Part I

Theory and Methods

1

Introduction: Spatially Explicit Landscape Simulation Models

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1.1 Why Do We Need Spatially Explicit Landscape Simulation Models?

Many, if not most, management decisions concerning the environment affect and are affected by the landscape. City and county planning authorities make decisions about land use and infrastructure that directly affect the landscape. Farmers make decisions about what to grow and how to grow it that affect and are affected by the landscape. Individual homeowners and businesses make decisions about their own behavior that affects and is affected by the landscape. Therefore, understanding and modeling the spatial patterns of landscape processes and changes over time at several different scales is critical to effective environmental management. In recognition of this, the U.S. Environmental Protection Agency (EPA) has moved away from their traditional "media-based" approach to environmental management and toward a more "place-based" approach. To operationalize this approach, we need to develop a deeper understanding of the complex spatial and temporal linkages between and among ecological and economic systems on the landscape and to use that understanding to develop effective and adaptive policies. This will require new methods that are comprehensive, adaptive, integrative, multiscale, and pluralistic, and which acknowledge the huge uncertainties involved. Landscape modeling studies at local, regional, and global scales integrate natural and social sciences and develop a common framework for understanding linked ecological economic systems.

1.2 Basic Concepts of Spatially Explicit Landscape Simulation Models

Among landscape models there is a large variation in complexity and capabilities. Often, it is this variation that makes one model more suitable for certain applications than others. Landscape models are, by definition, spatially explicit. They can range across several other spectra of characteristics, including empirical to process-based, static to dynamic, simple to complex, and low to high spatial and temporal resolution.

As a rule of thumb, more complex, higher-resolution models will resolve issues in more detail, but are more difficult and time-consuming to calibrate and run, and beyond a certain point, they may, in fact, provide decreasing predictability (Costanza and Maxwell, 1994). The spatially explicit landscape simulation models (SELSMs) we discuss in this book are, in general, process-based, medium to high spatial and temporal resolution, relatively complex, dynamic, nonlinear simulations of the landscape. They deal with a range of ecological and socio-economic variables, including carbon, water, nitrogen, phosphorus, plants, consumers (including humans), and a range of ecosystem services under various climate, economic, and policy scenarios. They can exhibit "catastrophic," irreversible changes of system structure and function at specific sites (Costanza et al., 1990; Voinov et al., 1999) and can, therefore, be used to test hypotheses about system sustainability across a range of scales.

The general structure of these models is illustrated in Figure 1.1. The landscape at any point in time is described using a raster (cell based) representation. In each "cell," a dynamic simulation model describes local dynamics. The cells can then be connected by horizontal fluxes of material and information. The models are also often "multiscale" in both space and time. Each cell in the landscape has its own internal dynamics at one spatial scale, whereas the landscape as a whole has its dynamics at the next larger spatial scale. Within the cell, individual modules can represent a third scale. There are also both the short-time-scale dynamics of material and energy cycling in the system, combined with the longer-time-scale dynamics of land use change. Figure 1.2 describes the overall relationships between these multiscale dynamics and their relationship to policy decisions and outside forcing functions.

1.3 Horizontal Fluxes

Some landscape models include horizontal fluxes and exchange across cells, whereas others do not. One common horizontal flux for the ecological component of the models is water, controlled by a hydrological model. In addition to water, other possible horizontal fluxes include movement of air, animals, energy (such as fire, water waves, and fuels), and economic goods and services. The least complex interaction between horizontal and vertical fluxes is unidirectional, where horizontal fluxes provide the conditions for calculating vertical fluxes. A more complex approach would include bidirectional exchanges of information between the horizontal and vertical fluxes.

