# 7

# Modeling Human-Environmental Systems

## 7.0 SUMMARY

This chapter focuses on the integration and development of environmental models that include human decision making. While many methodological and technical issues are common to all types of environmental models, our goal is to highlight the unique characteristics that need to be considered when modeling human-environmental dynamics and to identify future directions for human-environmental modeling. To achieve this goal, we have separated this chapter into several sections. First, we propose and define a conceptual framework for describing human-environmental models based on three critical dimensions: time, space, and human decision making. Second, using our framework, we summarize and compare whether and how different models (urban or rural systems, health, epidemiology, pollution, or hydrology) include space, time, and human decision making. This provides both an assessment of the models examined and a test of the framework. Third, we discuss the theoretical implications for linking human-environmental dynamics within the context of these three dimensions. Finally, we consider lessons learned and future directions for developing human-environmental models.

This chapter is not a guide for readers to learn how to model human-environmental systems. Rather, readers will find this chapter useful for understanding the basic issues that models of human-environmental dynamics must address; for developing the ability to assess the strengths and weaknesses of various human-environmental models; and for identifying future directions in modeling human-environmental systems. Ultimately, we hope to convince readers that modeling human-environmental dynamics is a useful and exciting activity that can complement biophysically based models and provide understanding of human-environmental systems.

## 7.1 INTRODUCTION

Models are often simplistic, but in many cases critical, abstract representations of the complex dynamics of human-environmental systems. They can be categorized in several ways. Models can focus on topics such as urban or rural systems, health, epidemiology, pollution, or hydrology (Landis, 1995; White and Engelen, 1993). Models can be used for many purposes, such as research, decision making (policy, planning, and management), and education (Costanza and Ruth, 1998; Ford, 1999; Grove, 1999). Models can also be categorized by the methods and techniques used, which might range from simple regressions to advanced dynamic simulations (Agarwal et al., 2000; Clarke and Gaydos, 1997; Clarke and Gaydos, 1998; Lambin, 1994).

Given the possible variety and ever-growing number of human-environmental models, we do not attempt to provide Noah's list of models. Rather, our goal in this chapter is to provide a framework for categorizing and summarizing models of human-environmental dynamics that is both inclusive of purpose, method, and topic while permitting fundamental comparisons of models along the dimensions of time, space, and human decision making. The framework we propose is not an end in and of itself. We anticipate that this framework will provide the basis for assessing current progress in modeling human-environmental dynamics and identifying and prioritizing directions for model development in terms of topic, purpose, and methods.

This chapter is separated into the following sections. First, we propose and define a conceptual framework for describing human-environmental models based on critical dimensions of time, space, and human decision making. Second, using our framework, we summarize and compare different examples of models (urban or rural systems, health, epidemiology, pollution, or hydrology) along these dimensions. This provides both an assessment of the models and a test of the framework. Third, we discuss the theoretical implications for linking human-environmental dynamics within the context of these three dimensions. Finally, we consider lessons learned and future directions for developing models of human-environmental dynamics.

## 7.2 KEY FEATURES OF HUMAN-ENVIRONMENT MODELS

### 7.2.1 Time, Space, and Human Decision Making: A Framework for Reviewing Human-Environmental 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 context 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, a third dimension–what we refer to as the human decision making dimension–becomes important as well (Figure 7.1).

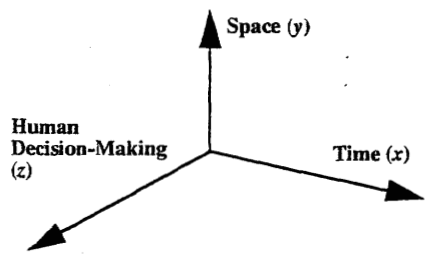


**Figure 7.1** The three dimensions of human-environmental models.

In reviewing and comparing human-environmental 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 from earlier parts of this book.

**Model Scale.** Real-world processes operate at different scales (Allen and Hoekstra, 1992; Ehleringer and Field, 1993). When we discuss the temporal scale of models, we usually talk in terms of time step and duration. Time step is the smallest 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. Duration refers to the length of time that the model is applied. Change in tree height might be modeled daily over the course of its life from seedling to mature tree by using a duration of 300 years. In this case, time step would equal one day and duration would equal 300 years.

When we discuss the spatial scale of models, we talk in terms of 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 system. Extent describes the total geographic area to which the model is applied. Consider a model of individual trees in a 50-ha forested area. In this case, an adequate resolution for individual trees might be 5 m and the model extent would equal 50 ha.

Most readers will find this discussion relatively straightforward and familiar. But how do we 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 and duration, and resolution and extent. Like time and space, however, we propose that an analogous approach can be used to articulate scales of human decision making in terms of two components: agent and domain.

Agent refers to the human actor(s) in the model who are making decisions. The individual is the most familiar human decision making agent. But there are many human models that capture decision making processes at higher levels of social organization, such as household, neighborhood, county, state or province, or nation. These can all be considered agents in models and can be linked. For example, Figure 7.2 illustrates an example of a hierarchical approach to agents and domains for the study of urban ecosystems. 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 articulated in a geographically explicit model through the use of boundary maps or GIS layers.

