models, 15 (79 percent) could be classified as spatially interactive rather than merely representative. The same number of models were modular. Models that were not modular were conceptually simple and/or included few elements. Interestingly, a majority of the models did not state they were spatially explicit. Another observation was the level of temporal complexity: some models include multiple time steps, time lags, and negative or positive feedback loops.

Table 3.1 Summary Statistics of Model Assessment

Review Criteria	**# (%) of Models**	**Model #s**
Spatial interaction	15 (79%)	All but 5,9,12,13
Temporal complexity	6 (31%)	1,2,3,4,15,16
Human Decision Making – Level 1	3	1,6,9
Human Decision Making – Level 2	2	12,
Human Decision Making – Level 3	7	5,7,10,11,13,17,18
Human Decision Making – Level 4	4	2,3,4,8,
Human Decision Making – Level 5	2	14,16
Human Decision Making – Level 6	1	15

In tables 3.2, 3.3, and 3.4, we provide a summary and assessment of land-use change models. Table 3.2 gives basic information about each model: type, modules, what the model explains (dependent variables), independent variables, and the strengths and weaknesses of each model. Table 3.3 describes the spatial characteristics of each model: spatial representation or interaction, resolution, and extent. Table 3.4 details the temporal characteristics of each model: time step and duration as well as the human decision-making elements complexity, jurisdictional domain, and temporal range of decision making. A list of definitions is provided in the glossary at the end of this report. We discuss some of our findings in Section 4.

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation *Name of model, if any, and citation*	**Model Type** *Technical, descriptive terms*	**Components/ Modules** *Different models, or submodels or modules that work together*	**What It Explains / Dependent Variable**	**Other Variables** *Description of other sets of variables in the model*	**Strengths**	**Weaknesses**
1. General Ecosystem Model (GEM) (Fitz et al. 1996)	Dynamic systems model	14 Sectors (modules), e.g. Hydrology Macrophytes Algae Nutrients Fire Dead organic matter Separate database for each sector	Captures feedback among abiotic and biotic ecosystem components	103 input parameters, in a set of linked databases, representing the modules, e.g. Hydrology Macrophytes Algae Nutrients Fire Dead organic matter	Spatially dependent model, with feedback between units and across time Includes many sectors Modular, can add or drop sectors Can adapt resolution, extent, and time step to match the process being modeled	Limited human decision making
2. Patuxent Landscape Model (PLM) (Voinov et al. 1999)	Dynamic systems model	Based on the GEM model (#1, above), includes the following modules, with some modification: 1) Hydrology 2) Nutrients 3) Macrophytes 4) Economic model	Predicts fundamental ecological processes and land-use patterns at the watershed level	In addition to the GEM variables, it -adds dynamics in carbon-to-nutrient ratios -introduces differences between evergreen and deciduous plant communities -introduces impact of land management through fertilizing, planting and harvesting of crops and trees	In addition to the strengths of the GEM, the PLM incorporates several other variables that add to its applicability to assess the impacts of land management and best management practices.	Limited consideration of institutional factors
3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkamp and Fresco 1996a)	Discrete, finite state model	1) Regional biophysical module 2) Regional land-use objectives module 3) Local land-use allocation module	Predicts land cover in the future	*Biophysical drivers* Land suitability for crops Temperature/Precipitation Effects of past land use (may explain both biophysical degradation and improvement of land, mainly for crops) Impact of pests, weeds, diseases *Human Drivers* Population size and density Technology level Level of affluence Political Structures (through command and control, or fiscal mechanisms Economic conditions Attitudes and values	Covers a wide range of biophysical and human drivers at differing temporal and spatial scales	Limited consideration of institutional and economic variables

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b)	Discrete finite state model	CLUE-CR an application of CLUE (#3, above) Same modules	Simulates top-down and bottom-up effects of land-use change in Costa Rica	Same as CLUE (#3, above)	Multiple scales - local, regional, and national Uses the outcome of a nested analysis, a set of 6x5 scale-dependent land-use/land-cover linear regressions as model input, which is reproducible, unlike a specific calibration exercise	Authors acknowledge limited consideration of institutional and economic factors
5. Area base model (Hardie et al. 1997)	Area base model, using a modified multinomial logit model	Single module	Predicts land-use proportions at county level	Land base - classified as farmland, forest, and urban/other uses County average farm revenue Crop costs per acre Standing timber prices Timber production costs Land quality (agricultural suitability) Population per acre Average per capita personal income Average age of farm owners Irrigation	Uses publicly available data Incorporates economic (rent), and landowner characteristics (age, income) and population density Incorporates the impact of land heterogeneity Can account for sampling error in the county-level land-use proportions and for measurement error incurred by the use of county averages	An extended dataset over longer time periods would improve the model's predictions Long-term forecasts run the risk of facing an increasing probability of structural change, calling for revised procedures
6. Mertens et al. 1997	Univariate spatial models	Multiple univariate models, based on deforestation pattern in study area 1) Total study area 2) Corridor pattern 3) Island pattern 4) Diffuse pattern Each model runs with all four independent variables separately.	Frequency of deforestation	All four models run with all four independent variables: 1) Road proximity 2) Town proximity 3) Forest-cover fragmentation 4) Proximity to a forest/non-forest edge	Presents a strategy for modeling deforestation by proposing a typology of deforestation patterns In all cases, a single variable model explains most of the variability in deforestation.	Does not model interaction between factors

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
7. Chomitz et al. 1996	Econometric (multinomial logit) model	Single module, with multiple equations	Predicts land use, aggregated in three classes: Natural vegetation Semi-subsistence agriculture Commercial farming	Soil nitrogen Available phosphorus Slope Ph Wetness Flood hazard Rainfall National land Forest reserve Distance to markets, based on impedance levels (relative costs of transport) Soil fertility	Used spatially disaggregated information to calculate an integrated distance measure based on terrain and presence of roads Also, strong theoretical underpinning of Von Thunen's model	Strong assumptions that can be relaxed by alternate specifications Does not explicitly incorporate prices
8. Gilruth et al. 1995	Spatial dynamic model	Several subroutines for different tasks	Predicts sites used for shifting cultivation in terms of topography and proximity to population centers	Site productivity (# of fallow years) Ease of clearing Erosion hazard Site proximity Population, as function of village size	Replicable Tries to mimic expansion of cultivation over time	Long gap between data collection; does not include impact of land-quality and socioeconomic variables
9. Wood et al. 1997	Spatial Markov model	Temporal and spatial land-use change Markov models	Land-use change	Models under development	Investigating Markov variations, which relax strict assumptions associated with the Markov chain approach Explicitly considers both spatial and temporal change	Not strictly a weakness, this is a work in progress and, hence, has not yet included HDM factors.
10. CUF (California Urban Futures) (Landis 1995; Landis et al. 1998)	Spatial simulation	Population growth submodel Spatial database, various layers merged to project Developable Land Units (DLUs) Spatial Allocation submodel Annexation-incorporation submodel	Explains land use in a metropolitan setting, in terms of demand (population growth) and supply (underdeveloped land available for re-development) of land	Population growth, DLUs, and intermediate map layers with: Housing prices Zoning Slope Wetlands Distance to city center Distance to freeway or BART station Distance to sphere-of-influence boundaries	Underlying theory of parcel allocation by population growth projections and price, and incorporation of incentives for intermediaries-developers, a great strength Large-scale GIS map layers with detailed information for each individual parcel in 14 counties provide high realism and precision.	Compresses long period (20 years) in a single model run; has no feedback of mismatch between demand and supply on price of developable land/housing stock; does not incorporate impact of interest rates, economic growth rates, etc.

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
11. LUCAS (Land-Use Change Analysis System) (Berry et al. 1996)	Spatial stochastic model	1) Socioeconomic module 2) Landscape change module 3) Impacts module	Transition probability matrix (of change in land cover) Module 2 simulates the landscape change. Module 3 assesses the impact on species habitat.	Module 1 variables: Land cover type (vegetation) Slope Aspect Elevation Land ownership Population Density Distance to nearest road Distance to nearest economic market center Age of trees Module 2: Transition matrix and same as Module 1, to produce a land-cover maps Module 3: Utilizes land-cover maps	Model shows process (the TPM), output (new land-use map), and impact (on species habitat), all in one, which is rare and commendable. Is modular and uses low-cost open-source GIS software (GRASS)	LUCAS tended to fragment the landscape for low-proportion land uses, due to the pixel-based independent-grid method. Patch-based simulation would cause less fragmentation, but patch definition requirements often lead to their degeneration into one-cell patches
12. Wear et al. 1998	Simple log weights	Single module	Predicts area of timberland adjusted for population density	Raw timberland Population density (per county)	Simple and powerful indicator of forest sustainability, of the impact of human settlement decisions on one forest function --its role as timberland	Limited consideration of human decision making and other forest goods and services
13. Wear et al. 1999	Logit model	Single module	Predicts the probability of land being classified as potential timberland	Population per square mile Site index Slope Two dummy variables defining ease of access to a site	Includes several biophysical variables	Includes only basic human choice variables, e.g., population density
14. Swallow et al. 1997	Dynamic model	Three components: 1) Timber model 2) Forage production function 3) Non-timber benefit function	Simulates an optimal harvest sequence	Present values of alternative possible states of the forest, using the three model components	The long time horizon, and the annual checking of present values under alternate possible states of the forest makes it a useful forest management tool for maximizing multiple-use values.	Authors note that the optimal management pattern on any individual stand or set of stands requires specific analysis rather than dependence on rules of thumb.

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
15. NELUP (O'Callahan 1995)	General systems framework Economic component uses a recursive linear planning model	1) Regional agricultural economic model of land use at catchment levels 2) Hydrological model 3) Ecological model	Explains patterns of agricultural and forestry land use under different scenarios	*Variable types include:* Soil characteristics Meteorological data Parish census data Input/output farm data Species Land cover	Uses land cover to link market forces, hydrology, and ecology in a biophysical model of land use Uses mostly publicly available data, especially in the economic model, which greatly aids transferability	Limited institutional variables
16. NELUP - Extension (Oglethorpe et al. 1995)	Linear planning model at farm level	Four sub-models for farm types 1) Lowland and mainly arable 2) Lowland mainly grazing livestock 3) Dairy 4) Hill	Maximizes income Profit is the dependent variable.	Level of farm activity Gross margin per unit of farm activity Fixed resources, represented as physical constraints	Detailed farm-level model, with extensive calibration Farmers shown as rational profit-maximizing beings, but also includes the impact of off-farm income	Limited institutional variables.
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)	Dynamic, non-linear, price endogenous, mathematical programming model	Three submodels : 1) Forest sector - transition timber supply model 2) Agricultural sector that is optimized with the forest sector submodel 3) Carbon sector for terrestrial carbon	Allocation of land in the forest and agricultural sectors. Objective function maximizes the discounted economic welfare of producers and consumers in the U.S. agriculture and forest sectors over a nine-decade time horizon	*Forest sector variable groups:* Demand functions for forest products Timberland area, age-class dynamics Production technology and costs *Agricultural sector variables:* Water Grazing Labor Agricultural demand Imports/exports. *Carbon sector variables:* Tree and ecosystem carbon *Additional variables:* Land transfer variables	Incorporates both agriculture and forest land uses Price of products and land is endogenous The model is dynamic, thus changes in one decade influence land-use change in the next decade Good for long-term policy impacts	Broad scale means that land capability variations within regions are not taken into account.

Table 3.2 In-Depth Overview of Models Reviewed

Model Name/ Citation	Model Type	Components/ Modules	What It Explains / Dependent Variable	Other Variables	Strengths	Weaknesses
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998)	Overlay of GIS layers with statistical urban growth projections	1) Statistical model of urban growth 2) Policy simulation and evaluation model 3) Map and data layers of habitat types, biodiversity, and other natural factors	The interaction among the probabilities of urbanization, its interaction with habitat type and extent, and, impacts of policy changes on the two	Slope and elevation Location and types of roads Hydrographic features Jurisdictional boundaries Wetlands and flood zones Jurisdictional spheres of influence Various socioeconomic data Local growth policies Job growth Habitat type and extent maps	Increases understanding of factors behind recent urbanization patterns Allows projection of future urban growth patterns, and of the impact of projected urban growth on habitat integrity and quality.	Human decision making not explicitly considered Further, errors are likely from misclassification of data at grid level or misalignment of map feature boundaries Errors also possible from limitations in explaining historical urban growth patterns
19. Clarke et al. 1998; Kirtland et al. 2000	Cellular automata model	Simulation module consists of complex rules Digital data set of biophysical and human factors	Change in urban areas over time	Extent of urban areas Elevation Slope Roads	Allows each cell to act independently according to rules, analogous to city expansion as a result of hundreds of small decisions Fine-scale data, registered to a 30 m UTM grid	Does not unpack human decisions that lead to spread of built areas Does not yet include biological factors

Table 3.3 Spatial Characteristics of Each Model

Model	**Spatial Complexity**		**Spatial Scale**	
	Representation	**Interaction**	**Resolution**	**Extent**
	Static. Represents data on a map and may portray variation as well	*Dynamic. Includes effect of variation on processes as well as feedback between neighboring units and location of parcel within the larger scale*	*Rastor or vector. The area of the basic unit of analysis. A grid if rastor.*	*Location and total area covered by model, e.g., grid area x # of grids*
1. General Ecosystem model (GEM) (Fitz et al. 1996)	Yes	Yes. Feedback between units	Raster Entire model runs for each spatial unit Trial unit of 1 sq. km can vary	A trial simulation for the Florida Everglades/ Big Cypress area Approx. 10,000 acres
2. Patuxent Landscape Model (PLM) (Voinov et al. 1999)	Yes	Yes Feedback between units	Raster Hydrological model: 200 m and 1 km	58905 cells (200 m) or 2352 cells (1 sq. km) The Patuxent watershed (Maryland, USA), covering 2353 sq. km
3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkamp and Fresco 1996a)	Yes	Yes Attributes of one grid unit affect land-use outcomes in another unit.	Raster In the generic CLUE model, size determined by extent divided by grid scale neutral matrix of 23x23 cells Can be scaled up or down	See next model, CLUE-CR, for an application
4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b)	Yes	As above	Raster Run at local, regional, and national levels One grid unit = 0.1 degrees or 6 minutes (= 7.5x7.5 km = 56.25 sq. km at the equator)	Multiple extents that correspond to different modules National: Costa Rica, 933 aggregate grid units Regional: 16 to 36 aggregate grids Local: 1 grid unit
5. Area Base Model (Hardie et al. 1997)	Yes Relies on land heterogeneity to explain the coexistence of several land uses and the shift between them	No	Neither raster nor vector Data averaged at county level Average county area = 315,497 acres	Five southeastern U.S. states - Florida, Georgia, South Carolina, North Carolina, Virginia = 147,423,760 acres

Table 3.3 Spatial Characteristics of Each Model

Model	Spatial Complexity		Spatial Scale	
	Representation	Interaction	Resolution	Extent
6. Mertens e al. 1997	Yes	Yes Status of pixel is dependent on other spatial factors.	Raster 80 m x 80 m (Landsat Pixel size)	Southeast Cameroon. Area not specified, but is the overlap between 2 Landsat images
7. Chomitz et al. 1996	Yes	Yes Spatial variation in several variables, influences other variables, e.g., wetness and roads and slope to assess impedance to markets	Uses vector data only	Central and South Belize, approx. 2/3 of the total area of 22,000 sq. km
8. Gilruth et al. 1995	Yes	Dynamic, spatially explicit model	Raster 100 m x 100 m cells, in a 60x60 cell grid, resampled from 120x120 grid	6 sq. km area, representative of a 60 sq. km Diafore watershed, in the Tougue district, Guinea
9. Wood et al. 1997	Yes	No	Raster Cell size of 80 m (x 80m)	One department, Velingara, in south-central Senegal
10. CUF (California Urban Futures) (Landis 1995; Landis et al. 1998)	Yes	Yes	Vector. Individual sites, with property boundaries Model run at city and county levels	Nine counties of the San Francisco Bay area (Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano, Sonoma) and five adjacent ones, (Santa Cruz, Sacramento, San Joaquin, Stanislaus, Yolo)
11. LUCAS (Land-Use Change Analysis System) (Berry et al. 1996)	Yes	Tentatively Yes, if the transition probability for one pixel, affected by factors in another pixel	Raster Each pixel in this example represents 90 X 90 m, and has an attached table with unique attributes.	Two watersheds, the Little Tennessee river basin in North Carolina and the Hoh river watershed on the Olympic Peninsula in Washington State
12. Wear et al. 1998	Yes Displays variations among counties	No	Neither County-level aggregate data	Southern states of the USA
13. Wear et al. 1999	Yes Variations among counties	No	Vector. Fine scale, forested plots in private ownership	Five-county region around Charlottesville, in Virginia - Albermarle, Fluvanna, Louisa, Greene, and Nelson
14. Swallow et al. 1997	Yes	Yes Takes interactions among stands into account	Still conceptual, neither raster nor vector Model simulates multi-stand dynamics. Stands can vary in size.	Multiple stands Case study uses a simplified ecosystem of two stands.