An example of a landscape model that does not include horizontal fluxes between cells uses the TEM unit model (Vorosmarty et al., 1989), and a water transport model based on residence time to remove excess water from each cell. Creed et al. (1996) created a landscape model with unidirectional information exchange by applying RHESSys (Band et al., 1991) for hydrologic exchanges and BIOME-

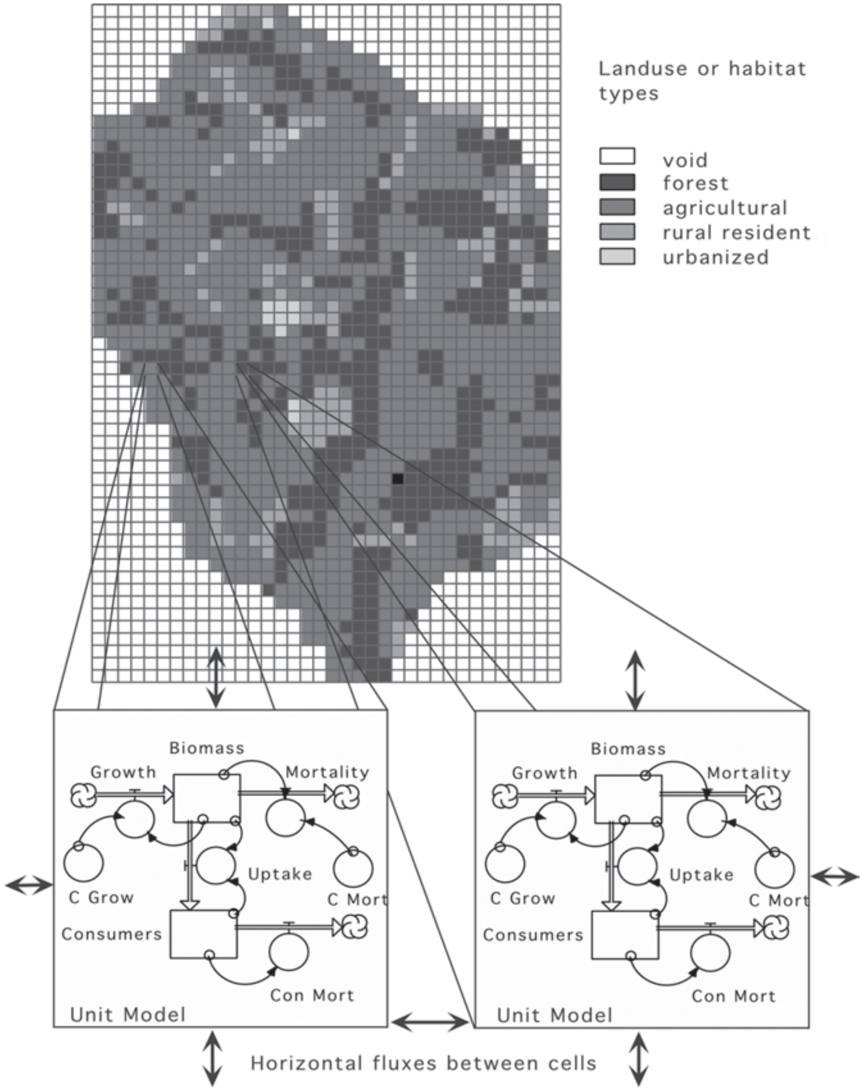

FIGURE 1.1. The landscape at any point in time is described using a raster (cell-based) representation. In each "cell" (raster or polygon), a dynamic simulation model describes local dynamics. The cells can then be connected by horizontal fluxes of material and information.

BGC for vertical fluxes. Multidirectional exchanges are used in Patuxent Landscape Model (PLM) and CENTURY to move water and materials between landscape cells (Parton et al. 1994; Voinov et al. 1999).

Computational capabilities, research objectives, and data availability determine the optimum complexity and modes of information exchange between horizontal and vertical fluxes. In general, simulations with large spatial and temporal extents (e.g., global scenarios run at monthly or yearly time steps with a total time