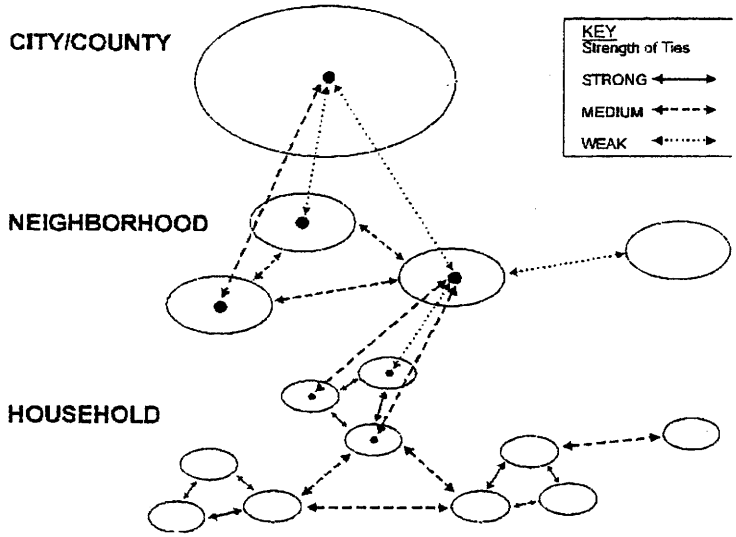


**Figure 7.2** Multiple agents and domains (adapted from Grove et al., 2000).

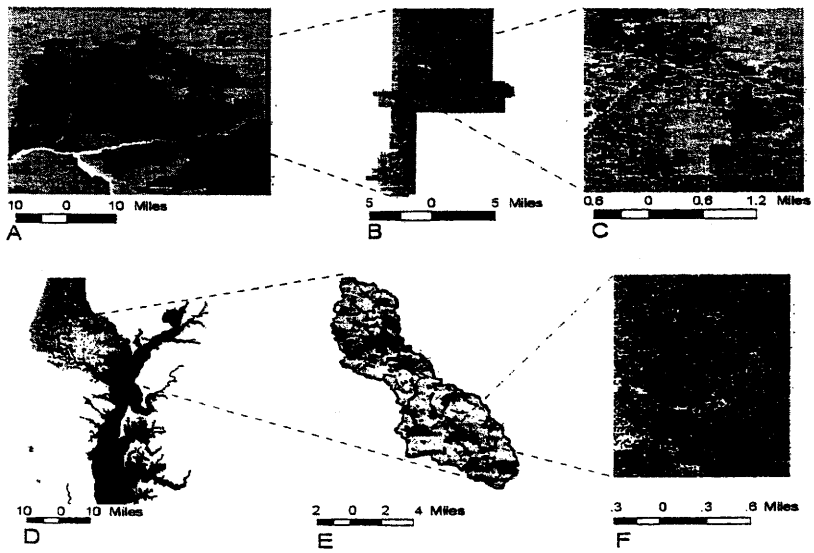


**Figure 7.3** Spatial representation of a hierarchal approach to modeling urban systems (Grimm et al., 2000). Figure shows three levels of spatial scale for the Central Arizona-Phoenix (upper) and Baltimore ecosystem (lower) studies.

In a model of farmer behavior (agent = individual) the farm is the domain within which farmers make decisions. In this example, we might also model other agents operating in the same region (e.g., other parcels), such as nonfarming households, public land managers, or conservation groups, whose boundaries would also be depicted by the same domain map. Institutionally, agents overlap spatially, since the farmer might receive extension advice about her livestock from an agent of the Department of Agriculture; have her cows inspected by the agent of an Department of Health; and receive financial subsidies from an agent of the Forest Service for planting trees in riparian buffer areas.

Using another example and a different scale of human decision making, consider 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 to the model might include the behavior of the forester within the organizational context of the state-level natural resource agency.

**Model Complexity.** The second important and distinct attribute of human-environmental models is the approach(s) 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 be represented with an index, where a low score signifies only simple processing and a high score signifies more complex behaviors and interactions. Consider an index for *temporal complexity* of models: A model that is low in temporal complexity is a model that has one, or possibly a few, time steps and a short duration. A model with a middle to high score for temporal complexity is one that has many time steps and a longer duration. Models with a high score for temporal complexity are ones that have 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.

An index of *spatial complexity* would represent the "spatial explicitness" of a model. There are two general types of spatially explicit models: spatially representative or spatially interactive. A model that is spatially representative can incorporate, produce, or display data in at least two and sometimes three spatial dimensions—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 cells neighboring it. 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 score for spatial complexity would be one with little or no capacity to represent data spatially, a model with a medium score for spatial complexity would be able to represent data spatially, and a model with a high score would be spatially interactive in two or three spatial dimensions.

What might we use to characterize an index for model complexity of human decision making? We use the phrase *HDM complexity* to describe the capacity of a human-environmental model to handle decision making processes. In Table 7.1, we present a classification scheme for estimating HDM complexity using an index from 1 to 6. A model with a low score for human decision making complexity (1) is a model that does not include any

**Table 7.1** 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 socio-economic 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 socio-economic 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 |

human decision making. In contrast, a model with a high score (5 or 6) is a model that includes one or more types of actors explicitly or can handle multiple agents interacting across domains, as shown in Figures 7.2 and 7.3. In essence, Figures 7.2 and 7.3 represent a hierarchical approach to social systems where lower-level agents interact to generate higher-level behaviors and higher-level domains affect the behavior of lower-level agents (Grimm et al., 2000; Grove et al., 2000; Vogt et al., 2000;).

### 7.2.2 Application of the Framework

The three dimensions of human-environmental models—space, time, and human decision making—and two distinct attributes for each dimension—scale and complexity—provide the foundation for comparing and reviewing human-environmental models. Figure 7.4 presents the framework with the three dimensions represented and the models located in terms of their spatial, temporal, and HDM complexity along each axis.

Human-environmental models can be placed somewhere within the three dimensional space of Figure 7.4 to represent graphically their comparative focus, strengths, and abilities. Consider a time series modeling effort. Suppose a hydrologist is interested in modeling the quantity of water held in a city's reservoir over time and wants to use historic data on reservoir levels and other relevant information to forecast levels in the future.

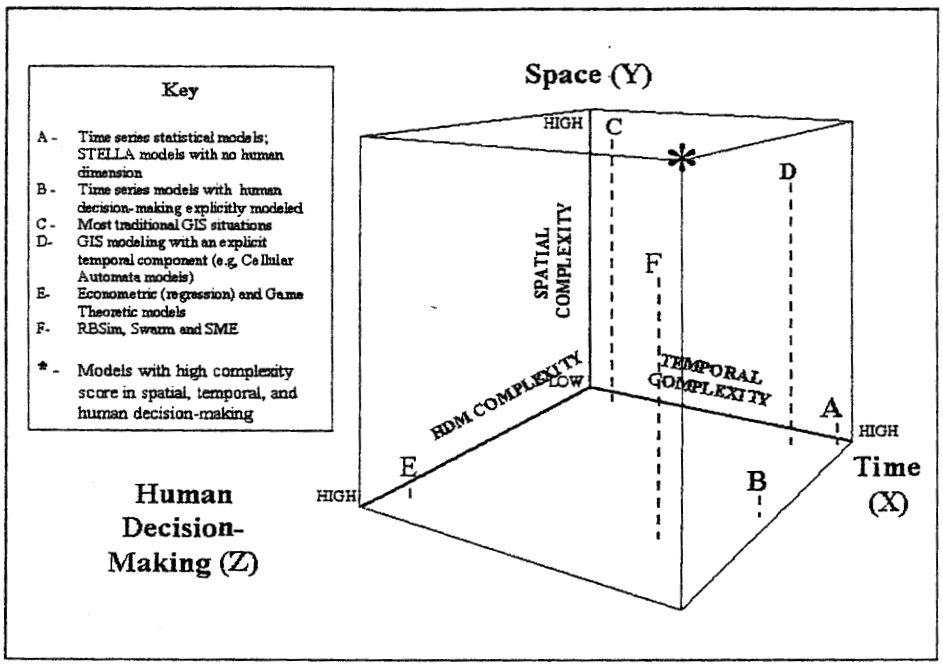


**Figure 7.4** A framework for reviewing human-environmental models.

He or she may decide that the appropriate analytic technique for this question is to develop a regression or autoregression model. Often, time series statistical analyses focus on variations over time (such as reservoir water levels) without considering spatial or human decision making complexity. Such modeling approaches might have a high score for temporal complexity but would have a low score for spatial or human decision making complexity (Figure 7.4, A). Continuing with our reservoir example, a time series model that explicitly included human decision making, such as household decisions over water consumption in response to changes in water costs or to drought-based conservation practices, would have a higher complexity score along the human decision making axis (Figure 7.4, B).