Table 3.3 Spatial Characteristics of Each Model

Model	Spatial Complexity		Spatial Scale	
	Representation	Interaction	Resolution	Extent
15. NELUP (O'Callahan 1995)	Yes Incorporates variation	Yes Variation affects neighboring units.	Raster Ecological model: 1 sq. km units The main economic model treats the whole catchment as a macro farm, but accounts for land-use variation using the land-cover data.	River Tyne catchment in Northern England - 3000 sq. km
16. NELUP - Extension (Oglethorpe et al. 1995)	Yes Developed four submodels to capture variation	Yes Not in submodel itself, but in the total NELUP model	Neither Farm level	Multiple farms Trial runs for 10 and 14 farms, and will cover the entire catchment.
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)	Yes Divides USA in 11 regions that may be represented on a map	Yes. Model at subcontinental scale, and changes in inventory and prices in one region affect prices and inventory in other regions.	Vector Demand: one national region Supply: subnational region	The entire USA, except, Hawaii and Alaska
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998)	Yes	Yes, as impact of changes in one cell - in terms of highway, growth policies, population and job growth, influences probability of urbanization of surrounding cells	Raster One-hectare grid cell (100x100 m)	County level in California Pilot study for Santa Cruz County Model data sets developed for nine counties
19. Clarke et al. 1998; Kirtland et al. 2000	Yes	Yes Each cell acts independently, but according to rules that take spatial properties of neighboring locations into account	Raster Converted vector data, e.g., roads to raster Base data registered at 30x30 m Model run at 1 sq. km level	Initial run for 256 sq. km region around San Francisco in central California, USA

Table 3.4 Temporal and Human Decision-Making Characteristics of Each Model

Model	Temporal Scale		Human Decision Making		
	Time Step	**Duration of Model Run**	**Complexity**	**Domain**	**Temporal Range**
	Time period for one iteration of the model. Modules may have different time steps -a function of the particular process	*Time step x number of runs*	*A 6-point scale for human decision making or human choice (rank and rationale)*	*Jurisdictional domain*	*Short-run decision-making period and longer-run decision-making horizon*
1. General Ecosystem Model (GEM) (Fitz et al. 1996)	Initial simulation runs at 0.5-day time step The time step can vary across modules- to match the dynamics of particular sectors.	Can match the cycle of process being modeled	Level: 1 Not covered in core model	Not really considered	Not really considered, as there is no explicit socioeconomic component in the basic GEM model
2. Patuxent Landscape Model (PLM) (Voinov et al. 1999)	Hydrological module: one-day time step Land-use map from the economic model imported at a one-year interval	Experimental run compared 1990 land-use patterns with complete forest	Level: 4 Incorporates human decisions as a function of economic and ecological spatial variables. Predicts probabilities of land-use conversion as functions of predicted values in residential and alternative uses and the costs of conversion	Maximizes rent as a function of the value in different uses and the costs of conversion, hence generally referring to private decision making, but aggregated at the grid level	Annual iteration to capture variations in land use
3. CLUE Model (Conversion of Land Use and Its Effects) (Veldkamp and Fresco 1996a)	One month to update model variables Changes in land-use types however, are made on decisions for each year	Set by user Example scenario is for several decades	Level: 4 It applies several human drivers.	Incorporates collective decision-making levels, from local to national	Considers the temporal range of decision making explicitly, in determining, for example the time period for updating changes in land-use types as well as minimum economic age and rotation length of the 10 different land-use types

Table 3.4 Temporal and Human Decision-Making Characteristics of Each Model

Model	Temporal Scale		Human Decision Making		
	Time Step	Duration of Model Run	Complexity	Domain	Temporal Range
4. CLUE-CR (Conversion of Land Use and Its Effects – Costa Rica) (Veldkamp and Fresco 1996b)	One month	One-month time step Run 252 times	Level: 4 Human demographic drivers only	As above, applied to Costa Rica	As in CLUE, above
5. Area Base Model (Hardie et al. 1997)	No Cross-sectional study with 1982 data At second stage, 5-year time step as pooled 1987 data	Mostly 1982 to 1987 data	Level: 3 Land-use proportions are modeled as dependent on rent from land as well as average age, income, and population density	While decision making is mostly at landowner level, the study explanatory variable, land-use proportions, is consistent with the county-level data.	Not considered in this cross-sectional study
6. Mertens et al. 1997	13 years. Single time step	13 years, 1973-86	Level: 1 Human decision making not included directly Implicit in the inclusion of variable like distance from road and town	Not considered	Not considered
7. Chomitz et al. 1996	Cross-sectional analysis, hence time period not applicable	Most data collected between 1989-92	Level: 3 Human decision making implicit in the inclusion of variables that impact rent - distance to market, soil quality	Not considered	Not considered
8. Gilruth et al. 1995	Two years Based on the average cultivation period in the exterior fields	1953 to 1989	Level: 4 Tries to predict location of shifting cultivation decisions on the basis of biophysical variables over time, with feedback	Subwatershed, with a small enough scale to capture large clearing No attempt to model individual fields	Model time step tries to mimic the estimated fallow period of two years; however, too long a period between the base and final year - 36 years

Table 3.4 Temporal and Human Decision-Making Characteristics of Each Model

Model	Temporal Scale		Human Decision Making		
	Time Step	Duration of Model Run	Complexity	Domain	Temporal Range
9. Wood et al. 1997	Two steps: Four years (1973-78) and 12 years (1978-90) Will add a third step by including 1985	17 years (1973-90)	Level: 1 Not included	Mostly at farm and field level, while model operates at department level	Considered implicitly, in choice of time step, to capture agricultural land-use change over longer time periods, rather than the decision making associated with each crop cycle
10. CUF (California Urban Futures) (Landis 1995; Landis et al. 1998)	Same as duration? Not clear from reference whether annual data are collected	1990-2010 Model takes 1990 base data and forecasts growth in 2010.	Level: 3. Human choice seen as determined by market price and other environmental and zoning constraints No feedback, excessive demand does not lead to increase in prices, in the model	Model operates at the level of individual parcels, which is the level at which decisions are usually taken	Not considered explicitly Model run compresses 20 years into one run Such housing decisions are often made quickly Model uses base-year price data It may inadequately represent exogenous factors in later years of the model A shorter time step may be better
11. LUCAS (Land-use Change Analysis System) (Berry et al. 1996)	Five Years Single time step	15 years (1975-91)	Level: 3 Human choice modeled via a probability function for land-cover change, with basic socioeconomic determinants and no feedback	Not considered explicitly Grid does not include ownership, though it is at fine enough scale to broadly reflect private decision making in U.S.	Not considered explicitly
12. Wear et al. 1998	Nine years	18 yrs - 1974,1983,1992 (two time steps or three observations in forest inventory years)	Level: 2 Demographic drivers determine impact.	Not considered explicitly The impact of individual decisions is aggregated to county level	Not considered explicitly

Table 3.4 Temporal and Human Decision-Making Characteristics of Each Model

Model	Temporal Scale		Human Decision Making		
	Time Step	**Duration of Model Run**	**Complexity**	**Domain**	**Temporal Range**
13. Wear et al. 1999	No Cross-sectional, 1990s data	Single run, no duration	Level: 3 Human choice included at basic determinant level (population density), along with the impact of several biophysical factors, on the probability of a certain land use	Average population data at aggregate county block level, correlated with individual plots	Cross-sectional study, hence not considered explicitly
14. Swallow et al. 1997	One year	Run of 250 years, sufficiently far into the future that heavy discounting makes a change in the time horizon inconsequential	Level: 5 A land management model The explanatory variable, optimal harvest rotations, provides a decision support tool	Focused on multiple stands, which is the level at which decisions are usually made, particularly if there are multiple owners	Land management decisions are usually made annually, or even more occasionally, especially for forests. The long time horizon, and the annual checking of present values under alternate possible states of the forest makes it a useful forest management tool.
15. NELUP (O'Callahan 1995)	Economic model uses annual data from parish-level records The time step of the hydrologic model was not available.	Economic submodel tested with annual data, 1981-88	Level: 6 The model overtly models choices of farmers, while actions of other actors are included in the form of technology or policy constraints.	The main economic model treats the whole catchment as a macro-farm, thus perhaps overestimating factor mobility.	The annual time step corresponds to time scale of broad agricultural decision making.
16. NELUP - Extension (Oglethorpe et al. 1995)	Annual financial and cost data	10-year period, 1981-82 to 1991-92	Level: 5 This submodel includes choices of farmers. When combined with the rest of the NELUP model, it would rank at 6. Also tries to model their risk-averse behavior	The model resolution perfectly matches the decision-making unit - the individual farm.	The annual time step corresponds to the time scale of broad agricultural decision making.

Table 3.4 Temporal and Human Decision-Making Characteristics of Each Model

Model	Temporal Scale		Human Decision Making		
	Time Step	Duration of Model Run	Complexity	Domain	Temporal Range
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al. 1996)	Decadal – 10 years	100 years, 1990-2089 Policy analysis limited to 50 years, 1990-2039	Level: 3 Human choice seen as economic rational decision making based on returns under alternative uses with limited feedback from the environment Accounts for changes in inter-temporal and price complexity	Demand region: nation Factor decision making is modeled at subnational regional level, with aggregation from individual landowner level, rather than at farm level	A decadal time step is consistent with the slow rate of changes in forest sector, but not the annual decision-making cycle in agriculture. To compensate, the agricultural objective function is weighted by a factor reflecting the harvest of agricultural products each year during a decade.
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al. 1998)	Not apparent	15 years, 1995 to 2010 Projections made for the latter year	Level: 3 Human decision making in the urbanization context implicitly a function of highway facilities, natural constraints, growth policies, and job and population growth Useful depiction of zoning policies	Calculates impacts at one-hectare grid level, a bit broader than individual decision-making levels in the urban context. Also includes the impacts of scale decision making, i.e., county or subcounty-level zoning	Long enough model period to capture longer term shifts in urbanization and its determinants
19. Clarke et al. 1998; Kirtland et al. 2000	Annual Used linear interpolation to estimate annual changes between datasets	Used about 90 years of data for validation to project urban growth a 100 years from 1990	Level: 2 While human decisions not explicitly modeled, their impact taken into account	Operates at a broader scale of 1 sq. km, utilizing the aggregate impact of hundreds of human decisions that affect urbanization	Annual time step appropriate to reflect aggregate changes in built area, as most buildings are ready in less than a year

4. DISCUSSION

In this section we discuss the major issues related to modeling land-use change as determined through our model review. In particular, we discuss trends in land-use modeling and the theoretical foundations behind these trends. Methodological evolution has allowed exploration of new modeling approaches, and we discuss the application of these new methodologies to land-use change modeling. Finally, we discuss various constraints facing the modeling community and certain opportunities based on the current direction of modeling and new methodological possibilities.

Trends in Temporal, Spatial, and Human Decision-Making Complexity

A graphical representation of the temporal time step and duration and the spatial resolution and extent of the models (Figure 4.1) facilitates several observations. These diagrams are constructed by plotting four values on an x-y plot: time step and duration on the x-axis and resolution and extent on the y-axis (see inset in lower left corner of Figure 4.1). The plotted area for each model then represents the spatial and temporal scales under which the model operates (colors of models in Figure 4.1 simply aid the reader in distinguishing them). Figure 4.1 shows that the 19 models examined in the report together cover a wide range of scales, from less than a day to more than 100 years in time and from less than one hectare to more than 1 million km^2 in space. Yet this range of scales is not covered by any one model. Clearly, models seem to be associated with a particular spatio-temporal niche. Several more temporal-specific conclusions can be drawn from these diagrams.

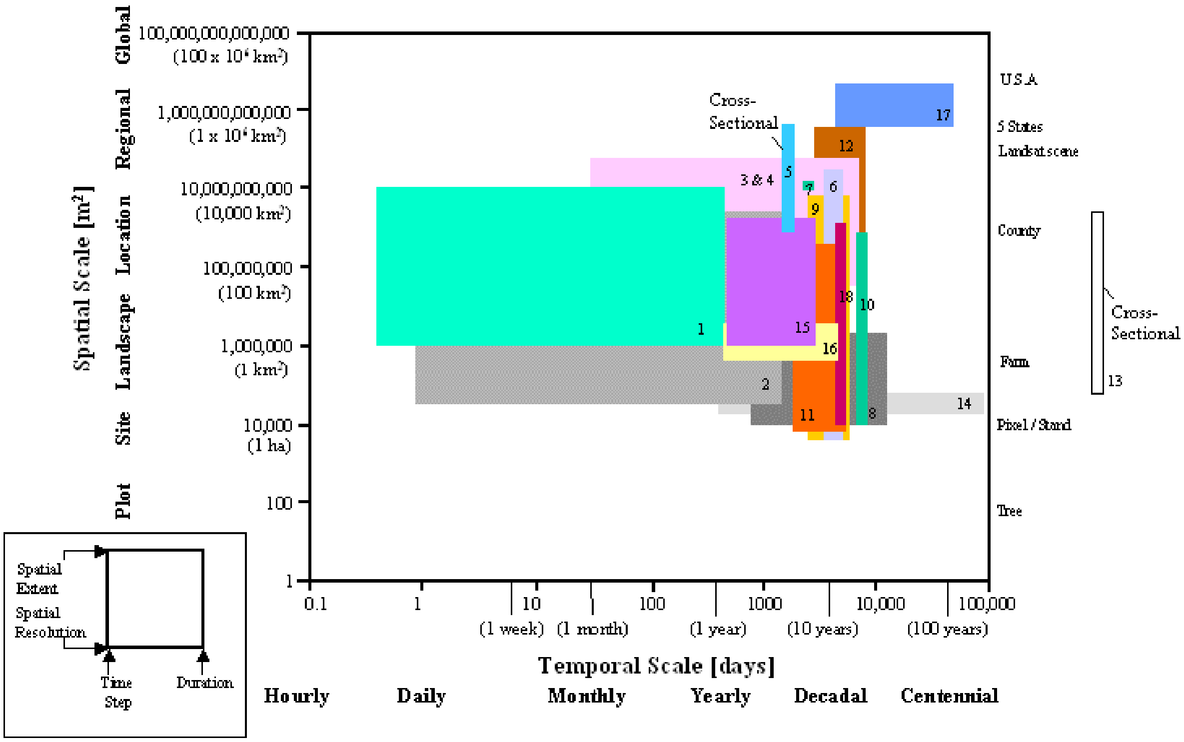

Figure 4.1 Spatial and Temporal Characteristics of Reviewed Models

Temporal Complexity

Many models with separate ecological modules operate at fine time steps, for example, a day or a month (exceptions include certain climate-focused models). This fine temporal resolution allows these models to more accurately represent rapid ecological changes with time in certain biophysical spheres, e.g., hydrology. Second, models with multiple time steps (e.g., models 1, 2, 3, 4, 15, 16) can span both fine and coarse time steps and reflect the temporal complexity of different socioeconomic and biophysical sectors more effectively. Third, some of the more complex models (CLUE and CLUE-CR) also incorporate time lags and take into account the time taken for different crops and other land uses to provide economic returns as well as provide a two-year buffer against food shortages by carrying over yield surpluses from previous years.