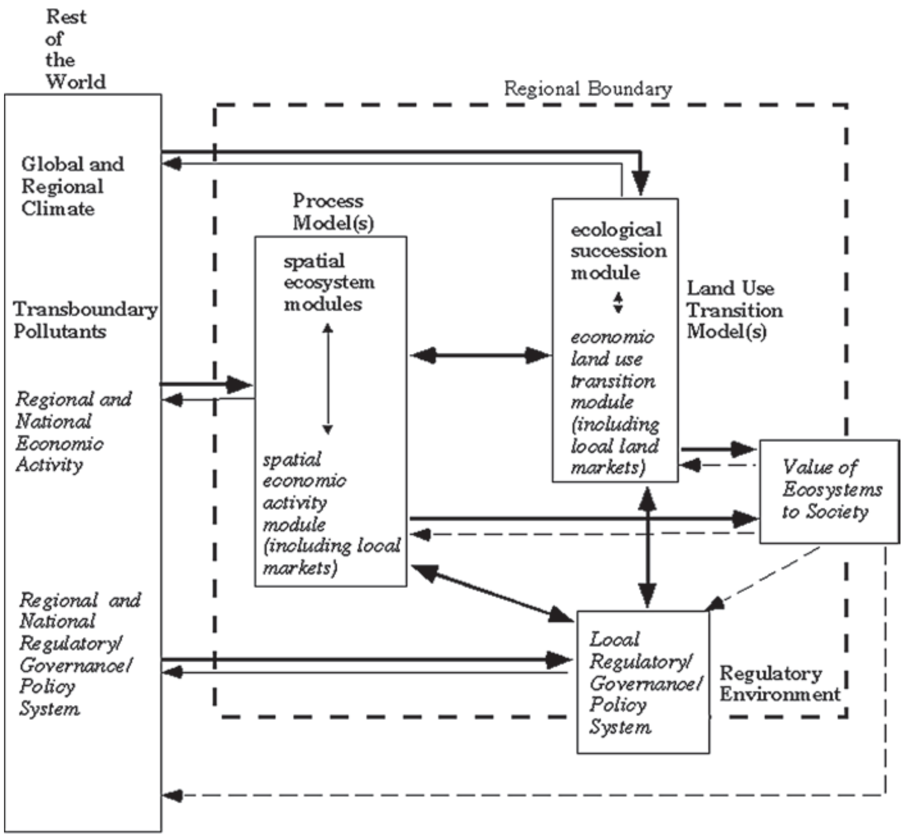

FIGURE 1.2. The overall relationships between multiscale dynamics and their relationship to policy decisions and outside forcing functions.

frame of centuries) perform best at lower complexities and with no horizontal fluxes. Simulations at smaller time steps and higher spatial resolution (e.g., regional models at daily or hourly time steps run for decades) often allow a more complex structure and multidirectional exchange potential.

The General Ecosystem Model (GEM), (Fitz et al., 1996), for example, aims for an intermediate level of complexity so that the model is flexible enough to be applied to a range of ecosystems. Although we take into account most important ecological processes, there is still a good deal of empiricism in the way these processes are formalized. Any process-based model represents a balance between the process-based paradigm and empirical relationships in the description of individual processes (Voinov et al., 1998). This limits the generality of the model, potentially requiring additional testing and calibration when switching to other scales or areas. However, it allows us to keep the whole model within reasonable limits of complexity. In addition, by developing the modular structure in LHEM (see Chapter 3), we streamline the model and reduce the full complexity by applying only those modules that are relevant to the simulation objectives.

1.4 Scaling

Ecological and economic systems are complex, adaptive systems (Gell-Mann, 1995). They are characterized by nonlinearities, autocatalysis, complex, time-delayed feedback loops, emergent phenomena, and chaotic behavior (Kauffman, 1993; Patten and Jorgensen, 1995). This means that the whole is significantly different from the simple sum of the parts. This, in turn, makes scaling (the transfer of understanding across spatial, temporal, and complexity scales) not only a difficult problem but also probably the core problem in understanding complex systems (Ehleringer and Field, 1993; O'Neill et al., 1989).