A modeling approach that would have a high score for temporal complexity is based on dynamic systems software (for example, STELLA, ModelMaker, Powersim). This type of software allows a modeler to represent systems as stocks, flows, and processes and to run the model over a series of time periods (Costanza and Gottlieb, 1998; Hannon and Ruth, 1997). STELLA does not have its own spatial modeling capabilities; and if a model based on STELLA does not include a human component, it would have a low score for both the spatial and human decision making complexity (Figure 7.4, A). STELLA models have the capacity to explicitly model human decision making; consequently, the complexity score for any STELLA model along the human decision making axis depends on the specific processes included in the model.

Geographic information systems (GIS) are the obvious spatial modeling technology and models that include GIS have high scores for spatial complexity. Many GIS applications in the 1970s, 1980s, and early 1990s have low temporal and human decision making scores (Figure 7.4, C) because most GIS applications developed during that period used data layers developed for only one or possibly two time points and concentrated on the heterogeneity of biophysical, landscape characteristics. Similar to statistical modeling, however, GIS has powerful abilities and can, in some applications, have high scores for temporal and/or human decision making complexity. For example, cellular automata (CA) models (Clarke et al., 1997; Clarke and Gaydos, 1998) are one special type of raster-based modeling that explicitly captures change over time in a spatial context. CA models have higher scores for temporal complexity than standard GIS systems (Figure 7.4, D). Similar to STELLA modeling, the relative location of a CA model along the human decision making axis depends on the specific social processes included in the model.

What about models with high scores for human decision making complexity? Econometric models are one type of modeling approach that would rank higher in this dimension because they often explicitly try to model human behavior (Figure 7.4, E). For instance, in political science or sociological research, surveys and regression analysis are often used to understand better how various factors influence individual behavior. Most of these types of regression models would have low scores for temporal and spatial complexity unless the modeler explicitly included spatial or temporal parameters (for an example of regression integrated with spatiotemporal modeling, see Veldkamp and Fresco, 1996).

Game theoretic modeling is another approach that models human decision making complexity very well (Figure 7.4, E). Game theorists explicitly try to understand why humans behave the way they do under certain bargaining or collective action situations (see, for example, Roth, 1985; Ostrom et al., 1994). This modeling approach can include some temporal complexity. For example, there has been substantial work by experimental economists who have developed predictive models of repeated human decision making over several time periods (Kagel and Roth, 1997; Smith et al., 1994).

Combinations of techniques to model all three dimensions have begun to emerge (Figure 7.4, F). For example, Swarm, is an agent based modeling framework that can handle temporal, spatial, and human decision making complexity (see, for example, Popper and Smuts, 1999; http://www.swarm.org). Swarm is a software package that allows for the development of multiagent simulation of complex systems and has the capacity to develop spatiotemporal models of human decision making. Recently, Swarm has been used to model agents in various economic decision making scenarios (Luna and Stefannson, 2000). These agent-based approaches can span space, time, and decision making dimensions and cross social and biophysical scales by modeling agents at different scales.

The Recreation Behavior Simulator, or RBSim, developed by Itami and Gimblett, provides another example of modeling in all three dimensions. RBSim combines GIS and autonomous human agents to simulate human decision making and movement over geographic space and time (Gimblett et al., 1998; see also http://www.dlsr.com.au/software/rbsim). In these models, programs are written to capture the logic or decision rules of various types of decision makers or agents.

Finally, Costanza and colleagues' Spatial Modeling Environment (SME) combines GIS capabilities with STELLA to create a system to model landscape change in a fashion

similar to cellular automata (http://kabir.cbl.umces.edu/SMP/MVD/SME1.html). With the STELLA modeling embedded in SME, it is possible to model human decision making using the STELLA stock-flow-process environment. SME models with human decision making would also have high scores for all three dimensions of complexity.

We try to compare different types of models, but we should note that when two models are compared side by side, they might have identical scores of complexity for each dimension (Figure 7.4) even though they operate at different spatial, temporal, or human decision making scales. Alternatively, two models operating at identical scales could have different scores of complexity for each dimension. Thus, it is important to consider both sets of model attributes—scale and model complexity—when assessing whether human-environmental models are comparable.

The utility of this three-dimensional framework is that, first, it forces us to consider and clearly articulate the two important attributes of models: scale and complexity. Further, the framework encourages developers of human-environmental models to consider the appropriate scale(s) and levels of complexity necessary to address the problem or system they want to model. The following section considers how models of three different types of human-environmental systems relate to this framework.

## 7.3 EXAMPLES OF HUMAN-ENVIRONMENT MODELS

Researchers from a variety of disciplines have modeled a vast array of human-environmental systems. These various types of models differ in structure and design because of the nature of the systems being modeled, the methodological and disciplinary background of the modelers, and the different purposes of various models. Here we provide examples from three broad areas of human-environmental modeling in order to demonstrate the approaches that have been used to model human decision making; the effect of human populations on the environment; and the effect of the environment on human populations. This section discusses only a small, representative subset of different types of human-environmental models and is limited to models with (1) a substantial interface with the biophysical environment, and (2) some ability to represent spatial relationships. Elsewhere, several sources provide comprehensive reviews of various types of human-environmental models (Johnston and Barra, 2000; Southworth, 1995; Webster and Pauley, 1991; Wegener, 1994; Wilson, 1998)

The basic systems models discussed here deal with urban systems, land use/land cover change, and models related to environmental health. It should be noted that there is a considerable amount of content overlap among these three categories. The models described here can be distinguished in their focus, or more specifically, to what degree each model adds complexity or simplifies different model components. For example, both the California Urban Futures model (CUF) and the Agricultural Nonpoint Source Pollution model (AGNPS) deal with agricultural land use in some way. However, the AGNPS model has much more complexity for the ecological function of the agricultural system than the CUF model, and the CUF model has more complexity for location-economics, where the AGNPS has no content. This is natural since these two models were designed for entirely different purposes. These two examples illustrate how the purpose of a model determines how a particular system is modeled and which components are included in different models of similar systems.