Spatial Complexity

More than half of the models provide for spatial interaction and demonstrate the advantages of spatially explicit models that move beyond simple spatial representation. These models include the impact of variations across space and time of different biophysical and socioeconomic factors on land-use change. Figure 4.2 depicts the 19 models as in Figure 4.1, as well as displaying which models use a raster or vector approach (or neither). The spatio-temporal footprint of the Landsat data sets is also included.

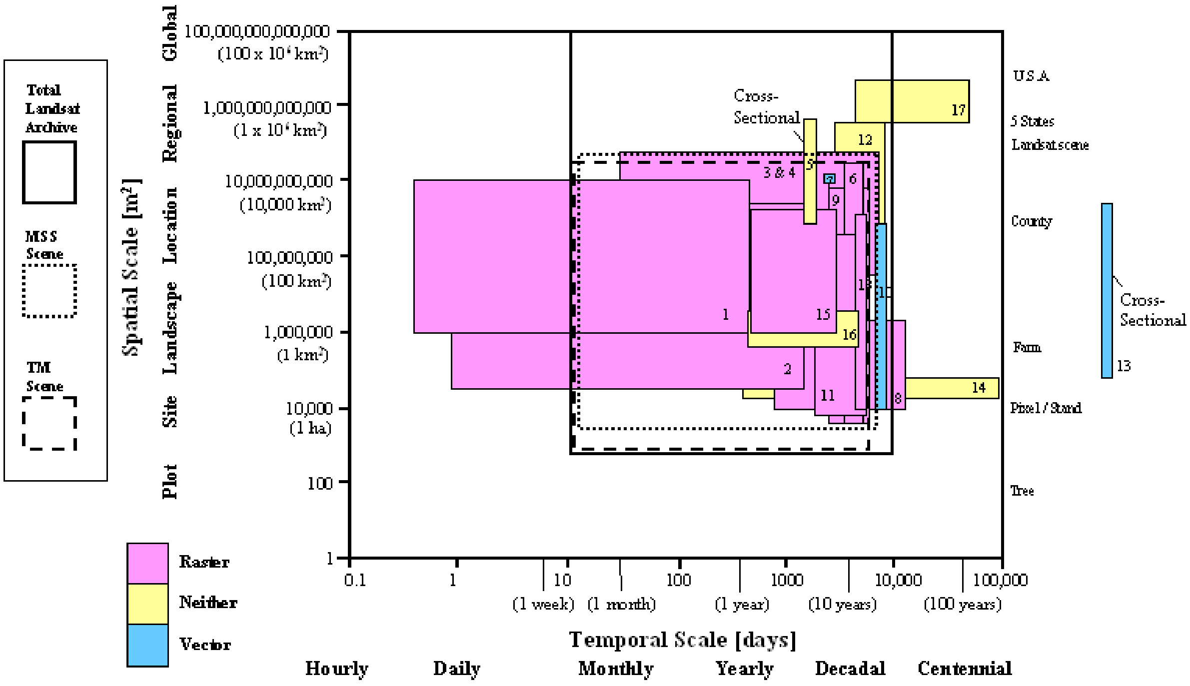

Figure 4.2 Raster and Vector Characteristics of Reviewed Models

Eleven of 19 models are raster based, four are vector based, and four are classified as neither. That may change, for example, if model #14 (Swallow et al. 1997) goes beyond the conceptual stage. The mechanistic vector models (#10 and #18) are focused at city and county levels and provide the finest spatial resolution. Their extent may be limited by availability of data. Most of the raster models have spatial resolutions that are larger than 30–80 meters, broadly mirroring the pixel size of common remote-sensing data (e.g., Landsat TM and MSS). Likewise, the raster models generally seem to have extents at or less than the area covered by one Landsat scene (185 kilometers x 185 kilometers).

The model with the largest extent (neither a raster nor a vector model) was the continental-scale FASOM model, with a 100-year time horizon, a good example of a dynamic, mathematical programming model that predicts allocation of land between agriculture and forestry, and is spatially representative but not spatially explicit.

Human Decision-Making Complexity

Figure 4.3 (a space–time–human–decision-making diagram) adds the level of complexity of human decision making to the graphical representation of temporal and spatial scales. Each model's level of human decision making is listed in Table 3.1. Models at level 3 (7 of 19) include significant levels of human decision making beyond demographic drivers, but are defined by the lack of feedback; thus, the CUF model allocates land based on cost, but does not factor in feedback on prices. At level 4, models incorporate feedback, but most do not overtly model a particular kind of actor. Thus, the PLM and CLUE/CLUE-CR models (#2, #3, and #4) have well-developed ecological sectors and extensive human decision-making elements as well as feedback among sectors, but do not explicitly model different types of actors. Model #8 (a land-use model that incorporates shifting cultivation decisions) is ranked at 4, based on its overall complexity in portraying human decision making. Models at level 5 (#14 and #16) and 6 (#15) explicitly model one or more kinds of actors. Model #14 simulates harvest decisions and includes both economic and non-economic criteria (e.g., habitat for wildlife). The NELUP model extension (#16) is a farm-level model that includes the impact of farming decisions on changes in intensity of land use and in land cover. The general NELUP model has ecological and economic components and farming decisions, and can serve as a decision support tool to provide feedback on the impact of collective-level policies (e.g., support prices or conservation programs). These characteristics position the NELUP model among the most detailed in terms of model specification in a variety of sectors affecting land-use change. However, it should be noted that a highly detailed model is not necessarily more suitable than a model with less specificity. The utility of a land-use change model can be measured primarily by its ability to demonstrate emergent patterns in land-use change processes and, secondarily, as a predictive tool.

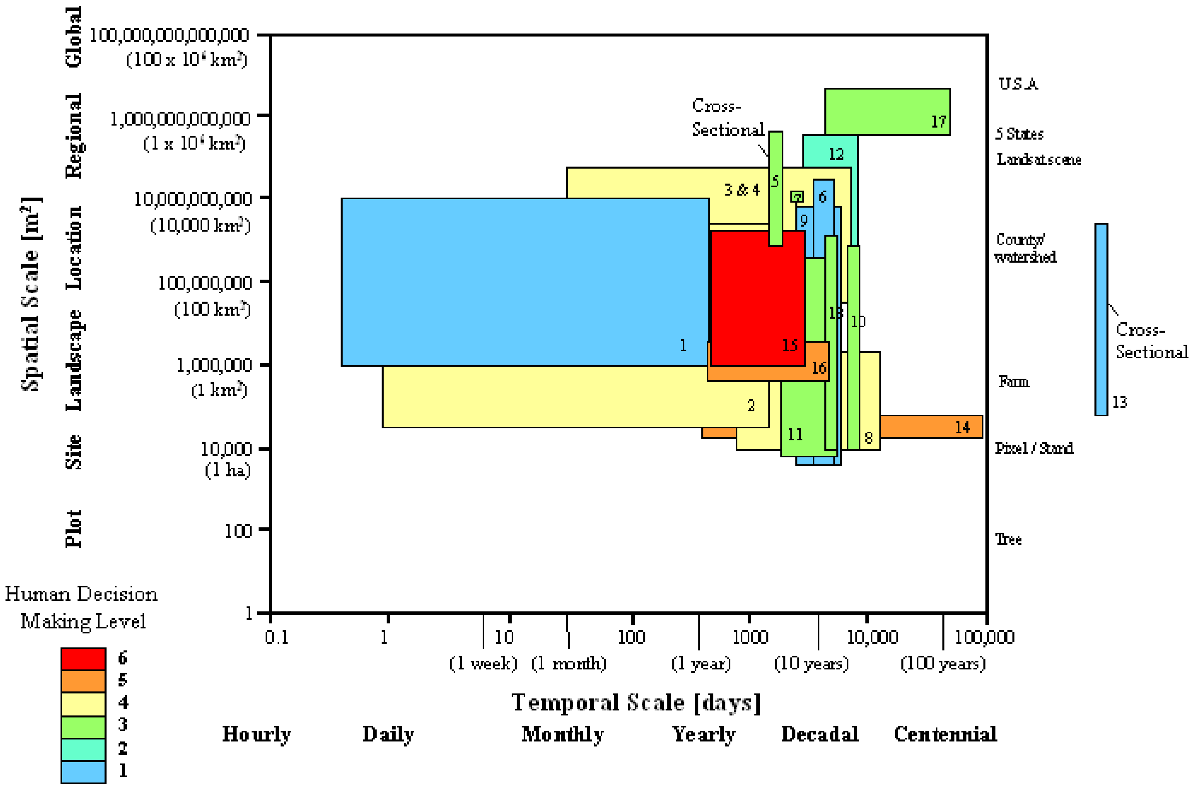

Figure 4.3 Human Decision-Making Complexity of Reviewed Models

Theoretical Trends

Social Drivers of Land-Use Change

Recently, a general consensus has emerged from working groups focusing on social drivers of global change, particularly as it relates to land-use change. Building upon the National Research Council's (NRC) report on *Global Environmental Change: Understanding Human Dimensions* (1992:2–3), a Long-Term Ecological Research (LTER) Network working group report to the National Science Foundation (NSF), *Toward a Unified Understanding of Human Ecosystems: Integrating Social Science into Long-Term Ecological Research* (2000), has articulated core social science areas that need to be studied in order to understand variations in human land-use, production, and consumption patterns.

To illustrate this further, we examine the simplified model in Figure 4.4, which describes a general, traditional, conceptual framework that many ecologists have used to study ecosystems. Although this conceptual model is powerful in its inclusion of both ecological and human-based processes, important interactions and feedbacks influencing long-term ecosystem dynamics are absent. An activity such as land use, traditionally seen as a driver, also can be viewed as the result of more fundamental social and ecological patterns and processes. Because many of these missing features relate to the social sciences, incorporating greater contributions from these disciplines together with existing biophysical/ecological models may greatly enhance our understanding of global change in general, and land-use change in particular.

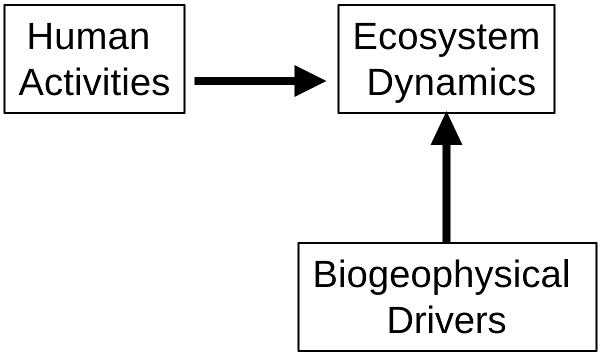

Figure 4.4 Traditional Conceptual Framework for Ecosystem Studies

In contrast to Figure 4.4, the LTER report proposes a more dynamic framework that explicitly links what is often divided into separate "natural" and human systems into a more integrated model (Figure 4.5).

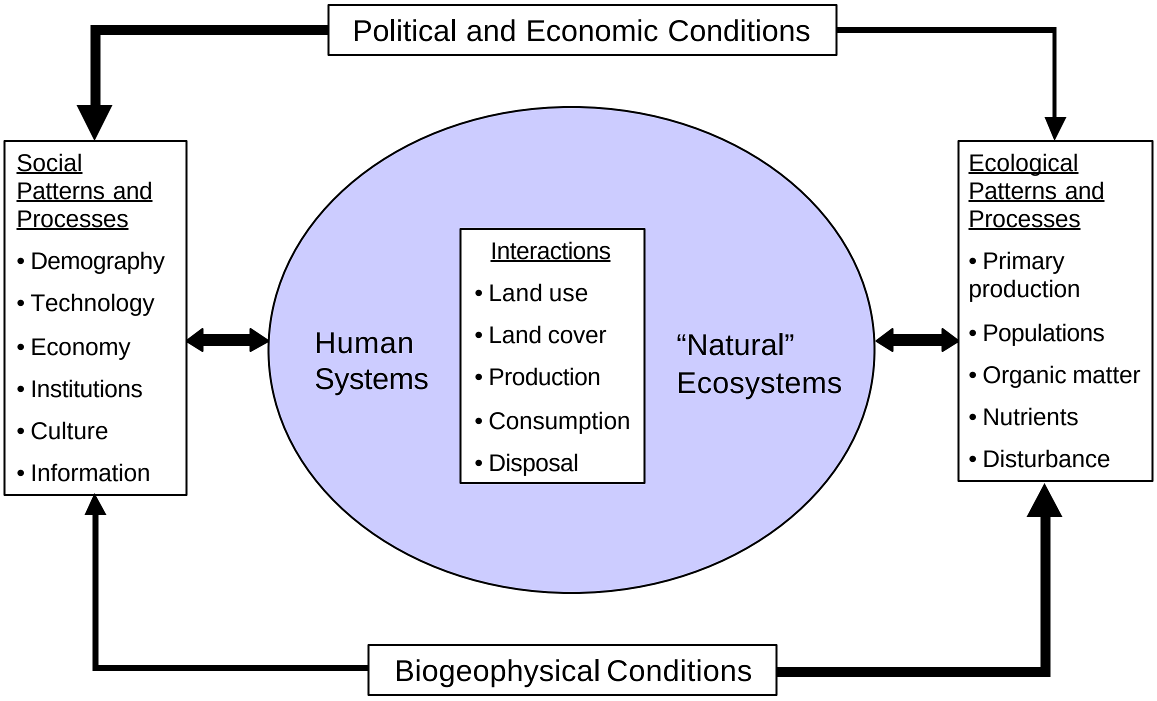

Figure 4.5. Conceptual Framework for Investigating Human Ecosystems

Although disciplinary training and traditional modeling often treat elements of human and ecological systems as distinct, this framework emphasizes dynamic linkages by focusing on the *interactions* at the interface of the human and ecological components of any human ecosystem. The LTER report defines the following interactions as the specific activities that mediate between the human and ecological elements of the broader human ecosystem:

- Land-use decisions
- Land cover and land-cover changes
- Production
- Consumption
- Disposal

While each of these activities can be examined independently, the report acknowledges their strong interdependencies. Though there might be other mediating activities as well, the LTER report proposes that the activities listed above are a good starting point, since they are already identified by both ecologists and social scientists as prominent and relevant processes.

Having defined a set of specific activities that are at the interface of the human and ecological aspects of any human ecosystem, the next step is to develop a perspective on what motivates these activities. To integrate the social, behavioral, and economic aspects of human ecosystems, the LTER report proposes a list of *social patterns and processes*. We further propose that this list can be used as a practical guide for modeling land-use change. These processes include the following:

- demography
- technology
- economy
- political and social institutions
- culturally determined attitudes, beliefs, and behavior
- information and its flow

One may expect that aspects of the last three drivers on the list—institutions, culture, and information will be difficult to integrate with more familiar biological factors. Certain aspects of each of these last three drivers (and the first three to a lesser extent) are constrained by human perception of the driver and how it is already integrated into the ongoing system. In a human ecosystem, all choices are not equally available to everyone; they are conditioned by perceptions and preconceptions as well as “physical” constraints.

To guide the development of land-use models that are more inclusive of social patterns and processes, we see a need for land-use model developers to consider one broad question and three subsidiary questions.

How did the social-ecological system develop into its current state, and how might it change in the future?

This question focuses on several critical aspects of the broader system, such as the nature of feedback linkages, rates of change, important system components, and the specifics of resource use and production. Three subsidiary questions are also important for land-use model development:

- *How have ecological processes influenced the social patterns and processes that have emerged?*
- *How have social patterns and processes influenced the use and management of resources?*
- *How are these interactions changing, and what implications do these changes bring to the state of the social-ecological system?*

These questions can help guide the development of an integrated land-use model as researchers attempt to characterize the fundamental aspects of system composition, system trends, and system operation. We recognize that such an integrated approach to modeling land-use change may necessitate a collaborative venture among scientists in different disciplines, each expanding from a traditional viewpoint. For most social scientists, this will mean a greater emphasis on the flows of matter and energy in human ecosystems. For ecologists, issues surrounding information flow and decision making may take on greater relevance.