The term "scale" in this context refers to both the resolution (spatial grain size, time step, or degree of complexity of the model) and extent (in time, space, and number of components modeled) of the analysis. The process of "scaling" refers to the application of information or models developed at one scale to problems at other scales. The scale dependence of predictions is increasingly being recognized in a broad range of ecological studies, including landscape ecology (Meentemeyer, 1989), physiological ecology (Jarvis and McNaughton, 1986), population interactions (Addicott et al., 1987), paleoecology (Delcourt et al., 1983), freshwater ecology (Carpenter and Kitchell, 1993), estuarine ecology (Livingston, 1987), meteorology and climatology (Steyn et al., 1981) and global change (Rosswall et al., 1988). However, "scaling rules" applicable to complex systems have not yet been adequately developed, and limits to extrapolation have been difficult to identify (Turner et al., 1989). In many of these disciplines, primary information and measurements are generally collected at relatively small scales (i.e., small plots in ecology, individuals or single firms in economics) and that information is then often used to build models and make inferences at radically different scales (i.e., regional, national, or global). The process of scaling is directly tied to the problem of aggregation, which is far from a trivial problem in complex, nonlinear, discontinuous systems (like ecological and economic systems).

1.5 Aggregation

Aggregation error is inevitable as attempts are made to represent n-dimensional systems with less than n state variables, much like the statistical difficulties associated with sampling a variable population (Bartel et al., 1988; Gardner et al., 1982; Ijiri, 1971). Cale et al. (1983) argued that in the absence of linearity and constant proportionality between variables—both of which are rare in ecological and economic systems—aggregation error is inevitable. Rastetter et al. (1992) give a detailed example of scaling a relationship for individual-leaf photosynthesis as a function of radiation and leaf efficiency to estimate the productivity of the entire forest canopy. Because of nonlinear variability in the way individual leaves process light energy, one cannot simply use the fine-scale relationship between photosynthesis and radiation and efficiency along with the mean values for the entire forest to represent total forest productivity without introducing significant aggregation error. Therefore, strategies to better understand aggregation error are necessary.

Rastetter et al. (1992) described and compared four basic methods for scaling that are applicable to complex systems:

1. *Partial transformations* of the fine-scale relationships to coarse scale using a statistical expectations operator
2. *Moment expansions* as an approximation to method 1
3. *Partitioning* or subdividing the system into smaller, more homogeneous parts (see Section 1.7)
4. *Calibration* of the fine-scale relationships to coarse-scale data

They go on to suggest a combination of these four methods as the most effective overall method of scaling in complex systems (Rastetter et al., 1992).

1.6 Hierarchy

Hierarchy theory provides an essential conceptual base for building coherent models of complex systems at multiple scales (Allen and Starr, 1982; Gibson et al., 2000; O'Neill et al., 1986; Salthe, 1985). Hierarchy is an organizational principle which yields models of nature that are partitioned into nested levels that share similar time and space scales. In a constitutive hierarchy, an entity at any level is part of an entity at a higher level and contains entities at a lower level. In an exclusive hierarchy, there is no containment relation between entities, and levels are distinguished by other criteria (e.g., trophic levels). Entities are to a certain extent insulated from entities at other levels in the sense that, as a rule, they do not directly interact; rather, they provide mutual constraints. For example, individual organisms see the ecosystem they inhabit as a slowly changing set of external (environmental) constraints and the complex dynamics of component cells as a set of internal (behavioral) constraints.

From the scaling perspective, hierarchy theory is a tool for partitioning complex systems in order to minimize aggregation error (Hirata and Ulanowicz, 1985; Thiel, 1967). The most important aspect of hierarchy theory is that ecological systems' behavior is limited by both the potential behavior of its components (biotic potential) and environmental constraints imposed by higher levels (O'Neill et al., 1989). A flock of birds that can fly only as fast as its slowest member or a forested landscape that cannot fix atmospheric nitrogen if specific bacteria are not present are examples of biotic potential limitation. Animal populations limited by available food supply and plant communities limited by nutrient remineralization are examples of limits imposed by environmental constraints. O'Neill et al. (1989) use hierarchy theory to define a "constraint envelope" based on the physical, chemical, and biological conditions within which a system must operate. They argue that hierarchy theory and the resulting "constraint envelope" enhance predictive power. Although they may not be able to predict exactly what place the system occupies within the constraint envelope, they can state with confidence that a system will be operating within its constraint envelope.