### 7.3.1 Urban Systems Modeling

A significant problem for urban planners in the 1970s and 1980s was the process of rapid urbanization and suburbanization. Even prior to the advent of GIS technologies, planners used overlay techniques with mylar maps to examine the spatial characteristics of urban areas. As GIS tools and techniques were developed and distributed in more user-friendly software platforms, GIS became a natural tool to model processes of urban growth. Because of these conditions, GIS was rapidly adopted within urban planning as a visualization and modeling tool. A large number of models of urban change were developed in the late 1980s and early 1990s. These models were used for simulation and scenario testing, allowing policy makers to observe the predicted effects of various policy prescriptions as well as different population growth and development scenarios. Here we present three urban growth models that can be differentiated by the following characteristics: spatial unit of analysis, data visualization, model complexity, choice of exogenous factors, and calibration/validation tools.

The CUF model (Landis, 1995; Landis and Zhang, 1998) was originally developed to predict urban development in a 14 county area in Northern California but has since been applied to a variety of urban areas for urban development predictions under different scenarios. The CUF-1 model uses a bottom-up approach: Population growth is modeled for individual subareas (incorporated cities/counties and developable land units [DLUs]). Since the initial CUF model was designed, the model has been revised (CUF-2) to include multiple land uses and calibrates model output from more recent data. The CUF-2 model also uses a smaller spatial unit of analysis (100m * 100m cells) than the CUF-1 model, which used only several hundred DLU areas to model a 14 county area in Northern California.

One of the most widely applied urban systems models is the Metropolitan Integrated Land Use system (METROPILUS) (Putman, 1983; 1992). The METROPILUS model is actually the integration of a series of model components, each focused on a particular aspect of land use/land cover change processes. Development began in the 1970s and the latest incarnation includes a user-friendly graphical user interface linked to ArcView GIS software package. The main model components are a residential allocation component, an employment allocation component, and a land use change component. The residential and employment model components can be used to predict population changes, and the land use change component estimates changes in land cover based on the demands placed on the landscape by the residential and employment components. This compartmentalized or modular approach to modeling is a common approach in human-environmental modeling as well as ecosystems modeling.

An alternative approach applied in the late 1980s and 1990s was the use of cellular automata, where the state of each unit of analysis is a function of three factors: (1) the cell's prior state, (2) the neighboring area, and (3) a series of state transition rules (Deadman et al., 1993). Examples of cellular automata models applied to urban areas include White and Engelen (1993), Batty and Xie (1994a, 1994b, 1994c) and Clarke (Clarke et al., 1997; Clarke and Gaydos, 1998). In the case of White and Engelen and Batty and Xie, an urban area is represented by a raster data structure of cells where the state of each cell at a specific time point is the product of the state of that cell at the prior time point and the

states of cells in a neighborhood surrounding that cell. These researchers have used this approach to model the affect of different policy prescriptions and scenarios, such as different population growth rates, zoning restrictions, and various economic development assumptions.

### 7.3.2 Rural Systems Modeling

Rural land use/land cover change or rural systems modeling is another major area of human-environmental systems modeling. This area of modeling overlaps with urban systems modeling in that the rural-urban interface is often an important factor in many urban and rural environments. However, rural systems modeling most often focuses on areas where agriculture and forest predominate and there is little direct effect from the encroachment of urban areas. These rural systems models can be differentiated from urban systems models in their focus and component complexity. In particular, rural systems models have more complexity in specifying the dynamics of agriculture and forestry land uses. A review of urban and rural systems models shows that most urban systems models focusing on urban expansion and land use change are concerned with the provision of services (e.g., transportation infrastructure) ( Johnson and Barra, 2000; Wegener, 1994). The exceptions are models of urban climates. In contrast, rural systems models have included more explicit linkages between land use decisions and landscape outcomes associated with environmental effects (e.g., carbon sequestration, groundwater contamination, biodiversity). For example, the CUF-2 model (Landis and Zhang, 1998) includes multiple land uses in modeling urban growth, but only one class is used to represent all agricultural land uses (crops, pasture, and forest land) while there are six classes of urban land uses. Furthermore, the CUF-2 model does not distinguish between crops or stages of forest growth.

Recently, rural systems models or land use/land cover change (LUCC) models have been the focus of researchers examining global change issues including deforestation/reforestation, biodiversity, carbon sequestration, and other land-atmosphere exchanges. (For a review, see Agarwal et al., 2000.) These models include spatially explicit models of land cover change, dynamic systems models, and models that predict emergent behavior in human systems.

One method of modeling LUCC is through the use of spatially explicit dynamic systems models. Costanza and colleagues have developed such a model for the Patuxent watershed by integrating a general ecosystem model with economic decision making (Voinov and Costanza, 1999; Voinov et al., 1999). This model has been implemented for the Patuxent watershed using the spatial modeling environment (SME), developed by the authors and colleagues. Originally focusing on hydrology and the surface and subsurface exchange of nutrients, the model uses the specification of economic development to incorporate land use change in the model rather than using land use change as an exogenous factor affecting the hydrological system. This dynamic approach provides powerful coupling techniques whereby feedbacks in each model component can be linked to other model components and provide a more realistic representation of human-environment

interactions.

There are many models that predict the behavior of rural systems from an ecosystem perspective. These models generally treat land use decisions as exogenous drivers to the model rather than modeling the land use decision making process itself. Various models have been developed for a range of different ecosystem types and for applications such as predicting crop productivity and forest succession in publicly managed lands.

One such model is the LANDIS model (He and Mladenoff, 1999; He et al., 1999a, 1999b; Mladenoff and He, 1999), which was developed to simulate forest landscape change under different harvesting and disturbance regimes. The LANDIS model uses a spatially explicit raster structure to simulate spatial interactions, such as seed dispersal, and produces a species-level output assuming different management practices and disturbances. The creators of this model stress that the LANDIS model is most useful as a tool to project plausible landscape outcomes under certain conditions rather than as a spatially explicit prediction tool (Mladenoff and He, 1999). This is an important concept in human-environmental dynamics and ecosystems modeling. Data availability limits the ability to predict the behavior of systems even if models exist to properly simulate those systems.