Current Social Drivers in Land-Use Models

Relevant human-driver variables from all land-use models that were reviewed for this report are summarized in Table 4.1 and Appendix 2. These drivers can be examined in the context of the social drivers identified by both the NRC and LTER reports. While some aspects of social drivers are clearly included in several models, such as demography (population size, density, growth), markets (land production profits and rent), institutions (zoning, tenure), and technology (types of and access to transportation), there was no clear and systematic consideration of each type of driver (and the relationships among them) in any one model. Certainly not all drivers are equally important over time, space, and at different scales. We propose that, similar to ecological models of forest growth (that might include the relative effects of nitrogen, water, and light availability and changes in atmospheric carbon on different tree species), there is a comparable need for land-use models that can include the relative effects of different social drivers on land-use change in the context of space, time, and scale. This is particularly crucial for assessing alternative future scenarios and relative impacts of different policy choices. We believe it is crucial for developers of land-use models to discuss and adopt a more comprehensive and systematic approach to including social drivers of land-use change within the context of the NRC and LTER reports and existing social science efforts.

Table 4.1 Summary of Model Variables That Characterize Relevant Human Drivers

Human Drivers or Social Patterns and Preferences	Model Variables	Model #s
	Population Size	2, 3, 4, 10, 15, 18
	Population Growth	2, 3, 4, 10, 18
	Population Density	2, 3, 4, 5, 10, 11, 12, 13, 18
	Returns to Land-Use (costs and prices)	2, 5, 10, 14, 16, 17
	Job Growth	10, 18
	Costs of Conversion	2, 10
	Rent	2, 3, 5, 16
Collective Rule Making	Zoning	2, 10, 15, 18
	Tenure	7, 11
Infrastructure/Accessibility	Relative Geographical Position to Infrastructure: Distance from Road	 2, 3, 4, 6, 10,11, 18
	Distance from Town/Market	6, 7, 10, 11, 18
	Distance from Village	8
	Presence of Irrigation	5
	Generalized Access Variable	13
	Village Size	8
	Silviculture	2, 15, 16, 17
	Agriculture	2, 15, 16, 17
	Technology Level	3, 4, 17
	Affluence	3, 4, 5
	Human Attitudes and Values	3, 4
	Food Security	3, 4
	Age	5

8 – population a proxy of village size
9 – measures both distance to downtown San Francisco as well as to the nearest sphere-of-influence boundary (as a proxy for infrastructure costs – water, drainage, electricity, etc.)
#14 – includes wealth and substitution effects of harvesting decisions across stands; includes non-timber benefits, e.g., of providing forage and cover to wildlife
#18 – not clear if economic rent is a variable

Multidisciplinary Approaches

Land-cover change is a complex process affected by a wide variety of social and ecological processes. The multidisciplinary nature of land-cover change is widely recognized in both the social and natural sciences, yet the institutional powers of the disciplines remain strong, and multidisciplinary science is still in its infancy. The broad spatial and temporal scales of the human dimension of land-cover change (that our reviewed models cross) demand that models also cross multiple disciplines. As the dimension becomes broader, more disciplines may need to be incorporated. Any model of land-cover change is probably limited by the personnel constructing it, in accordance with their disciplinary limits in understanding and funding. Some of the models we examined incorporated multiple disciplines; NELUP and GEM/PLM incorporated many biophysical disciplines, as well as social sciences and fields of modeling methods. Other models, especially the purely statistical ones, were more limited in scope. Broadly, the higher the ability of the model to deal with complexity, the more multidisciplinary the model is likely to be.

Temporal and Spatial Synchrony and Asynchrony

Human decision making does not occur in a vacuum. Rather, it takes place in a particular spatial and temporal context. Further, since decision making about land use usually concerns some biophysical process, we must include these processes in the discussion. The following section discusses the interaction of decision making and biophysical processes within the dimensions of space and time.

The spatial extent of human problems is sometimes smaller than key actors and sometimes larger. Equivalence between the spatial extent of a given biophysical process and the jurisdictional domain of at least one decision-making unit can often help actors make effective decisions. A lack of equivalence can present potential problems inhibiting the incorporation of all impacts of a process in decision making. In the real world, decisions are made at multiple scales with feedback from one scale to another. Also, actors at a finer scale may have evolved a decision-making system at a broader scale, without actually having an actor at that scale.

This problem of scale mismatch occurs when the physical scale of an ecological system varies substantially from that of at least one organized decision-making system that regulates human actions related to that system. Scale mismatch can occur, for example, when the physical system is much larger than any human decision-making system that affects it. Most global ecological problems currently are characterized by this kind of scale mismatch. These mismatches are often characterized as externalities. For example, until an international treaty or special regime is created, nation-states are smaller than the stratosphere, but actions taken within all nation-states affect the level of greenhouse gases contained in the stratosphere. Looking at the ozone in the atmosphere as a shield, substantial progress has been made in developing an international regime that has successfully limited the level of chlorofluorocarbons (CFCs) that can be emitted, as well as providing a warning system for when ozone levels are dangerously low (Sandler 1997, 106–115). While stratospheric ozone levels are still falling, measurable progress has been made. In regard to global warming, on the other hand, while various efforts to achieve an international regime to limit greenhouse gas emissions are underway, such a regime is still a long way from being realized (Young 1999).

Scale mismatch also can occur when the ecological system is smaller (or a dramatically different geographic shape) than any relevant decision-making regime. Wilson et al. (1999) analyze scale mismatches that occur in fisheries when managers in a large fishery agency perceive their task as managing a single large population of fish, when, in fact, multiple, small, spatially discrete populations actually characterize the fishery. If a fishery is characterized by "metapopulations" where local populations of fish are relatively discrete and reproduce separately to some degree, then management of the species at a broader scale may overlook the protection of specific spawning grounds and allow rapid extinction of local populations (Gilpin 1996). The extinction of local populations can adversely affect the spawning potential of the entire population. Similarly, if urban areas are governed only by large units of government, and neighborhoods are not well organized, many neighborhood-level functions are overlooked, leading eventually to serious problems throughout an urban area (McGinnis 1999).

At a regional scale, SO_2 emissions from midwestern U.S. coal-burning power plants carry downwind and cause high ozone levels (in the lower atmosphere) in several states on the east coast. This has led to regional initiatives, like the Ozone Transport Authority Group (OTAG) with 34 member states trying try to resolve the problem.

Furthermore, missing connections may arise, if potentially effective institutions exist at the appropriate scales but decision-making linkages between scales are ineffective. Decisions may also be based on information aggregated at an inappropriate scale, even though it may exist at the appropriate scale (Cleveland et al. 1996). An example of the latter is the biennial national forest cover analysis prepared by the Forest Survey of India. While forest cover is assessed at the level of small local units, it is aggregated and reported at the *district* level, which is a larger administrative unit, rather than at the watershed-based *forest division* level, at which forests are managed.

When human decisions relate to processes which change over time, there may be a temporal mismatch between the time step and duration of biophysical processes and the decision-making time horizons of the human actors. For example, elected officials on three- to five-year terms may make decisions on issues and processes that have long-term biophysical consequences, such as tree species with long rotations, or storage of nuclear waste. See earlier discussion on decision-making time horizons.

Humans usually use some form of discounting to compare preferences over time. The discount rate may be implicit or explicit. Thus, a farmer choosing between growing an annual crop and planting trees that are harvestable in 30 years is comparing the flows of costs and benefits over different periods of time. Since models do not have the luxury of implicit comparisons, they usually use a discount rate to compare such choices. Most models make such comparisons by adjusting the value of money as a function of time. However, linking biophysical and social models by valuing social, economic, and environmental systems with this single parameter involves many assumptions and has been controversial (Longerhan et al. 1994).

Figure 4.6 represents spatial and temporal interaction of decision-making and biophysical processes in a nine-box figure. The boxes in the middle of each row of edge boxes, with bold text (a, b, c, and d), represent the four factors whose interaction determines land use—space, time, human decision making, and biophysical processes. The corner boxes represent the results of the interaction of the two adjacent headings. Thus, box (ii) represents the temporal dimension of biophysical processes (i.e., time step and duration), while box (iii) represents the spatial dimension of human decision making. The center box represents the problems of mismatches between decision making and biophysical processes in the temporal and spatial dimensions, as discussed above.

Decision-making time horizon (i)	**Time** (a)	Time step and duration (ii)
Human Decision Making (c)	Temporal mismatch (v) Spatial mismatch	**Biophysical Processes** (d)
Jurisdictional domain (iii)	**Space** (b)	Resolution and extent (iv)

Figure 4.6 A Nine-Box Representation of the Interaction between the Three Dimensions of Space, Time, and Human Decision Making with Biophysical Processes

Land-use models and modeling tools or approaches may be viewed in terms of their sophistication or technical ability in portraying processes in each of the three dimensions of space, time and human decision making. In other words, they can be assessed in their ability to handle spatial, temporal, and/or human decision-making complexity.

Methodological Trends

Model Types

The models reviewed employ a range of modeling methods (Table 3.2). The CUF and CURBA models (10 and 18) both use a mechanistic GIS simulation, combining layers of information with growth projections. Both were noted for their detailed vector resolution. A range of statistical/econometric models (5, 6, 7, 9, 12, and 13) applied either raster or vector approaches (though at least two used neither) using aggregated county-level data, mostly without spatial complexity. Dynamic systems models include the GEM and its application, the PLM (1 and 2). The NELUP model (15) also utilized a general systems framework. Additionally, several other models utilized dynamic approaches (3, 4, 8, 11, 14, and 17). One model (19) applied a cellular automata approach to analyze urban expansion.

Systems Approach

Non-linearities and spatial and temporal lags are prevalent in many environmental systems. When models of environmental systems ignore the presence of non-linearities and spatial and temporal lags, their ability to produce insights into complex human-environmental systems may be significantly reduced.

Statistical approaches using historical or cross-sectional data are often used to quantify the relationships among the components of human-environmental systems. In this case, rich data sets and elaborate statistical models are often necessary to deal with multiple feedbacks among system components and spatial and temporal lags. Model results are often driven by data availability, the convenience of estimation techniques, and statistical criteria—none of which ensure that the fundamental drivers of system change can be satisfactorily identified (Leontier 1982; Leamer 1983). By the same token, a statistical model can only provide insight into the empirical relationships over a system's history or at a particular point in time, but it is of limited use for analyses of a system's future development path under alternative management schemes (Allen 1988). In many cases, those alternative management schemes may include decisions that have not been chosen in the past, and their effects are therefore not captured (represented) in the data of the system's history or present state.

Dynamic modeling is distinct from statistical modeling, because it builds into the representation of a phenomenon those aspects of a system that we know actually exist (such as the physical laws of material and energy conservation) and that describe input-output relationships in industrial and biological processes (Hannon and Ruth 1994, 1997). Therefore, dynamic modeling starts with this advantage over the purely statistical or empirical modeling scheme. It does not rely on historic or cross-sectional data to reveal those relationships. This advantage also allows dynamic models to be used in more applications than empirical models; dynamic models are often more transferable to new applications because the fundamental concepts on which they are built are present in many other systems as well.

To model and better understand non-linear dynamic systems requires that we describe the main system components and their interactions. System components can be described by a set of state variables (stocks), such as the capital stock in an economy or the amount of sediment accumulated on a landscape. These state variables are influenced by controls (flows), such as the annual investment in capital or seasonal sediment fluxes. The nature of the controls (size of the flows), in turn, may depend on the stocks themselves and other parameters of the system. Using this approach, models are constructed by identifying, choosing, and specifying values and relationships among stocks, flows, and parameters.

Many land-use change models focus on specific processes affected by a defined set of variables. An alternative approach is to examine land-use change as one component of a socio-ecological system. In developing this systems approach, one difficulty lies in deciding how to incorporate model complexity. Researchers from the social sciences may tend to add complexity on the social side while generalizing components on the biophysical side. Researchers in the natural sciences may do the opposite. A multidisciplinary team must struggle to find a compromise in complexity, making the model complex enough to operate properly and produce reasonable behavior without making any single part of the model overly complex. Another struggle is how to incorporate scale issues into this systems approach. A number of researchers have developed models that have provided great insight into highly complex systems (Costanza 1998; Voinov 1999). Many of these models operate at a set spatial scale, but there may be important processes or relationships that are not evident at that particular spatial scale.

Yet once a systems model has been constructed, what-if scenarios can be explored more easily than with other modeling approaches that are not systems oriented. In particular, a systems approach can examine what feedbacks exist in a socio-ecological system such as the impact of increases or decreases in agricultural productivity on the local market prices of those agricultural goods. This scenario-testing ability has proved valuable both to researchers and to policy experts in elucidating important relationships in a variety of different systems.

Modularity of Models

The multidisciplinary nature of land-cover change modeling is paralleled by modularity in the models themselves. Of the 19 models evaluated for this study, all but four were characterized by modular components. In general, modularity may help facilitate modeling land-cover change by assigning a particular disciplinary aspect of the model to a separate module. We found that the majority of the modular models tended to consider multiple disciplines. This was true for those models with explicit biophysical and social components, such as models 1, 2, 3, 4, and 15. This also held true for the largely biophysical models, which incorporate multiple processes in a single model.

The complexity of a model is also related to model modularity. Complex models typically involve the interaction of multiple parameters, and their creation and validation can be facilitated by utilizing multiple modular components; for example, modularity allows different processes to run at different time steps, different actors can be modeled simultaneously in different modules, and differences in their decision-making horizons can be incorporated by varying the time step of different modules. As we noted previously, there is a need for a modular approach to land-use change models that includes the relative effects of different social drivers such as demography; technology; economy; political and social institutions; culturally determined attitudes, beliefs, and behavior; information and its effect on land-use change, all in the context of space, time, and scale.

Data and Data Integration

Sources and Uses of Data

The explosion in availability of data in recent years has enabled the development of more rigorous models. Fundamentally, more data can enable more accurate calibration and validation of models. Data for independent variables are used to calibrate model runs and the time frame for data availability often determines the time step for particular modules. After calibration, models are often validated by comparing outputs of variables being modeled, typically land cover, with actual land-cover data. Model calibration and validation are perhaps the most critical and labor-intensive parts of model development.

Data are often differentiated by source and are either primary or secondary. Primary data collection can be tailored to specific requirements. If collected extensively at a regional scale, the source is spread out by necessity and the data must be very broadly aggregated. If, on the other hand, detailed information is collected intensively at a high concentration, say 100-percent sampling, resource considerations often lead to very localized coverage. Secondary data, by definition, are limited to what data are available already but often cover longer time scales and broader spatial scales (e.g., U.S. census data are averaged for census blocks, large subcity units). At least one model examined here (NELUP) consciously restricted itself to publicly available data so the model could be transferable to other locations.

Another issue relates to data form and availability over time. When data are sought covering the last several centuries, data sources are often limited and highly aggregated. By implication, it is much harder to look at past deforestation processes than current ones. Assessing older land-use changes may involve other disciplines (e.g., archeology) to understand land cover. Thus, the forest transition in the USA, where deforestation likely peaked around the end of the last century (1900), and Brazilian deforestation, which shows no signs of peaking yet, are almost always viewed in different light primarily because of data availability.

Satellite images offer an extensive source of land-cover data collected remotely at a cost typically significantly lower than manual collection. Several recent data trends are apparent here and include higher spatial and spectral resolution and higher frequency of acquisition with time. The number of satellites providing imagery has increased dramatically since the early use of satellite imagery. In the 1970s, the primary platform for publicly available imagery was the Landsat MSS instrument, while presently there is a wide variety of platforms, each with different imaging characteristics, including French SPOT panchromatic and multispectral instruments, data from the Indian IRS family of satellites, and radar imagery from the Japanese JERS satellite. Data are available at increasingly finer resolutions as well. The first satellite instrument used for public land-cover mapping in the 1970s (Landsat MSS) provided image data at a spatial resolution of 56 m x 79 m. The current Landsat 7 provides much finer resolution at 28.5 m x 28.5 m. The private IKONOS satellite launched in 1999 provides 1-meter panchromatic data and 4-meter multispectral data. Also, image data are available over an increasingly wider spectral range, which includes data in optical, thermal, and radar wavelengths.

There are several other trends that complicate the use of satellite data for land-use modeling. Satellite imagery is available from the early 1970s. Examining land-use change prior to this period requires the use of other remotely sensed data, such as aerial photography or ground-collected historical information. There are a variety of methodological issues related to comparing land-use data derived from different data sources. These considerations complicate the study of land-use change processes across long time periods. Perhaps more importantly, many land-use change processes are time dependent. For example, timber harvests in many areas of the USA are based on an approximately 40-year rotation cycle, while tropical subsistence rotations may be much shorter (five years). These temporal issues have serious implications for land-use change analysis in terms of identifying the relationship of these land-use changes within the context of varying study durations.

The Landsat system provides an excellent source of land-cover data over a fairly long duration (1972–present). However, between 1972 and 1982, only image data from the Landsat MSS instrument was available, but acquisition of MSS images was curtailed in 1992, after which only Thematic Mapper (TM) images were available. The difference in resolution between the MSS and TM instruments means that the more recent, finer data will have to be re-sampled to a broader resolution for comparison. There is also a question of data availability outside the USA. Several areas outside the USA have spotty image availability; e.g., from the mid-1980s to the early 1990s, there is extremely limited availability for West African Landsat TM scenes. This differential availability of imagery is due to market-oriented policies following the privatization of the Landsat system in the mid-1980s. Finally, we must consider questions of data migration and reading-device obsolescence. Data formats are proliferating, and data stored in older formats need to be migrated to newer formats as older formats become obsolete along with the accompanying hardware and software. The ability to read diverse formats affects data availability and may, in the extreme case, even render archives of little use. For example, the earliest Landsat satellites included a higher-resolution instrument, the Return Beam Vidicon (RBV), which at the time was thought to be a superior instrument to the MSS. However, these image data are stored on magnetic tape format which current data providers no longer use; this means the archives do not currently provide RBV data.

Despite the above caveats, the Landsat TM is a useful remotely sensed data source. It has global coverage, an excellent data set for the USA, and could potentially map the entire world at 16-day intervals (except for occurrences of cloud cover). Another broader-scale remote sensing source is the AVHRR with a lower resolution of 1.1 kilometer, but which provides daily data for the entire globe. AVHRR applications include a famine early-warning system (operational in a dozen African countries) that maps agricultural production based on land-cover parameters.

Aerial photographs, another form of remotely sensed data, often have a higher resolution than satellite images and can provide detailed information on land cover. For example, some counties in Indiana use aerial photos to determine land-use categories at extremely fine scales for property tax assessment. Aerial photographs have been available in the USA for more than half a century. However, they have both geometric and radiometric distortions, which make them not directly comparable with satellite images. Aerial photographs often vary in scale and season of acquisition; for example, aerial photos in Indiana were acquired every five years alternately in summer and winter and usually require manual interpretation, a skilled and labor-intensive task with a declining supply of interpreters.

Data Integration

Nearly all parameters used in land-cover change models have a spatial dimension, and much of the data can be organized effectively using a Geographic Information System (GIS). While some models may use parameters that are spatial in nature, these parameters may not be spatially explicit. For example, models 5, 12, 14, and 16 exhibit parameters neither as raster (grid cells) nor as vector (points, lines, or polygons). In our survey, these non-spatially explicit models may reflect unavailable data at more extreme scales (see Figure 4.2).

One of the strengths of GIS and spatial representation is the ability to integrate data from disparate sources. For example, consider a rural area where population data are collected as point data from villages. These point data can be used to create a surface of land-use intensity by creating a weighted interpolation surface modified by other community-level variables such as the sex ratio, occupation of village residents, and landholdings. This land-use intensity surface can be integrated with a land-use map to explore the relationship between land use and past land-use changes and to predict future changes. These data transformations are enabled by a GIS approach through the development of a spatial representation of the factors affecting the land-use system. There are varieties of sources of error associated with these data transformations, and researchers must carefully evaluate the contribution of these errors to the overall error in the model. However, even given these errors, spatial representation can allow relationships between social and biophysical factors to be explored, which would not be possible with non-spatially explicit methods of research.

Scale and Multiscale Approaches

We considered scale in three dimensions in this assessment. We have also demonstrated the broad equivalence of spatial (resolution and extent) and temporal (time step and duration) scales and their echoes in temporal (decision-making horizon) and spatial (jurisdictional domain) attributes of human decision making. Mertens and Lambin (1997) hint at the importance of both resolution and extent when they recognize the trade-off between analysis at broad scales (where the high level of aggregation of data may obscure the variability of geographic situations, thus diluting causal relationships) and fine scales (impractical, if there were no possibility of generalizing over large areas).

One of the issues in broader-scale decision-making modeling is that developing such a sector-level model involved “huge complexities likely to arise while trying to assess behavioural characteristics at the sector level” (Oglethorpe et al. 1995). Certainly, fine-scale models have particular benefits. Oglethorpe and O’Callaghan (1995) conclude that the farm-level model allows them to project land-use patterns and management practices arising as a result of agricultural market and policy changes, while demonstrating the short- and long-term consequences for the environment.

The resolution and extent of a model or its submodules are often based on the extent of computing power available, and scale at which certain biophysical processes operate. Increasingly, there is recognition that different land-use change drivers operate at different scales and that interscale dynamics should be included in land-use/cover change models (Veldkamp and Fresco 1996a).

The importance and challenge of scale and nested, hierarchical approaches cannot be overestimated. The physical, biological, and social sciences are struggling with the issue of scale, and these have implications for appropriate frameworks for collecting and analyzing data at different spatial and temporal scales. This issue infuses many activities that influence modeling, from data collection to data analyses and interpretation of results. In a "human" spatial sense, scales of interest range from individuals to groups or institutions of increasingly large size until they encompass global networks.

In a similar fashion, understanding processes acting at varying temporal scales is important to understand high-frequency processes as well as those operating over longer time periods. The importance of this challenge is even more pronounced when modelers consider integrated models. For example, some social and ecological processes may be associated with a particular scale, while other processes may occur across multiple scales. Further, ecological and social processes may not operate at the same scale, and linkages may have to be developed to connect across scales. Finally, it is unknown whether theories that explain processes at one scale can be used to explain processes at other scales. To date, no land-use model combining social and ecological processes has completed a multiscale approach. Thus, fundamental research and modeling paradigms may need to be rethought (Redman et al. 2000).

We will need to develop a number of capabilities for multiscale approaches and models of land-use change. These include the ability to identify the following (Redman et. al. 2000):

- Optimal scale(s) and resolution(s) for modeling underlying social and ecological patterns and processes of land-use change
- Time lags, non-linear relationships, and defining events that affect the responses among social and ecological processes of land-use change
- Spatial characteristics of certain phenomena such as shape, adjacency, and matrix, and how they affect social and ecological processes of land-use change
- Boundary conditions relative to space and time that might affect social and ecological processes of land-use change
- Large-scale data to explain small-scale behavior (ecological inferences) and small-scale data to explain processes at other scales of land-use change
- Data associated with one unit of analysis that can be dis- and reaggregated to another unit (e.g., from census tracts to watersheds) to model land-use change

Future Directions in Land-Use Modeling

Many of the models reviewed in this report have been under development for a number of years. Models that have evolved over a long period of development often have to accommodate changes in mission and expansion into new substantive areas important to the system being modeled but not originally included in earlier versions of the model. For example, the Patuxent Landscape Model (PLM) was originally designed as an ecologically based model of the Patuxent watershed in the eastern USA. Subsequent functionality has been added to the PLM to incorporate various social-based inputs, including population growth, agricultural policy, and land-use management. This new functionality has expanded the domain of the model but the social-based inputs are not necessarily optimally accommodated by the modeling framework developed for the original ecologically based components of the model.

This is not to detract from the considerable accomplishments of the PLM or the SME framework in which the PLM has been implemented. However, developing models in this fashion may lead to early design decisions which obstruct the performance of future model components added to the base model.

In another example, during a model design workshop in support of the FLORES model, the initial conversation among the workshop participants was used to design the overall framework for the model: the time step, spatial unit of analysis, and how the model components would interact. Certain compromises had to be made by each of the workshop groups representing separate components of the model.

Constraints

Availability of data for model validation imposes serious constraints in considering variables for inclusion. Models that utilize significant amounts of primary data are constrained in extent or duration, or both. Some model development approaches have deliberately restricted themselves to publicly available data, for replicability spatially.

Another issue in the land-use modeling community is the duplication of effort and sharing of models. We have observed that several models addressing similar systems are often developed independently. This has the advantage of demonstrating unique approaches to the same research questions and may produce better models by enacting some form of competition between models. Yet, the downside is the considerable documentation needed to allow model developers to understand each other’s code such that supplanted code may be cannibalized into other models. Issues of intellectual property rights need to be addressed as well.

Opportunities

In accordance with Moore’s Law, we have witnessed incredible increases in raw computing power. Desktop PCs can now run models that would have required a roomful of mainframe computers a decade ago. This development itself is a great enabler and has contributed immeasurably to expanding land-use modeling efforts. More computing power gives models the ability to expand their extents and durations and, at the same time, make resolutions and time steps smaller.

Modeling tools are also getting better: they do more with time and are more user-friendly. Development of modeling tools allows us to build more sophisticated models in all three dimensions. Various modeling frameworks have been developed that provide model developers with a set of tools suited to address common aspects of land-use systems. They are easier to learn and use than writing code and often have graphical interfaces. For example, STELLA provides a format for dynamic modeling that gives the user a very intuitive GUI and can be used to develop simple student models or complex research models. Another example is the SWARM simulation package, developed at the Santa Fe Institute, which has been used for modeling multi-agent systems and the interactions between the agents in those systems. A variety of other development tools are available to researchers. Many of these tools, such as STELLA, are commercially based, while others, such as SWARM, are accessible under various public licensing structures. Of course, many models we reviewed still depend on labor-intensive mathematical programming or econometrics for their core modeling (5, 13, 14, 15, and 16).

Open Source Approaches

Models involving time, space, and human decision making can be incredibly complex and depend upon knowledge from many disciplines. Until now, most models have developed in isolation. This is related to the fact that modelers have been funded through grants or focused funds from a particular organization with an interest in human-environmental modeling. Even in the context of large interdisciplinary research centers like the NSF networks cited previously, their efforts have been constrained by funds, staff, and expertise.

In contrast to traditional approaches to model development, recent advances in worldwide web technology have created new opportunities for collaboration in the development of human-environmental modeling. Recently, “open source” programming efforts have been used to solve complex computing problems (see for example, Kiernan 1999; Learmouth 1997; McHugh 1998; and http://www.opensource.org). Open source programming is based on a collaborative licensing agreement that enables people to freely download program source code and utilize it on the condition that they agree to provide their enhancements to the rest of the programming community. There have been several very successful, complex programming endeavors using the open source concept; the most prominent being the Linux computer operating system. However, there have also been some open source endeavors that have failed. But the Linux model has shown that extremely complex problems can be tackled through collaboration over the Internet and that this kind of collaboration can produce extremely robust results. For instance, Linux is known to be a very stable software program and it is largely because of what is referred to as “Linus’ Law” (Linus Torvalds is the initial developer of Linux): “Given enough eyeballs, all [problems] are shallow” (Raymond 1999). In other words, if we can get enough human eyes (and brains) with various skills and expertise working together, many problems, regardless of their complexity, can be solved because some individual or a team of individuals will come up with elegant solutions.

How is an open source approach to computing connected to human-environmental modeling? We propose that a similar approach to the development of human-environmental models provides the basis for focusing enough “eyeballs” on important human-environmental problems (Schweik and Grove, In press). A similar argument has been made for open source endeavors in other areas of scientific research (Gezelter 2000). Initiating such an open source modeling effort will require several components: (1) a web site to support modeling collaboration (e.g., data and interactions among individuals, such as bulletin boards and FAQs); (2) the establishment of one or more modeling “kernels” (core components of models using various technologies) that are designed in a modular fashion and allow relatively easy enhancements from participants; and (3) the development of mechanisms for sharing model enhancements that encourage participation and provide incentives that are comparable and as valued as publishing in peer-reviewed journals.

Over the last year, we have initiated the development of such a web site, called the "Open Research System" or ORS (open-research.org). The first step of this effort is to develop a web-based metadatabase that allows the open sharing of geographic and non-spatial datasets, and references to publications and reports. If a reader knows of a model not covered in this review or in the Appendix, he or she could visit this site, register, and submit a publication reference to the system database. This would allow other visitors to the site, through the search facility, to find the model publication. The next step of this project is to move toward extending the design to allow the sharing of various types of land-cover models in an open source approach.

We recognize that the application of the open source programming concept to human-environmental modeling might appear daunting and even seem radical. However, the Linux example shows how extremely complex problems can be solved when enough people work on them. Given the complexities involved in modeling time, space, and human decision making, the open source programming concept might be a vital modeling approach for creative solutions to difficult human-environmental modeling problems.

5. CONCLUSION

Land-use/land-cover change is a widespread, accelerating, and very significant process to humans. Land-use/land-cover change is both driven by human actions, and, in many cases, it also drives changes that impact humans. Modeling these changes is critical for formulating effective environmental policies and management strategies. This report details our efforts to inventory land-use change models through a review of literature, websites, and professional contacts. We then examined in detail 19 of these land-use change models, characterized their structure and function, and reviewed how they were applied. The models were compared in terms of scale and complexity, and how well they incorporate time, space, and human decision making. In this report, we examine the social drivers of land-use change and methodological trends exemplified in the models we reviewed. We also suggest some future strategies for overcoming modeling problems.

For this review we developed a framework to observe and describe multiple models in a single synoptic view. This framework is based on three critical dimensions: time, space, and human choice or decision making. These three dimensions can be thought of as three axes on a cube. How well a model incorporates these three dimensions (measured by its complexity) determines where that model would plot in this 3-D volume. In terms of temporal scale, models were characterized by time step (the smallest unit of time for a process to change) and duration (the total length of time that a model is applied). In terms of spatial scale, models were characterized by resolution (the smallest geographic unit in a model, such as a single grid cell in a raster model) and extent (the total area to which the model is applied). Likewise for human decision making, models were characterized by actor (the smallest body of humans making decisions) and domain (the broadest social organization incorporated in the model). Models were also characterized by their temporal complexity (a model's ability to handle a large number of time steps, a long duration, time lags and feedback responses) and spatial complexity (a model's ability to handle topological relationships, and be spatially representative and interactive). We also created a scale to measure a model's ability to handle human decision-making complexity, a six-level value. A model with a high complexity value would be able to handle multiple agents interacting across domains whose choices are overtly modeled.

All 19 models we reviewed were spatially representative and most (15) were spatially interactive. Eleven of the 19 models are raster based, four are vector based, and four are classified as neither. Several vector models were associated with scales of city and county levels and provided the finest spatial resolution. Their extent may be limited by availability of data. Most raster models have a spatial resolution and extent in the range of common remote-sensing data, such as Landsat. Many models with separate ecological modules operate at fine time steps, which allows models to more accurately represent rapid ecological changes. Models with multiple time steps can span both fine and coarse time steps and can incorporate temporal complexity of different socioeconomic and biophysical sectors more effectively.

We advocate the use of the LTER Network working group report list of social patterns and processes as a practical guide for incorporating social processes in modeling land-use change. This list includes: demography; technology; economy; political and social institutions; culturally determined attitudes, beliefs, and behavior; and information and its flow. We also advocate a more comprehensive and systematic approach to including social drivers of land-use change within the context of the NRC and LTER reports and existing social science efforts.

Several problems regarding land-use modeling were discussed. Models which cover broad spatial and temporal scales demand that we cross multiple disciplines; however, a model of land-cover change is limited by the personnel constructing it and their disciplinary limits in understanding and funding. The problem of scale mismatch can occur when the physical scale of an ecological system varies substantially from that of the decision making. Furthermore, missing connections may arise in modeling if potentially effective institutions exist at the appropriate scales but decision-making linkages between scales are ineffective. Also, humans usually use some form of discounting to compare preferences over time, and most such models make comparisons using the metric of money. However, linking biophysical and social models by valuing social economic and environmental systems with this metric is problematic.