The LANDIS model is most applicable to environments dominated by forest cover. A somewhat more complex system is an environment where there are a variety of land uses (e.g., forestry, agroforestry, crops, pasture) and numerous actors. The LANDIS model has a great deal of complexity in terms of forest dynamics and deals with a specific type of ecosystem (largely, forested). Landscapes with a high degree of human activity are typically characterized by a broad range of land uses (for example, forests, crops, pasture, residential). Models of these systems with a broader range of land uses often simplify different components in order to produce a model that performs acceptably for the research question at hand but lacks specificity in some areas. For example, Dale and colleagues created a model of forest cover dynamics for a study in Rondonia, Brazil (Dale et al., 1993, 1994), but this model lacks the species level complexity of the LANDIS model. Using a spatially explicit approach, Dale and others (1993, 1994) modeled the effects of land cover change drivers under different management scenarios on spatial patterns and composition of land cover. This model was unique in that it linked a dynamic model of land cover change to a spatial representation where each parcel was composed of multiple cells rather than using a coarser unit of analysis (e.g., parcel, municipal area, or region). This approach allowed land use activities to be modeled at the household level, the same level at which land use decisions were made in the particular study area, and predicted specific land cover outcomes at a parcel or regional level. This model used a robust spatiotemporal framework but treated land management scenarios as exogenous rather than modeling the occurrence of these land use activities.

Taking model integration one step further, some researchers have moved toward developing a modeling approach integrating land use, decision making, and ecological change in rural environments at fine spatial scales. One such effort is the Forest Land Oriented Resource Envisioning System (FLORES), a model constructed from a multidisci-

plinary team of researchers (Vanclay, 1998). During a three-week workshop in 1999, a team of researchers constructed a model of rural land use change for a test area in Indonesia by including the following major model components: crops—soils, trees—forest, household decision making, and biodiversity—fauna. This integrated model was developed using a dynamic modeling package and loosely coupled to a spatial information system.

A loosely coupled model is where model components exchange data through input/output of different model components rather than operating in an integrated modeling framework. Future plans are to produce a model that more closely integrates the existing model components in a spatial framework that would allow more explicit spatial interactions to occur in the model. What was unique about the FLORES model was the effort to balance the complexity of the agriculture, forest ecology, and human decision making components within a spatial framework. In regard to the space-time-HDM modeling framework, the FLORES model is well developed in terms of the temporal dynamics and human decision making but currently is not well developed along the spatial dimension.

### 7.3.3 Health, Epidemiology, Pollution, and Hydrology

A natural interface of human-environmental modeling is in health-related applications such as disease contagion, environmental impact assessments, and pollution modeling. This is a vast area of research and modeling. Here we present a very limited set of examples to demonstrate types of models that have been constructed for these applications. In particular, we present models from the areas of environmental impact modeling and spatial epidemiology.

The Agricultural Nonpoint Source Pollution model (http://www.sedlab.olemiss.edu/AGNPS98.html) has been widely used to predict nutrient and fertilizer passport in agricultural systems. It is a raster-based model that uses different exogenous land use decisions (e.g., fertilizer applications) and landscape characteristics (soil characteristics, topography, etc.) to predict soil erosion and nutrient transport in agricultural environments. The AGNPS model is an example of a spatially explicit model, including spatial interactions, that operates in a temporal framework. While the AGNPS model lacks a component to model land use decisions, the model has the ability to examine the effect of different land use strategies by using them as model drivers. There are a tremendous number of models related to environmental health issues in agricultural environments, and AGNPS is a widely used model that is representative of this area of modeling.

Agricultural and hydrological models are less commonly referred to as human-environmental models because the model often treats human decisions as exogenous to the system (e.g., AGNPS). A variety of researchers have been successful in developing loosely coupled models linking existing social and biophysical models. A loosely coupled model can be referred to as a model where the data are exchanged between model components through input/output, but the model behavior is not integrated between the model

components. We would argue that a major research challenge facing the modeling community is in developing tightly coupled models that balance model complexity on both the social and biophysical sides.

Other modeling applications related to the health aspect of human-environmental dynamics include the spaBraziltial modeling of disease vectors and transmission (Smith and Harris, 1991). Much of this research involves spatial examination of a combination of features, and thus GIS provides an ideal framework for these applications. There is a wide literature related to the application of GIS to epidemiology, although most of this work is empirical rather than modeling based. However, some researchers are developing models as a tool for predicting risk and exposure to different disease vectors or to predict disease incidence. For example, Castro and Singer (2000) used a spatial model to examine the relationship between land cover and malaria incidence in the Rondonia, Brazil. Other examples include spatial epidemiological models of HIV incidence (Salzberg and MacRae, 1993). Because their applications are more focused on exposure or threats to human population from some source, these models do not explicitly model human decision making. However, there is utility in this integration. One example would be a model of rural land use expansion as it relates to the encroachment on malaria-infested areas. A dynamic simulation could model how the decision making process determines the spatial expansion of settlements and how the associated land cover changes might affect the habitat for mosquitoes and, in turn, the exposure to malaria.

### 7.3.4 Summary

Figure 7.5 is an example of how some of the different models can be described in terms of spatial, temporal, and HDM complexity. As we have discussed previously, models that are positioned high on the space complexity axis are spatially explicit and allow for spatial

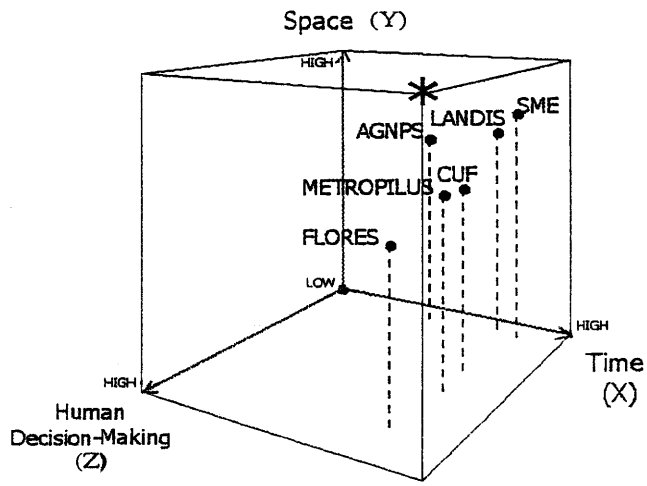


**Figure 7.5** Positions of models in relation to space, time, and decision making.

interactions. Models that are positioned high on the temporal complexity axis are dynamic, demonstrate feedbacks and equilibria in model states, and allow for varying time intervals. Models that are positioned high on the HDM complexity axis explicitly model agent decision making based on a set of heuristics defined in the model at multiple institutional scales. Some models were not designed to address all of these axes. Therefore, a low position on one axis does not mean the model is not as well constructed as another model, just that it is not as complex for that axis. In addition, model positions are approximate and adjusted to make the figure more readable. Within the context of a model's purpose, an important goal of future human-environmental models is to specify and develop models that have as high a position on all three axes as necessary (the asterik in figure 7.5)

## 7.4 MODELING COMPLEXITY AND HUMAN-ENVIRONMENTAL DYNAMICS

The physical and biological sciences have struggled to develop appropriate frameworks for environmental models at different spatial and temporal scales and levels of model complexity. The difficulty of this challenge increases greatly when theories of human decision making, scales, and complexity are included. As we noted earlier, scales and complexity of human decision making range from individuals to groups of increasingly large size until they encompass global networks. This section discusses specific theoretical issues for linking human-environmental dynamics within the context of space, time, and human decision making. Many of these issues have important implications for the complexity modelers might choose to include in their models.