Different modelling methodologies limit their application. Non-linearity and spatial and temporal lags are prevalent in environmental systems, yet statistical models can only provide insight into the empirical relationships over a system's history, but are of less use for analyses of a system's future development path under alternative management schemes. Dynamic modeling, which uses stocks and flows, is distinct from statistical modeling in that it can incorporate phenomenon whose aspects of a system are known to actually exist. Of the 19 models evaluated for this study, all but four were characterized by modular components. Modularity may facilitate land-cover change by assigning a particular disciplinary aspect of the model to separate modules. We found that the majority of the modular models tended to consider multiple disciplines.

Data availability can also affect modeling. Primary data collection can be tailored to specific requirements, but must be collected either thinly across a broad extent or concentrated in a localized coverage. Secondary data by definition are limited to what is available but often cover longer durations and broader spatial scales. Some models are deliberately restricted to publicly available data, for replicability. Satellite images offer an extensive source of land-cover data collected remotely at a cost typically lower than manual collection, however there are a variety of methodological issues related to comparing land-use data from different sources, which complicate the study of land-use change processes across broader scales of time and space.

Nearly all parameters used in land-cover change models have a spatial dimension, and much of this data can be organized effectively using Geographic Information System (GIS) technologies. One of the strengths of GIS and spatial representation is the ability to integrate data from disparate sources. Increasingly powerful computers mean models can run multiple modules at different time steps within short periods of time. Modeling tools are also getting better: they do more with time and are more user-friendly. Advancing development of modeling tools allows us to build more sophisticated models in all three dimensions. Finally, open source modeling, which is based on a collaborative licensing agreement that enables people to freely download program source code and utilize it on the condition that they agree to provide their enhancements to the rest of the programming community, offers additional hope for future modeling. There have been several very successful, complex programming endeavors using the open source concept, the most prominent being the Linux computer operating system, and these methods might spur the development of land-use/land-cover modeling as well.

We would like to conclude with some thoughts about land-use models and policy. Increasingly, the policy community is interested in land-use models that are relevant to their needs. This does not mean that land-use models have to be “answer machines.” Rather, we expect that land-use–change models will be good enough to be taken seriously in the policy process. King and Kraemer (1993:356) list three roles a model must play in a policy context: it should clarify the issues in the debate; it must be able to enforce a discipline of analysis and discourse among stakeholders; and it must provide an interesting form of “advice,” primarily in the form of what *not* to do—since no conscientious politician will ever simply do what a model suggests. Further, the necessary properties for a good policy model have been known since Lee (1973) wrote his “Requiem to Large-Scale Models”: (1) transparency, (2) robustness, (3) reasonable data needs, (4) appropriate spatio-temporal resolution, and (5) inclusion of enough key policy variables to allow for exploration of likely and significant policy questions.

To answer policy questions, policy makers will have to begin to identify the key variables and sectors that interest them, their scales of analysis, and the scenarios they anticipate. At the same time, land-use modelers should begin discussions with policy makers to understand their needs. Given policy makers’ needs, land-use modelers will have to translate those needs with particular attention to implicit and explicit temporal, spatial, and human decision-making scale and complexity and the interactions between scale and complexity. Further, land-use modelers will need to consider the relative significance of different drivers—demography;

technology; economy; political and social institutions; culturally determined attitudes, beliefs, and behavior; and information and its flow—on land-use change within the context of policy makers' needs. Finally, there is the need to provide a framework for collaboration and model development. We propose an open source approach. Perhaps there are others. Regardless, we believe land-use change is a sufficiently important and complex environmental issue that it urgently needs "many eyeballs and brains" working together.

APPENDIX 1: Results from Search of Literature and Web Sites

Acevedo, Miguel F., Dean L. Urban, and Magdiel Ablan. 1996. Landscape Scale Forest Dynamics: GIS, GAP, and Transition Models. In *GIS and Environmental Modeling: Progress and Research Issues,* ed. Michael F. Goodchild et al., 181–185. Fort Collins, Colo.: GIS World Books.

Adams, D. M., R. J. Alig, J. M. Callaway, B. A. McCarl, and S. M. Winnett. 1996. The Forest and Agricultural Sector Optimization Model (FASOM): Model Structure and Policy Applications. Research Paper PNW-RP-495. Portland, Ore.: U.S. Department of Agriculture, Pacific Northwest Research Station.

Adams, R., et al. 1995. Assessing the Performance of the NELUP Hydrological Models for River Basin Planning. *Journal of Environmental Planning and Management* 38(1):53–76.

Angelsen, Arild. 1999. Agricultural Expansion and Deforestation: Modelling the Impact of Population, Market Forces, and Property Rights. *Journal of Development Economics* 58(1):185–218.

Angelsen, A., and D. Kaimowitz. 1999. Rethinking the Causes of Deforestation: Lessons from Economic Models. *World Bank Research Observer* 14(1):73–98.

Aspinall, Richard J., and Diane M. Pearson. 1996. Data Quality and Spatial Analysis: Analytical Use of GIS for Ecological Modeling. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 35–38. Fort Collins, Colo.: GIS World Books.

Baron, J. S., et al. 1998. Effects of Land Cover, Water Redistribution, and Temperature on Ecosystem Processes in the South Platte Basin. *Ecological Applications* 8(4):1037–1051.

Baskent, E. Z. 1999. Controlling Spatial Structure of Forested Landscapes: A Case Study towards Landscape Management. *Landscape Ecology* 14(1):83–97.

Bass, B., R. E. Byers, and N. M. Lister. 1998. Integrating Research on Ecohydrology and Land Use Change with Land Use Management. *Hydrological Processes* 12(13–14):2217–2233.

Berge, Erling. 1998. Modeling the Human Impact on Resource Systems. Workshop in Political Theory and Policy Analysis Working Paper. Bloomington: Workshop in Political Theory and Policy Analysis, Indiana University.

Berry, Michael W., Brett C. Hazen, R. L. MacIntyre, and Richard O. Flamm. 1996. LUCAS: A System for Modeling Land-Use Change. *IEEE Computational Science and Engineering* 3(1):24.

Berry, M. W., and K. S. Minser. 1997. Distributed Land-Cover Change Simulation Using PVM and MPI. Presented at the Land Use Modeling Workshop, USGS EROS Data Center, Sioux Falls, S.Dak., June 5–6.

Bockstael, Nancy E. 1996. Modeling Economics and Ecology: The Importance of a Spatial Perspective. *American Journal of Agricultural Economics* 78(5):1168.

Bockstael, N. E., et al. 1995. Ecological Economic Modeling and Valuation of Ecosystems. *Ecological Economics* 14:143–159.

Booth, Ginger. 1997. Gecko: A Continuous 2-D World for Ecological Modeling. *Artificial Life* 3(3):147.

Bradshaw, T. K., and B. Muller. 1998. Impacts of Rapid Urban Growth on Farmland Conversion: Application of New Regional Land Use Policy Models and Geographical Information Systems. *Rural Sociology* 63(1):1–25.

Bretherton, Francis. 1996. Why Bother? In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 3–5. Fort Collins, Colo.: GIS World Books.

Chen, Tzu-Chun, and Shu-Li Huang. 1998. Towards a Symbiosis: Urban Development and Environmental Quality in the Taipei Metropolitan Region. *Journal of Environmental Planning and Management* 41(1):77.

Chomitz, Kenneth M., and David A. Gray. 1996. Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize. *World Bank Economic Review* 10(3):487–512.

Clarke, Keith C. 1997. Land Transition Modeling With Deltratrons. Presented at the Land Use Modeling Workshop, USGS EROS Data Center, Sioux Falls, S.Dak., June 5–6.

Clarke, Keith C., Stacy Hoppen, and Leonard J. Gaydos. n.d. Methods and Techniques for Rigorous Calibration of a Cellular Automaton Model of Urban Growth. Accessed June 20, 2000, at http://geo.arc.nasa.gov/usgs/clarke/calib.paper.html.

Cleveland, C., R. Costanza, T. Eggertsson, L. Fortmann, B. Low, M. McKean, E. Ostrom, J. Wilson, and O. Young. 1996. A Framework for Modeling the Linkages between Ecosystems and Human Systems. Beijer Discussion Paper Series No. 76. Sweden: Beijer Institute of Ecological Economics, Royal Swedish Academy of Sciences.

Costanza, Robert, Carl Fitz, Tom Maxwell, and Fred Sklar. n.d. The Conservation Area Landscape Model (CALM). Accessed 1999 at http://dino.wiz.uni-kassel.de/model_db/mdb/calm.html.

———. n.d. General Ecosystem Model. Accessed 1999 at http://dino.wiz.uni-kassel.de/model_db/mdb/gem.html.

Costanza, Robert, and Ruth Matthias. 1998. Using Dynamic Modeling to Scope Environmental Problems and Build Consensus. *Environmental Management* 22(2):183–195.

Costanza, Robert, et al. 1993. Modeling Complex Ecological Economic Systems. *Bioscience* 43(8):545–555.

Costanza, Robert, et al. 1998. Integrated Ecological Economic Modeling of the Patuxent River Watershed Maryland. Draft paper as of 1/18/98

Dahlstrom, Roger K. 1997. Practical Computer Applications for Land Use Planning and Analysis. *Northern Illinois University Law Review* 17(3):399–417.

Dale, V. H., et al. 1993. Causes and Effects of Land-Use Change in Central Rondonia, Brazil. *Photogrammetric Engineering and Remote Sensing* 59(6):997–1005.

Dale, V. H., et al. 1994. Modeling Effects of Land Management in the Brazilian Amazonian Settlement of Rondonia. *Conservation Biology* 8(1):196–206.

Dale, V. H., et al. 1998. Assessing Land-Use Impacts on Natural Resources. *Environmental Management* 22(2):203–211.

Dale, V. H., et al. In press in 1999. Ecological Principles and Guidelines for Managing the Use of Land: A Report from the Ecological Society of America. *Ecological Applications*.

Darwin, R., et al. 1996. Land Use and Cover in Ecological Economics. *Ecological Economics* 17(3):157–181.

Dietz, Thomas. 1994. Rethinking the Environmental Impacts of Population, Affluence and Technology. *Human Ecology Review* 1.

Duncan, B. W., et al. 1999. Coupling Past Management Practice and Historic Landscape Change on John F. Kennedy Space Center, Florida. *Landscape Ecology* 14(3):291–309.

Ehrhardt-Martinez, Karen. 1998. Social Determinants of Deforestation in Developing Countries: A Cross-National Study[A]. *Social Forces* 77(2):0567–597.

Field, C. K., P.A. Silver, and A.M. Lott. 1996. Estimating the Effects of Changing Land Use Patterns on Connecticut Lakes. *Journal of Environmental Quality* 25(2):325–333.

Fitz, H. C., E. B. DeBellevue, R. Costanza, R. Boumans, T. Maxwell, L. Wainger, and F. H. Sklar. 1996. Development of a General Ecosystem Model for a Range of Scales and Ecosystems. *Ecological Modelling* 88:263–295.

Force, Jo Ellen, and Gary E. Machlis. 1997. The Human Ecosystem Part II: Social Indicators in Ecosystem Management. *Society and Natural Resources* 10(4):369.

Geoghegan, J., et al. 1998. Socializing the Pixel and Pixelizing the Social in Land-Use and Land Cover Change. In *People and Pixels: Linking Remote Sensing and Social Science*, ed. Diana Liverman et al., 51–69. Washington, D.C.: National Academy Press.

Geoghegan, Jacqueline, Lisa A. Wainger, and Nancy E. Bockstael. 1997. Spatial Landscape Indices in a Hedonic Framework: An Ecological Economics Analysis Using GIS. *Ecological Economics* 23:251–264.

Gilruth, Peter T., Stuart E. Marsh, and Robert Itami. 1995. A Dynamic Spatial Model of Shifting Cultivation in the Highlands of Guinea, West Africa. *Ecological Modelling* 79:179–197.

Gimblett, H. Randy, and Robert M. Itami. 1997? Modelling the Spatial Dynamics and Social Interaction of Human Recreators Using GIS and Intelligent Agents. Working paper.

Gu, K. 1996. An Integrated Land Use-Transport-Environment Model: CityPlan. *Road and Transport Research* 5(1):26.

Gustafson, Eric J., and Thomas R. Crow. 1998. Simulating Spatial and Temporal Context of Forest Management Using Hypothetical Landscapes. *Environmental Management* 22(5):777–787.

Hardie, Ian W., and Peter J. Parks. 1997. Land Use with Heterogeneous Land Quality: An Application of an Area Base Model. *American Journal of Agricultural Economics* 79(2):299–310.

Hastings, Alan. 1990. Spatial Heterogeneity and Ecological Models. *Ecology* 71(2):426–428.

Hayden, F. Gregory. 1993. Ecosystem Valuation: Combining Economics, Philosophy, and Ecology. *Journal of Economic Issues* 27(2):409–420.

Hazen, B. C., and M. W. Berry. 1997. The Simulation of Land-Cover Change Using a Distributed Computing Environment. *Simulation Practice and Theory* 5:489–514.

Howard, D. M., P. J. A. Howard, and D. C. Howard. 1995. A Markov Model Projection of Soil Organic Carbon Stores Following Land Use Changes. *Journal of Environmental Management* 45:287–302.

Hurtt, George C., et al. 1998. Terrestrial Models and Global Change: Challenges for the Future. *Global Change Biology* 4:581–590.

The IMAGE 2 Model. 1994. Accessed 1999 at http://gcte.org/Highlights/alcamo.html.

Jankowski, P. 1992. An Architecture for a Modeling Support System for Simulation of Environmental Processes. *Computers and Geosciences* 18(8):1075–1093.

Johnson, Alan R. 1996. Spatiotemporal Hierarchies in Ecological Theory and Modeling. In *GIS and Environmental Modeling: Progress and Research Issues,* ed. Michael F. Goodchild et al., 451–456. Fort Collins, Colo.: GIS World Books..

Johnston, Carol A., Yosef Cohen, and John Pastor. 1996.. Modeling of Spatially Static and Dynamic Ecological Processes. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 149–154. Fort Collins, Colo.: GIS World Books.

Jun, Myung-Jin. 1999. An Integrated Metropolitan Model Incorporating Demographic-Economic Land Use and Transport Models. *Urban Studies* 36(8):1399.

Kackley, John, and Piotr Jankowski. 1996. Graphical Modeling System Supporting Dynamic Processing in a Raster GIS. *Computers, Environment and Urban Systems* 19(5/6):391–407.

Keller, C. Peter, and James D. Strapp. 1996. Multicriteria Decision Support for Land Reform Using GIS and API. In *GIS and Environmental Modeling: Progress and Research Issues,* ed. Michael F. Goodchild et al., 363–366. Fort Collins, Colo.: GIS World Books.

Khomjakv, Pyotr M., and Sergey A. Pegov. 1998. The Automated Regional Ecological Forecast System. Accessed 1999 at http://dino.wiz.uni-kassel.de/model_db/mdb/arefs.html.

Kineman, John J. 1996. Global Ecosystems Database Project: An Experiment in Data Integration for Global Change. In *GIS and Environmental Modeling: Progress and Research* Issues, ed. Michael F. Goodchild et al., 79–84. Fort Collins, Colo.: GIS World Books.

Kyler, D. C. 1984. Integrative Models in Environmental Planning and Policy Making. *Journal of Environmental Education* 15(3)(Spring):17–24.

Lambin, Eric. 1994. Modelling Deforestation Processes: A Review. TREES Series B: Research Report No. 1. European Commission Joint Research Centre and the European Space Agency. Luxembourg: Office for Official Publications of the European Community.

Landis, John D. 1992. BASS II: A New Generation of Metropolitan Simulation Models. Working Paper 573, University of California at Berkeley, Institute of Urban and Regional Development. Berkeley: University of California.

———. 1995. Imagining Land Use Futures: Applying the California Urban Futures Model. *APA Journal* 61(4):438–457.

Landis, John D., Juan Pablo Monzon, Michael Reilly, and Chris Cogan. 1998. Development and Pilot Application of the California Urban and Biodiversity Analysis (CURBA) Model. Presented at the 1998 ESRI International User Conference, October 7–9. Accessible at <http://www.esri.com/library/userco…oc98/PROCEED/TO600/PAP571/P571.HTM>

Landis, John, and Peter Stine. n.d. BRD Decision Support System (DSS) Activities: Development and Pilot Application of the California Urban and Biodiversity Analysis (CURBA) Model. Working paper. Accessed 1999 at http://biology.usgs.gov/dss/stine2.html.

Landis, J., and M. Zhang. 1998a. The Second Generation of the California Urban Futures Model: Part 1: Model Logic and Theory. *Environment and Planning A* 30:657–666.

——. 1998b. The Second Generation of the California Urban Futures Model: Part 2: Specification and Calibration Results of the Land-Use Change Submodel. *Environment and Planning B: Planning and Design* 25(6):795–824.

Lange, Glenn-Marie. 1998. Applying an Integrated Natural Resource Accounts and Input-Output Model to Development Planning in Indonesia. *Economic Systems Research* 10(2):113–135.

LeBlanc, R. T., R. D. Brown, and J. E. FitzGibbon. 1997. Modeling the Effects of Land Use Change on the Water Temperature Unregulated Urban Streams. *Journal of Environmental Management* 49(4):445–469.

Liu, Jianguo, and Peter S. Ashton. 1998. FORMOSAIC: An Individual-Based Spatially Explicit Model for Simulating Forest Dynamics in Landscape Mosaics. *Ecological Modelling* 106:177–200.

Lonergan, Steve, and Scott Prudham. 1994. Modelling Global Change in an Integrated Framework: A View from the Social Sciences. In *Changes in Land Use and Land Cover: A Global Perspective*, ed. W. B. Meyer and B. L. Turner II, 411–435. Cambridge: Cambridge University Press.

Machlis, Gary E., and Jo Ellen Force. 1997. The Human Ecosystem Part I: The Human Ecosystem As an Organizing Concept in Ecosystem Management. *Society and Natural Resources* 10(4):347.

Mackey, B. G., et al. 1996. Spatial Analysis of Boreal Forest Ecosystems. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 187–190. Fort Collins, Colo.: GIS World Books.

Mankin, P. C., and R. E. Warner. 1999. A Regional Model of the Eastern Cottontail and Land-Use Changes in Illinois. *Journal of Wildlife Management* 63(3):956–963.

Martinez, F. J. 1992. The Bid-Choice Land-Use Model: An Integrated Economic Framework. *Environment and Planning A* 24:871–885.

Maxwell, Thomas, and Robert Costanza. 1997a. An Open Geographic Modeling Environment. *Simulation* 68(3):175–185.

———. 1997b. An Open Geographic Modeling System. Presented at Land Use Modeling Workshop, EROS Data Center, Sioux Falls, S.Dak., June 5–6.

McClean, C. J., et al. 1995. Land Use Planning: A Decision Support System. *Journal of Environmental Planning and Management* 38(1):77–92.

Mertens, Benoit, and Eric F. Lambin. 1997. Spatial Modelling of Deforestation in Southern Cameroon. *Applied Geography* 17(2):143–162.

Miller, David R. 1996. Knowledge-Based Systems for Coupling GIS and Process-Based Ecological Models. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 231–234. Fort Collins, Colo.: GIS World Books.

Mitasova, H., et al. 1996. Modeling Spatial and Temporal Distributed Phenomena: New Methods and Tools for Open GIS. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 345–351. Fort Collins, Colo.: GIS World Books.

Mladenoff, David J., et al. 1996. LANDIS: A Spatial Model of Forest Landscape Disturbance, Succession, and Management. In *GIS and Environmental Modeling: Progress and Research Issues*, Michael F. Goodchild et al., ed. 175–179. Fort Collins, Colo.: GIS World Books.

Morisette, J. T., S. Khorram, and T. Mace. 1999. Land-Cover Change Detection Enhanced with Generalized Linear Models. *International Journal of Remote Sensing* 20(14):2703–2721.

Moxey, A. P., B. White. 1995. The Economic Component of NELUP. *Journal of Environmental Planning and Management* 38(1):21.

Muller, Michael R., and John Middleton. 1994. A Markov Model of Land-Use Change Dynamics in the Niagara Regions, Ontario, Canada. *Landscape Ecology* 9(2):151–157.

Nijkamp, Peter, and Jeroen C. J. M. van den Bergh. 1997. New Advances in Economic Modelling and Evaluation of Environmental Issues. *European Journal of Operational Research* 99:180–196.

Norgaard, Richard B. 1994. The Process of Loss: Exploring the Interactions between Economic and Ecological Systems. *American Zoologist* 34:145–158.

Nyerges, T. L. 1991. Geographic Information Abstractions: Conceptual Clarity for Geographic Modeling. *Environment and Planning A* 23:1483–1499.

O'Callaghan, J. R. 1995. NELUP: An Introduction. *Journal of Environmental Planning and Management* 38(1):5–20.

Oglethorpe, D. R., and J. R. O'Callaghan. 1995. Farm-Level Economic Modelling within a River Catchment Decision Support System. *Journal of Environmental Planning and Management* 38(1):93–106.

Pan, D., et al. 1999. Temporal (1958–1993) and Spatial Patterns of Land Use Changes in Haut-Saint-Laurent (Quebec, Canada) and Their Relation to Landscape Physical Attributes. *Landscape Ecology* 14(1):35–52.

Pijanowski, Bryan C., et al. 1997. A Land Transformation Model: Conceptual Elements, Spatial Object Class Hierarchies, GIS Command Syntax and an Application for Michigan's Saginaw Bay Watershed. Presented at Land Use Modeling Workshop, EROS Data Center, Sioux Falls, S.Dak., June 5–6.

Poudevigne, I., and D. Alard. 1997. Agricultural Landscape Dynamics: A Case Study in the Odessa Region, the Ukraine, and a Comparative Analysis with the Brionne Basin Case Study, France. *Ekologia-Bratislava* 16(3):295–308.

Prato, Tony. 1999. Multiple Attribute Decision Analysis for Ecosystem Management. *Ecological Economics* 30:207–222.

Riebsame, W. E., H. Gosnell, and D. M. Theobald. 1996. Land Use and Landscape Change in the Colorado Mountains I: Theory, Scale, and Pattern. *Mountain Research and Development* 16(4):395–405

Riebsame, W. E., and W. J. Parton. 1994. Integrated Modeling of Land Use and Cover Change. *Bioscience* 44(5):350.

Rushton, S. P., and A. J. Cherrill. 1995. The Ecological Modelling System of NELUP. *Journal of Environmental Planning and Management* 38(1):35.

Saaty, Thomas L., and Luis G. Vargas. 1994a. The Case of the Spotted Owl vs. the Logging Industry. In *Decision Making in Economic, Political, Social and Technological Environments.* The Analytic Hierarchy Process, vol. VII, 279–284.

———. 1994b. How to Make a Decision in *Decision Making in Economic, Political, Social and Technological Environments.* The Analytic Hierarchy Process, vol. VII, 1–25.

Schelhas, John. 1996. Land Use Choice and Change: Intensification and Diversification in Lowland Tropics of Costa Rica. *Human Organization* 55(3):298.

Schimel, David S., VEMAP Participants, and B.H. Braswell. 1997. Continental Scale Variability in Ecosystem Processes: Models, Data, and the Role of Disturbance. *Ecological Monographs* 67(2):251–271.

Shakya, Keshab M., and William A. Leuschner. 1990. A Multiple Objective Land Use Planning Model for Nepalese Hill Farm. *Agricultural Systems* 34(2):133.

Skop, E., and J. S. Schou. 1999. Modeling the Effects of Agricultural Production: An Integrated Economic and Environmental Analysis Using Farm Account Statistics and GIS. *Ecological Economics* 29(3):427–442.

Steyaert, Louis T. 1996. Status of Land Data for Environmental Modeling and Challenges for Geographic Information Systems in Land Characterization. In *GIS and Environmental Modeling: Progress and Research Issues,* ed. Michael F. Goodchild et al., 17–27. Fort Collins, Colo.: GIS World Books.

Sutton, Keith. 1989. Malaysia’s FELDA Land Settlement Model in Time and Space. *Geoforum* 20(3):339–354.

Theobold, D. M., H. Gosnell, and W. E. Riebsame. 1996. Land Use and Landscape Change in the Colorado Mountains II: A Case Study of the East River Valley. *Mountain Research and Development* 16(4):407–418.

Theobald, David M., and Mark D. Gross. 1994. EML: A Modeling Environment for Exploring Landscape Dynamics. *Computers, Environment and Urban Systems* 18(3):193–204.

Theobald, David M., and N. Thompson Hobbs. 1998. Forecasting Rural Land-Use Change: A Comparison of Regression and Spatial Transition-Based Models. *Geographical and Environmental Modelling* 2(1):65–82.

Theobald, David M., James R. Miller, and N. Thompson Hobbs. 1997. Estimating the Cumulative Effects of Development on Wildlife Habitat. *Landscape and Urban Planning* 39:25–36.

Thornes, J. B., et al. 1996. Testing the MEDALUS Hillslope Model. *Catena* 26:137–160.

Thornton, P. K., and P. G. Jones. 1998. A Conceptual Approach to Dynamic Agricultural Land-Use Modelling. *Agricultural Systems* 57(4):505–521.

Turner, Monica G. 1987. Spatial Simulation of Landscape Changes in Georgia: A Comparison of Three Transition Models. *Landscape Ecology*. 1(1):29–36.

———. 1988. A Spatial Simulation Model of Land Use Changes in a Piedmont County in Georgia. *Applied Mathematics and Computation* 27:39–51.

Turner, Monica G., D. N. Wear, and R. O. Flamm. 1996. Land Ownership and Land-Cover Change in the Southern Appalachian Highlands and the Olympic Peninsula. *Ecological Applications* 6(4):1150–1172.

Turner, Monica G., et al. 1995. Usefulness of Spatially Explicit Population Models in Land Management. *Ecological Applications* 5(1):12–16.

Vargas, Luis G. 1991. Why the Analytic Hierarchy Process Is Not Like Multiattribute Utility Theory. In *Multiple Criteria Decision Support: Proceedings of the International Workshop Held in Helsinki, Finland, August 7–11, 1989*. New York: Springer-Verlag.

Veldkamp, A., and L. O. Fresco. 1996a. CLUE: A Conceptual Model to Study the Conversion of Land Use and Its Effects. *Ecological Modelling* 85:253–270.

———. 1996b. CLUE-CR: An Integrated Multi-Scale Model to Simulate Land Use Change Scenarios in Costa Rica. *Ecological Modelling* 91:231–248.

Voinov, Alexey, and R. Costanza. 1999. Watershed Management and the Web. *Journal of Environmental Management* 56:231–245.

Voinov, Alexey, H. Voinov, and R. Costanza. 1999. Surface Water Flow in Landscape Models: 2. Patuxent Watershed Case Study. *Ecological Modelling* 119(2-3):211–230.

Voinov, Alexey, R. Costanza, L. Wainger, R. Boumans, F. Villa, T. Maxwell, and H. Voinov. 1999. Patuxent Landscape Model: Integrated Ecological Economic Modeling of a Watershed. *Environmental Modelling and Software* 14:473–491.

Wadsworth, R. A., and J. R. O'Callaghan. 1995. Empirical Searches of the NELUP Land Use Database. *Journal of Environmental Planning Management* 38(1):107–116.

Walker, Robert, and Alfredo Kingo Oyama Homma. 1996. Land Use and Land Cover Dynamics in the Brazilian Amazon: An Overview. *Ecological Economics* 18:67–80.

Wallin, David O., Frederick J. Swanson, and Barbara Marks. 1994. Landscape Pattern Response to Changes in Pattern Generation Rules: Land-Use Legacies in Forestry. *Ecological Applications* 4(3):569–580.

Wear, D. N., and P. Bolstad. 1998. Land-Use Changes in Southern Appalachian Landscapes: Spatial Analysis and Forecast Evaluation. *Ecosystems* 1(6):575–594.

Wear, D. N., M. G. Turner, and R. O. Flamm. 1996. Ecosystem Management with Multiple Owners: Landscape Dynamics in a Southern Appalachian Watershed. *Ecological Applications* 6(4):1173–1188.

Wilkie, David S., and John T. Finn. 1988. A Spatial Model of Land Use and Forest Regeneration in the Ituri Forest of Northeastern Zaire. *Ecological Modelling* 41:307–323.

Wood, Eric C., J. E. Lewis, G. G. Tappan, and R. W. Lietzow. 1997. The Development of a Land Cover Change Model for Southern Senegal. Presented at Land Use Modeling Workshop, EROS Data Center, Sioux Falls, S.Dak., June 5–6. Accessible at http://www.ncgia.ucsb.edu/conf/landuse97/papers/wood_eric/pecdoc.html.

Worrall, F., and T. P. Burt. 1999. The Impact of Land-Use Change on Water Quality at the Catchment Scale: The Use of Export Coefficient and Structural Models. *Journal of Hydrology* 221(1–2):75 –90.

Wu, F. 1998. Stimulating Urban Encroachment on Rural Land with Fuzzy-Logic-Controlled Cellular Automata in a Geographical Information System. *Journal of Environmental Management* 53(4):293–307.

Yeh, T. S., and B. de Camray. 1996. Time As a Geometric Dimension for Modeling the Evolution of Entities: A Three Dimensional Approach. In *GIS and Environmental Modeling: Progress and Research Issues*, ed. Michael F. Goodchild et al., 397–403. Fort Collins, Colo.: GIS World Books.

Yin, Yongyuan, John T. Pierce, and Ernie Love. 1995. Designing a Multisector Model for Land Conversion Study. *Journal of Environmental Management* 44:249–266.

Zavala, M. A., and T. V. Burkey. 1997. Application of Ecological Models to Landscape Planning: The Case of the Mediterranean Basin. *Landscape and Urban Planning* 38:213–227.

Zheng, D. L., and R. J. Alig. 1999. Changes in the Non Federal Land Base Involving Forestry in Western Oregon, 1961–94.

APPENDIX 2:
Plots of Human Driver Variables Represented in the Models across Space and Time

In file APPENDIX 2.doc
Contains an introduction and 20 Power Point graphs on 11 pages

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GLOSSARY

Analytical model: Quantifies functional relationships and estimates parameters by means of empirical data

Area base model: Allocates proportions of a given land base to predefined land-use categories

Complexity: The complexity of human decision making refers to the specificity and detailed consideration given in a model to the decisions that humans make that affect land-use change. We have developed a scale of complexity that ranges from 1 to 6 for this exercise.

Conceptual model: Theoretical description of socioeconomic and physical processes

Control (or flow) variables: System elements that represent the action or change in a state

Discrete finite state model: Model that is discrete (space represented as cells or blocks) and finite state (represents an object as being in only a few, finite number of states or conditions)

Duration: The length of time for which the model is applied. The duration of a model's results may be reported as the number of time steps used (e.g., 100 annual times steps), the period of the model (100 years), or the model dates (January 1, 1900, to January 1, 2000).

Dynamic systems model: Systems models that attempt to capture changes in real or simulated time.

Extent: The total geographic area to which the model is applied

Human Decision-Making: Refers to how models incorporate human elements. Human decision-making sections of models vary in terms their theoretical precursors and may be simply linked deterministically to a set of socioeconomic or biological drivers, or may be based on some game theoretic or economic models. Three attributes of human decision making that are important to consider in thinking about diverse models of land-use change are complexity, jurisdictional domain, and temporal range.

Jurisdiction: Refers to the spatial scope of human decision making. If desired, a jurisdictional domain may be split up to reflect resolution, the decision-making domain for a particular actor, and to reflect spatial extent, in this case the total area over which the actor(s) has(have) influence, or the jurisdictional range.