### 7.4.1 General Issues

As modelers work to develop human-environmental models, it is essential that they identify the optimal scale(s) for their specific questions. In this context and because human-environmental dynamics are complex, it is important to recognize that certain human-environmental processes may be associated with specific scales in some cases, while processes may occur across multiple scales in other cases. Further, human-environmental processes to be addressed by the model might not operate at the same scale(s), and linkages may have to connect across scales (Redman et al., 2000).

### 7.4.2 Time

Human and environmental processes might work at different rates. Further, rates of change, such as the land cover change shown in Figure 7.6, are not necessarily linear over time. Thus, modelers need to consider whether there are time lags, nonlinear relationships, defining events, and positive and negative feedback loops that affect the responses among social and environmental processes (Costanza and Ruth, 1998; Gladwell, 2000; Grove, 1999). For instance, time lags might exist between changes in land use and transport of nitrogen in groundwater since groundwater flows might occur at a much slower rate than land use change from an agricultural to a residential land use. Similarly, forest stand characteristics (structure and composition) are more likely to reflect historic, selective harvest-

ing preferences and practices than current ownership preferences and practices. This is due to the fact that changes in vegetation growth, species dynamics, and soil fertility change at

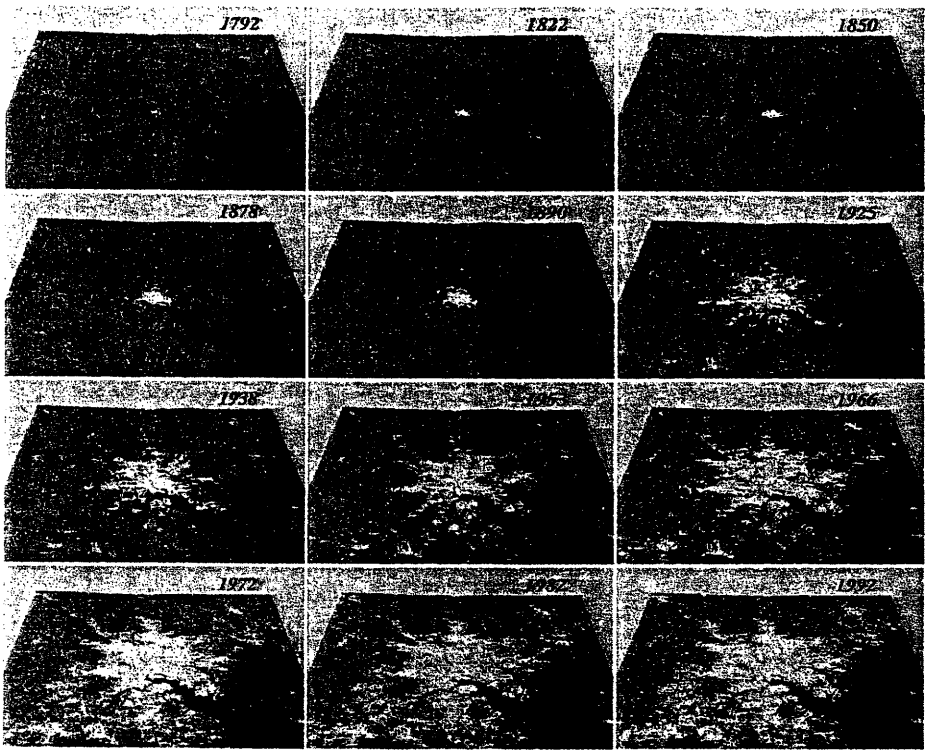


**Figure 7.6** Perspective view of urban growth in Baltimore, Maryland, over 200 years (1792–1992). Yellow polygons are built-up areas as determined from historical maps and satellite imagery, green areas are forests, and blue areas are water (Chesapeake Bay). *Source*: Penny Masuoka, UMBC, NASA Goddard Space Flight Center and William Acevedo, USGS, NASA Ames Research Center.

much slower rates than land ownership. In both cases, human and environmental legacies affect current human-environmental dynamics.

### 7.4.3 Space

Studies of how spatial characteristics affect ecological dynamics, particularly with GIS and computer modeling, have been an area of great interest (Forman and Godron, 1986; Gustafson, 1998; Naveh and Lieberman, 1994; Pickett and Cadenasso, 1995; Turner, 1989; Turner and Gardner, 1990). Examples of types of spatial metrics include measures of (1) landscape composition (for example, number of categories, proportions, diversity [evenness and richness]), (2) landscape configuration (such as size, shape, density, connectivity, fractal, and patch neighborhood), and (3) scale/structure (for instance, trendsurface, correlogram, and semivariogram) (Gustafson, 1998; McGarigal and Marks, 1995). However, comparable GIS and modeling efforts have not focused on how the spatial char-

acteristics of certain phenomena, such as adjacency, shape, and matrix, affect human processes and the relationships among human-environmental processes (Grove, 1999). For instance, spatial adjacency (neighborhood analysis) might be included in models of human decision making to account for whether neighboring industrial areas affect residential locational decisions. The size and shape of an area (spatial metrics of a patch) might affect human processes. For example, as people commute from one commercial area to another, are individuals more likely to travel across a narrow or a wide residential area? Finally, the location of an area within a regional matrix (patch matrix analyses) might affect human decision making. For instance, how does access to a diversity of work, recreation, and other leisure amenities affect residential choices made by single adults and retired couples in urban areas? Each of these spatial examples can have implications for modeling human–environmental dynamics. These spatial interactions are complicated further by the fact that boundary conditions of areas might need to be considered as well, since the permeability of social and environmental areas might affect the flows of materials, nutrients, fauna, flora, persons, diseases, and ideas.