Linear planning model: Model that optimizes a linear function subject to several linear constraints, expressed as linear inequalities or equalities

Resolution: The smallest spatial unit of analysis for the model. For example, in a raster or grid representation of the landscape, each unit or cell area is usually treated as a constant size.

Spatial complexity: Refers to the presence of a spatial component of a model or information. Spatial complexity may be representative or interactive.

Spatial dynamic model: Models that are spatially explicit and dynamic as well

Spatial interaction: Models are based on topological relationships. Topology is a mathematical procedure for explicitly defining spatial relationships, usually as lists of features, and using the concepts of connectivity, area definition, and contiguity.

Spatial Markov model: Spatially explicit models that carry over memory from one state to the next, but usually from only the last state; e.g., the probability that the system will be in a given state (land class) at some time t2, is deduced from the knowledge of its state at time t1.

Spatial representation: Spatially representative models are able to display data as maps. However, they do not include topology and spatial interactions.

Spatial stochastic model: Spatially explicit model that is interactive and incorporates random changes to determine transition probabilities from one land cover to another.

State variables: Elements that make up the system for which the model is being developed

Time step: The smallest temporal unit of analysis of the model variable

REFERENCES

Adams, D. M., R. J. Alig, J. M. Callaway, B. A. McCarl, and S. M. Winnett. 1996. The Forest and Agricultural Sector Optimization Model (FASOM): Model Structure and Policy Applications. Research Paper PNW-RP-495. Portland, Ore.: U.S. Department of Agriculture, Pacific Northwest Research Station.

Berge, E. 1998. Modeling the Human Impact on Resource Systems. Workshop in Political Theory and Policy Analysis Working Paper. Bloomington: Workshop in Political Theory and Policy Analysis, Indiana University.

Berry, M. W., B. C. Hazen, R. L. MacIntyre, and R. O. Flamm. 1996. LUCAS: A System for Modeling Land-Use Change. *IEEE Computational Science and Engineering* 3(1):24.

Berry, M. W., and K. S. Minser. 1997. Distributed Land-Cover Change Simulation Using PVM and MPI. Presented at the Land Use Modeling Workshop, USGS EROS Data Center, Sioux Falls, S.Dak., June 5–6.

Bockstael, N. E. 1996. Modeling Economics and Ecology: The Importance of a Spatial Perspective. *American Journal of Agricultural Economics* 78(5):1168.

Bockstael, N. E., et al. 1995. Ecological Economic Modeling and Valuation of Ecosystems. *Ecological Economics* 14:143–159.

Brondízio, Eduardo, P. Mausel, and Emilio Moran. In press. Integrating Biogeography, Remote Sensing, and Human Ecology in the Study of Land Use/Land Cover Dynamics in Amazonia. In *Biogeography and Remote Sensing*, ed. K. Lulla. Hong Kong: Geocarto.

Chomitz, K. M., and D. A. Gray. 1996. Roads, Land Use, and Deforestation: A Spatial Model Applied to Belize. *World Bank Economic Review* 10(3):487–512.

Clarke, K. C. 1997. Land Transition Modeling with Deltratrons. Presented at the Land Use Modeling Workshop, USGS EROS Data Center. Sioux Falls, S.Dak., June 5–6.

Clarke, K. C., S. Hoppen, and I. J. Gaydos. n.d. Methods and Techniques for Rigorous Calibration of a Cellular Automation Model of Urban Growth. Accessed June 20, 2000, at http://geo.arc.nasa.gov/usgs/clarke/calib.paper.html.

Cleveland, C., R. Costanza, T. Eggertsson, L. Fortmann, B. Low, M. McKean, E. Ostrom, J. Wilson, and O Young. 1996. A Framework for Modeling the Linkages between Ecosystems and Human Systems. Beijer Discussion Paper Series No. 76. Sweden: International Institute of Ecological Economics, Royal Swedish Academy of Sciences.

Costanza, R., B. S. Low, E. Ostrom, and J. Wilson. In press. *Institutions, Ecosystems, and Sustainability.* Washington, D.C.: Island Press.

Costanza, R., and R. Matthias. 1998. Using Dynamic Modeling to Scope Environmental Problems and Build Consensus. *Environmental Management* 22(2):183–195.

Costanza, R., et al. 1993. Modeling Complex Ecological Economic Systems. *Bioscience* 43(8):545–555.

Dahlstrom, R. K. 1997. Practical Computer Applications for Land Use Planning and Analysis. *Northern Illinois University Law Review* 17(3):399–417.

Dietz, T. 1994. Rethinking the Environmental Impacts of Population, Affluence and Technology. *Human Ecology Review* 1.

Endre, A. N., and G. Green. 2000. The Ethnography of Landscape: GIS and Remote Sensing in the Study of Forest Change in West African Guinea Savanna. *American Anthropologist* 102(2):271–289.

Evans, T. P., G. Green, and L. Carlson. Under review. Multi-Scale Analysis of Landcover Composition and Landscape Management of Public and Private Lands in Indiana. Chapter in *Remote Sensing and GIS Applications in Biogeography and Ecology*, ed. A. Millington, S. Walsh, and P. Osborne. Submitted to Kluwer Publications.

Evans, Tom P., Aaron Manire, Fabio de Castro, Eduardo Brondízio, and Stephen McCracken. Accepted pending revisions. A Dynamic Model of Household Decision Making and Parcel Level Landcover Change in the Eastern Amazon. *Ecological Modeling*.

Evans, T. P., and E. Moran. Under review. Spatial Integration of Social, Political, and Biophysical Factors Contributing to Landcover Change. Submitted to *Population and Development Review*.

Evans, T. P., E. Ostrom, and C. Gibson. 2000. Scaling Issues in the Social Sciences. Paper presented at EFIEA Matrix workshop "Scaling Issues in Integrated Assessment," Mechelen, Netherlands, July 12–19.

Fitz, H. C., E. B. DeBellevue, R. Costanza, R. Boumans, T. Maxwell, L. Wainger, and F. H. Sklar. 1996. Development of a General Ecosystem Model for a Range of Scales and Ecosystems. *Ecological Modelling* 88:263–295.

Force, J. E., and G. E. Machlis. 1997. The Human Ecosystem Part II: Social Indicators in Ecosystem Management. *Society and Natural Resources* 10(4):369.

Gibson, C., E. Ostrom, and T.-K. Ahn. 2000. The Concept of Scale and the Human Dimensions of Global Change. *Ecological Economics* 32(2):217–239.

———. 1998. Scaling Issues in the Social Sciences. A Report for the International Human Dimensions Programme on Global Environmental Change, IHDP Working Paper No. 1. Bonn, Germany: IHDP.

Gilruth, P. T., S. E. Marsh, and R. Itami. 1995. A Dynamic Spatial Model of Shifting Cultivation in the Highlands of Guinea, West Africa. *Ecological Modelling* 79:179–197.

Hardie, I. W., and P. J. Parks. 1997. Land Use with Heterogeneous Land Quality: An Application of an Area Base Model. *American Journal of Agricultural Economics* 79(2)299–310.

Hazen, B. C., and M. W. Berry. 1997. The Simulation of Land-Cover Change Using a Distributed Computing Environment. *Simulation Practice and Theory* 5:489–514.

King, J. L., and K. L. Kraemer. 1993. Models, Facts, and the Policy Process: The Political Ecology of Estimated Truth. In *Environmental Modeling with GIS*, ed. M. F. Goodchild, B. O. Parks, and L. T. Steyaert, 353–360. New York: Oxford University Press.

Kirtland, D., L. Gaydos, K. Clarke, L. DeCola, W. Acevedo, and C. Bell. *An Analysis of Human Induced Land Transformations in the San Francisco Bay/Sacramento Area*. <http://edcwww2.cr.usgs.gov/umap/pubs/WRR_paper.html> Accessed June 20, 2000.

Kyler, D. C. 1984. Integrative Models in Environmental Planning and Policy Making. *Journal of Environmental Education* 15(3)(Spring):17–24.

Lambin, E. F. 1994. Modelling Deforestation Processes: A Review. TREES Series B. *European Commission Research Report No. 1* EUR 15744:1–108.

Landis, J. D. 1995. Imagining Land Use Futures: Applying the California Urban Futures Model. *APA Journal* 61(4):438–457.

Landis, J. D., J. P. Monzon, M. Reilly, and C. Cogan. 1998. Development and Pilot Application of the California Urban and Biodiversity Analysis (CURBA) Model. Presented at the 1998 ESRI International User Conference, October 7–9. Accessible at http://www.esri.com/library/userco…oc98/PROCEED/TO600/PAP571/P571.HTM.

Landis, J. D., and M. Zhang. 1998. The Second Generation of the California Urban Futures Model: Part 2: Specification and Calibration Results of the Land-Use Change Submodel. *Environment and Planning B.* 25(6):795–824.

Lee, D. B. Jr. 1973. Requiem for Large-Scale Models. *AIP Journal* (May):163–177.

Lonergan, S., and S. Prudham. 1994. Modeling Global Change in an Integrated Framework: A View from the Social Sciences. In *Changes in Land Use and Land Cover: A Global Perspective*, ed. W. B. Meyer and B. L. Turner II, 411–435. Cambridge: Cambridge University Press.

Martinez, F. J. 1992. The Bid-Choice Land-Use Model: An Integrated Economic Framework. *Environment and Planning A.* 24:871–885.

Maxwell, T., and R. Costanza. 1997a. An Open Geographic Modeling Environment. *Simulation* 68(3):175–185.

———. 1997b. An Open Geographic Modeling System. Presented at Land Use Modeling Workshop, EROS Data Center. Sioux Falls, S.Dak., June 5–6.

McCracken, Stephen, Eduardo Brondízio, Donald Nelson, Emilio Moran, Andrea Siqueira, and Carlos Rodriguez-Pedraza. 1999. Remote Sensing and GIS at Farm Property Level: Demography and Deforestation in the Brazilian Amazon. *Photogrammetric Engineering and Remote Sensing* 65(11):1311-1320.

Mertens, B., and E. F. Lambin. 1997. Spatial Modelling of Deforestation in Southern Cameroon. *Applied Geography* 17(2):143–162.

Moran, Emilio F., Eduardo S. Brondízio, and Stephen D. McCracken. In press. Trajectories of Land Use: Soils, Succession, and Crop Choice. In Patterns and Processes of Land Use and Forest Change in the Amazon, ed. C. Wood et al. Gainesville: University of Florida Press.

Moran, Emilio F., Eduardo. S. Brondízio, Joanna Tucker, Maria Clara Silva-Forsberg, Italo Falesi, and Stephen D. McCracken. In press. Strategies for Amazonian Forest Restoration: Evidence for Afforestation in Five Regions of Amazonia. In Amazônia 2000: The Challenge for Sustainable Development, ed. A. Hall. London: University of London, Institute for Latin American Studies.

Moxey, A. P., B. White, and J. R. O’Callahan. 1995. The Economic Component of NELUP. *Journal of Environmental Planning and Management* 38(1):21–33.

Natural Resources Conservation Service, United States Department of Agriculture. 1999. Summary Report 1997: Natural Resources Inventory. Iowa State University Statistical Laboratory (http://www.nhq.nrcs.usda.gov/NRI)

Norgaard, R. B. 1994. The Process of Loss: Exploring the Interactions between Economic and Ecological Systems. *American Zoologist* 34:145–158.

O’Callaghan, J. R. 1995. NELUP: An Introduction. *Journal of Environmental Planning and Management* 38(1):5–20.

Oglethorpe, D. R., and J. R. O’Callaghan. 1995. Farm-Level Economic Modelling within a River Catchment Decision Support System. *Journal of Environmental Planning and Management* 38(1):93–106.

Ramankutty, N., and J. A. Foley. 1999. Estimating Historical Changes in Global Land Cover: Croplands from 1700 to 1992. *Global Biogeochemical Cycles* 13(4):997–1028.

Redman, C., J. M. Grove, and L. Kuby. 2000. Toward a Unified Understanding of Human Ecosystems: Integrating Social Sciences into Long-Term Ecological Research. White Paper of the Social Science Committee of the LTER Network. Accessible at http://www.lternet.edu/research/pubs/informal/socsciwhtppr.htm.

Riebsame, W. E., and W. J. Parton. 1994. Integrated Modeling of Land Use and Cover Change. *Bioscience* 44(5):350.

Rushton, S. P., and A. J. Cherrill. 1995. The Ecological Modelling System of NELUP. *Journal of Environmental Planning & Management* 38(1):35–52.

Schimel, D. S., VEMAP Participants, and B. H. Braswell. 1997. Continental Scale Variability in Ecosystem Processes: Models, Data, and the Role of Disturbance. *Ecological Monograph* 67(2):251–271.

Schweik, C. M., and G. M. Green. 1999. The Use of Spectral Mixture Analysis to Study Human Incentives, Actions, and Environmental Outcomes. *Social Science Computer Review* 17(1):40–63.

Sussman, R. W., G. M. Green, and L. K. Sussman. 1994. Satellite Imagery, Human Ecology, Anthropology, and Deforestation in Madagascar. *Human Ecology* 22:333–354.

Swallow S. K., P. Talukdar, and D. N. Wear. 1997. Spatial and Temporal Specialization in Forest Ecosystem Management under Sole Ownership. *American Journal of Agricultural Economics* 79:311–326.

Thornes, J. B., et al. 1996. Testing the MEDALUS Hillslope Model. *Catena* 26:137–160.

Turner, M. G., et al. 1995. Usefulness of Spatially Explicit Population Models in Land Management. *Ecological Applications* 5(1):12–16.

Veldkamp, A., and L. O. Fresco. 1996a. CLUE: A Conceptual Model to Study the Conversion of Land Use and Its Effects. *Ecological Modelling* 85:253–270.

———. 1996b. CLUE-CR: An Integrated Multi-Scale Model to Simulate Land Use Change Scenarios in Costa Rica. *Ecological Modelling* 91:231–248.

Vitousek, P. M., H. A. Mooney, J. Lubchenco, and J. M. Melillo. 1997. Human Domination of Earth’s Ecosystems. *Science* 277(15 July):494–499.

Voinov, A., R. Costanza, L. Wainger, R. Boumans, F. Villa, T. Maxwell, and H. Voinov. 1999. Patuxent Landscape Model: Integrated Ecological Economic Modeling of a Watershed. *Environmental Modelling and Software* 14:473–491.

Walker, R., and Alfredo Kingo Oyama Homma. 1996. Land Use and Land Cover Dynamics in the Brazilian Amazon: An Overview. *Ecological Economics* 18:67–80.

Walsh, S. J., T. P. Evans, W. F. Welsh, B. Entwisle, and R. R. Rindfuss. 1999. Scale-Dependent Relationships between Population and Environment in Northeastern Thailand. *Photogrammetric Engineering and Remote Sensing* 65(1):97–105.

Wear, D. N., R. Apt, and R. Mangold. 1998. People, Space, Time: Factors That Will Govern Forest Sustainability. *Transactions of the 63rd North American Wildlife and Natural Resources conference, March 20–25, 1998*, 348–361. Washington, D.C.: Wildlife Management Institute.

Wear, D. N., and P. Bolstad. 1998. Land-Use Changes in Southern Appalachian Landscapes: Spatial Analysis and Forecast Evaluation. *Ecosystems* 1(6):575–594.

Wear, D. N., R. Liu, J. M. Foreman, and R. M. Sheffield. 1999. The Effects of Population Growth on Timber Management and Inventories in Virginia. *Forest Ecology and Management* 118:107–115.

Wood, E. C., J. E. Lewis, G. G. Tappan, and R. W. Lietzow. 1997. The Development of a Land Cover Change Model for Southern Senegal. Presented at Land Use Modeling Workshop, EROS Data Center, Sioux Falls, S.Dak., June 5–6. Accessible at http://www.ncgia.ucsb.edu/conf/landuse97/papers/wood_eric/pecdoc.html.

Yin, Y., J. T. Pierce, and E. Love. 1995. Designing a Multisector Model for Land Conversion Study. *Journal of Environmental Management* 44:249–266.