### 7.5.4 Human Decision Making

Coucelis (2001) has noted in Chapter 2 of this book that although human-environmental modeling might be primarily an applied field, it is not exempt from the need to be theoretically well grounded. It is too easy to develop models that look good but have an underlying ontology that is less plausible than a computer game. Since it is unlikely that we will ever have a "theory of everything" for human-environmental systems, we must develop our ability to assemble a wide variety of partial theories from the physical, biological, and social sciences. In other words, integrated approaches to human-environmental models are more than a matter of replacing integrated models with coupled models: rather, integrated approaches have to make sure that the assemblage of concepts, ontologies, approaches, theories, degrees of confidence, and spatiotemporal structures within a single framework respect the strengths and weaknesses of each part and yield a whole that is logically coherent (Coucelis, 2001).

This issue of an overall, coherent approach to modeling human-environmental systems is critical. Coucelis (2001) cites Smyth (1998, p. 192) to observe that it is convenient to think of the modeled world as a microworld defined by an ontology consisting of contents, spatial structure, temporal structure, "physics" (rules of behavior), and rules of inference or logic. The notion of such a microworld is useful for reminding us that models are not the real thing and that they need to be internally consistent (Coucelis, 2001).

We agree with Coucelis (2001) that human-environmental models often include a variety of disciplines and syntheses, which means that human-environmental models will assemble several kinds of "physics," some based on causal hypotheses (A appears to cause B), some on statistical regularities (A is statistically associated with B), others on empirical rules of thumb (when A, usually B), and others still on arbitrary rules of behavior specified by the modeler (if A is the case, then do B). Combining such a variety of partial "physics" into a complete model that is free of internal contradictions is a challenge for

which few guidelines exist, and which becomes more difficult as the assemblage from different domains become more remote from each other. While it might be challenging to link models of rainfall and runoff to determine the likelihood that an area will flood, it is quite another to link models of industrialization and species extinctions in order to understand the relationship between urbanization and biodiversity (Coucelis, 2001).

We noted earlier that we are unlikely to have a "theory of everything" for human-environmental systems. However, many insights into the challenge of developing integrated approaches to human-environmental models that are based on different types of "physics" can be found in existing literature. Thus, we propose that the theoretical approaches to human decision making are most likely to be found among midlevel theories and not grand, unified theories of human-environmental systems (Burch and Grove, 1999; Ostrom, 1998; Parker et al., 1999; Pickett et al., 1999). This idea of midrange theory and its utility comes from Merton (1968, p.39), who notes that midrange theories "lie between the minor but necessary working hypotheses that evolve in abundance during day-to-day research and the all inclusive systematic efforts to develop unified theory that will explain all the observed uniformities of ... behavior, ... organization, and ... change. Mid-range theories are empirically grounded theories—involving sets of confirmed hypotheses—and not merely organized descriptive data or empirical generalizations which remain logically disparate and unconnected." Midrange theories connect observations, inferences, hypotheses, and empirically based research. While midrange theories may not be logically derived from a single, all-embracing theory, they may be consistent with one (Merton, 1968). Finally, rather than deriving a model of human-environmental dynamics from a single, all-embracing theory, a midrange theory approach provides the basis for progressively developing a more general model that is adequate for consolidating groups of midrange theories.

Many midrange theories that are appropriate for human-environmental modeling have been available for some time. For instance, social scientists have worked for a long time to include human-environmental interactions. Firey's (1990) comprehensive review of sociological work since 1926 demonstrates that substantial theoretical and empirical efforts have existed for some time and anticipated many of the concerns for integrating human-environmental dynamics. Firey's (1990, p.23) analysis of these works translates diverse terms into a unified lexicon. As he notes,

*When Mukerjee speaks of the "entire circle of man's life and well-being," he is placing into a single system such diverse factors as social organization, flora, fauna, fertility, climate, and topography. When Vance refers to the "cotton system" he has in mind a "complex whole" partaking of certain attributes of the physical environment–chemical, climatic, and genetic–and of certain attributes of the sociocultural order–structural, attitudinal, and organizational. When Odum speaks of "balance," Zimmerman of "real communities," Landis of "patterns," Kaufman of "stability," and Gibbs and Martin of "sustenance organization," there is implied some reference to a system whose components are not exclusively physical nor exclusively social or cultural. In these expressions there is a dual reference to two orders of phenomena, both of which have been articulated into a*

*single conceptual construct. This concept of a resource system has two features, which particularly recommend it as a point of departure for further sociological research on natural resources. First, it is congruent with a great deal of important work that is being done in systematic sociological theory, centering on the concept of "social system." Second, it is noncommittal as to the mode of formulating causal relationships among the variables that enter into a system. In other words, either physical or sociocultural variables can be taken as independent, so that, with appropriate measures of both, a wide variety of hypotheses can be formulated and tested.*

We propose that many of these studies are relevant, informative, and important to rediscover for modeling the "physics" of different scales and levels of complexity of human-environmental dynamics. For this integration of midlevel theory in human-environmental models to occur, however, it is crucial to link appropriate midlevel physical, biological, and social theories (Pickett et al., 1999) to appropriate temporal and spatial scales and levels of complexity (Grove, 1999; Redman et al., 2000).

## 7.5 LESSONS LEARNED AND FUTURE DIRECTIONS

What then are the pressing needs related to future human-environmental modeling efforts? The preceding discussion proposed that much existing theoretical and empirical research on human-environmental systems is relevant and important to modeling efforts of human-environmental systems today. It also emphasized that human-environmental processes can be, and usually are, temporally and spatially complex as they interact with various scales of human decision making. Given the need to mine existing literature that might be relevant to specific human-environmental modeling questions, the following discussion focuses on three sets of activities or issues we think are particularly important in general to the development of future human-environmental models: (1) standard conventions for reporting scale across time, space, and human decision making, (2) closing the data gap, and (3) new forms of collaboration in the development of human-environmental models.

### 7.5.1 Conventions for Reporting Scale and Complexity

A significant hurdle we must overcome in the context of human-environmental modeling is the failure to articulate and document temporal, spatial, and human decision making scale(s). Many modeling techniques have the capacity to model across multiple scales of time, space, or human decision making. But in literature documenting applications of certain models, even though it is possible to articulate the temporal and spatial scale of a model application, we often find that many model summaries do not do this. Further, when models include a human decision making component, we are constrained by the lack of a well-specified language of scale that researchers can agree on and consistently report.

In our view, this failure to articulate and document the scale(s) of human-environmental models becomes problematic when we try to compare model results of similar systems, since it is well known that relationships among variables change depending on the scale of analysis (Root and Schneider, 1995; Turner et al., 1989). If we unknowingly compare results of two models operating at different scales, we might draw incomplete or

incorrect conclusions that could lead to false theoretical understandings of the processes at work.

We cannot stress enough the theoretical implications of this issue, since scale probably drives many of the conflicts perceived to exist among different disciplines in the social sciences. For example, the arguments and differences existing among psychologists (Lynch, 1960; Sommer, 1969), sociologists (Bailey and Mulcahy, 1972; Catton, 1992, 1994; Field and Burch, 1988; Firey, 1945; Schnore, 1958; Young, 1974, 1992;), geographers (Agnew and Duncan, 1989), and political scientists (Masters, 1989) might be attributed more to the use of different scales and criteria (vis. Allen and Hoekstra, 1992) than questions of who is right or wrong. For instance, psychologists and sociologists argue about whether individual behaviors create social structures or whether social structures determine individual behaviors. Rather than seeing this as a mutually exclusive dichotomy, it may be more appropriate to conceive of such a question as a matter of scale and to ask about the relative relationship between individual behavior and social structure for a given question (Vogt et al., 2000). With this approach, questions are more resolvable by actually promoting discussions among modelers of human-environmental systems.

In the context of future modeling endeavors, we propose that *any* paper reporting model results should clearly report the scale(s) used. Temporal and spatial scale are relatively straightforward: Each of their scale components in Table 7.1 can be articulated clearly using generally accepted scientific measurements. This could be true as well for the scale components of human decision making if we can come to some agreement on a standard language and definitions for agent and domain. The terms we have proposed are our attempt to move us toward such a common set of terms. Regardless of the final set of terms, we propose that the clear articulation of temporal, spatial, and human decision making scale(s) is as essential to a paper as the abstract or the list of keywords.

A similar argument could be made for documenting a model's complexity, but more discussion is probably needed to build consensus for indices of temporal, spatial, and human decision making complexity. Earlier, we presented an index for estimating human decision making complexity for individual models (Table 7.1). Similar indices need to be developed for estimating the temporal and spatial complexity axes of Figure 7.4. Once we come to some agreement about these measures of scale and complexity, we will have moved forward significantly in our ability to compare the results of models using similar scales and/or complexity and to know when not to compare results because of differences in scale and/or complexity. Further, we might be able to evaluate whether various models using different scales and complexity can be linked if we understand the location of a particular model within the human-environmental modeling framework (Figure 7.4). This is crucial for developing multiscale or hierarchical approaches to modeling human-environmental systems.

### 7.5.2 Closing the Data Gap

An important challenge to modeling human-environmental systems is our lack of digitally available data. Several research organizations are starting to collect data for particular geographic regions, and these data are purposefully relevant to human-environmental model-

ing (see, for example, the Human Dimensions of Environmental Change research program sponsored by the U.S. National Science Foundation at http://www.nsf.gov/sbe/hdgc/hdgc-cntr.htm, and the U.S. NSF funded Long-Term Ecological Research groups at http://www.lternet.edu/ or the International Human Dimensions of Global Change research program at http://www.uni-bonn.de/ihdp/). While these groups collect time-series, spatially distributed, physical, biological, and social data for their areas of geographic focus, data for many other areas are either dispersed or absent. This data gap can hinder many human environmental modeling efforts that are empirically based.

With the tremendous advances made in the Internet (largely because of World Wide Web technologies), the sharing of data has become much easier. Recent endeavors such as the U.S. National Spatial Data Inventory (NSDI, located at www.fgdc.gov/nsdi/nsdi.html) and the Federal Geographic Data Committee (FGDC, located at www.fgdc.gov/fgdc/fgdc.html) have made significant progress in establishing standards for documenting information about spatial datasets (commonly called metadata) and developing a network of spatial data clearinghouses (see www.fgdc.gov/clearinghouse/clearinghouse.html). These are important advances for modelers because they provide global access to well-documented data sets (i.e., usable) that might be available for a particular area. Further, we are beginning to see Internet browser technologies that allow people to search for spatial data for a particular geographic location (e.g., MapInfo's "metadata browser").

Finally, there have been several attempts recently to overcome the quantitative data gaps for modeling purposes by integrating statements about qualitative changes in human behavior and environmental impacts (trajectories) based on regional case studies. For example, see Kuipers (1994), Kasperson and others (1995), Petschel-Held and others (1999), and Petschel-Held and Lüdeke (2000). In short, important progress is being made for solving the data gap problem. While much of the effort has focused on complete spatial datasets, additional attention will need to focus on time series data and data related to human decision making.

### 7.5.3 New Collaborative Forms for Development of Models

Models involving time, space, and human decision making can be incredibly complex and depend on 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 Internet and Web technologies have created new types of opportunities for collaboration in the development of human-environmental modeling. Already, "open source" programming efforts have been used to solve complex computing problems (see, for example, Kiernan, 1999; Learmonth, 1997; McHugh, 1998, and http://www.opensource.org). The principle of open source programming is based on a collaborative licensing agreement that enables

people to download program source code freely 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. There have also been some open source endeavors that have failed. 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's 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 eyes with various skills and expertise working on a problem, every problem, regardless of complexity, can be solved because an individual or a team of individuals will come up with elegant solutions.

Yet 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 three components: (1) a Web site to support modeling collaboration (e.g., data and interactions among individuals, such as bulletin boards and FAQs); (2) establishment of one or more modeling kernels (these would be core components of models using various technologies) that are designed in a modular fashion and allow relatively easy enhancements from participants; and (3) 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.

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 look at 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.

## 7.6 CONCLUSION

Our goal in this chapter has been to contribute to the further development of human-environmental models. To achieve this goal, we proposed a conceptual framework for summarizing and comparing human-environmental models. We then reviewed several types of human-environmental models and related them, in a general way, to the framework. Based on these discussions, we identified some key issues that are inherent to modeling temporal, spatial, and human decision making scale and complexity. Finally, we discussed some new directions for modeling human-environmental dynamics. In the end, however, we have

only mapped some possibilities and ideas for modeling human-environmental dynamics. We hope that others will improve on this initial effort for two reasons. First, we believe that modeling human-environmental dynamics is an interesting and exciting activity. Second, as the prevalence and significance of human-environmental interactions continue to grow, decision makers, researchers, and educators will find it increasingly important to have accurate, timely, and extensive information and understanding about the systems they inhabit and depend on for life.

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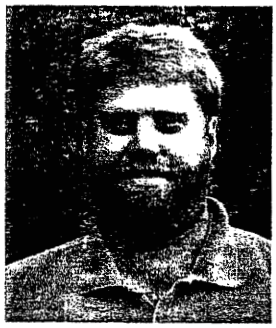

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