Viewing landscapes through the lens of hierarchy theory should serve to illuminate the general principles of life systems that occur at each level of the hierarchy. Although every level will necessarily have unique characteristics, it is possible to define forms and processes that are isomorphic across levels (as are many laws of nature). Troncale (1985) has explored some of these isomorphisms in the context of general system theory. In the context of scaling theory, we can seek isomorphisms that assist in the vertical integration of scales. These questions feed into the larger question of scaling, and how to further develop the four basic methods of scaling mentioned in Section 1.4 for application to complex systems.

1.7 Fractals and Chaos

One well-known isomorphism is the "self-similarity" between scales exhibited by fractal structures (Mandelbrot, 1977, West et al., 1997), which may provide another approach to the problem of scaling. This self-similarity implies a regular and predictable relationship between the scale of measurement (here meaning the resolution of measurement) and the measured phenomenon. For example, the regular relationship between the measured length of a coastline and the resolution at which it is measured is a fundamental, empirically observable one. It can be summarized in the following equation:

$$L = ks^{(1-D)}, \tag{1}$$

where L is the length of the coastline or other "fractal" boundary, s is the size of the fundamental unit of measure or the resolution of the measurement, k is a scaling constant, and D is the fractal dimension.

Primary questions concern the range of applicability of fractals and chaotic systems dynamics to the practical problems of modeling ecological economic systems. The influence of scale, resolution, and hierarchy on the mix of behaviors one observes in systems has not been fully investigated, and this remains a key question for developing coherent models of complex ecological economic systems.

1.8 Resolution and Predictability

The significant effects of nonlinearities raise some interesting questions about the influence of resolution (including spatial, temporal, and component) on the performance of models and, in particular, their predictability. Costanza and Maxwell (1994) analyzed the relationship between resolution and predictability and found that although increasing resolution provides more descriptive information about the patterns in data, it also increases the difficulty of accurately modeling those patterns. There may be limits to the predictability of natural phenomenon at particular resolutions, and "fractallike" rules that determine how both "data" and "model" predictability change with resolution.

Some limited testing of these ideas was done by resampling land use map datasets at several different spatial resolutions and measuring predictability at each. Colwell (1974) used categorical data to define predictability as the reduction in uncertainty (scaled on a 0–1 range) about one variable given knowledge of others. One can define spatial autopredictability (P_a) as the reduction in uncertainty about the state of a pixel in a scene, given knowledge of the state of adjacent pixels in that scene, and spatial cross-predictability (P_c) as the reduction in uncertainty about the state of a pixel in a scene, given knowledge of the state of corresponding pixels in other scenes. P_a is a measure of the internal pattern in the data, whereas P_c, is a measure of the ability of some other (i.e., modeled) pattern to represent that pattern.

A strong linear relationship was found between the log of P_a and the log of resolution (measured as the number of pixels per square kilometer). This fractallike characteristic of "self-similarity" with decreasing resolution implies that predictability, like the length of a coastline, may be best described using a unitless dimension that summarizes how it changes with resolution. One can define a "fractal predictability dimension" (DP) in a manner analogous to the normal fractal dimension (Mandelbrot, 1977, 1983). The resulting DP allows convenient scaling of predictability measurements taken at one resolution to others.

Cross-predictability (P_c) can be used for pattern matching and testing the fit between scenes. In this sense, it relates to the predictability of models versus the internal predictability in the data revealed by P_a. Whereas P_a generally increases with increasing resolution (because more information is being included), P_c generally falls or remains stable (because it is easier to model aggregate results than fine-grain ones). Thus, we can define an optimal resolution for a particular modeling problem that balances the benefit in terms of increasing data predictability (P_a) as one increases resolution, with the cost of decreasing model predictability (P_c). Figure 1.1 shows this relationship in generalized form.

A basic question is whether these results hold for complete landscape models (like the PLM; see Chapter 8) and whether they are generalizable to all forms of resolution (spatial, temporal, and complexity).

1.9 Complexity

Complex systems also exhibit complex webs of causality, making traditional hypothesis testing problematic. For example, if A causes B which then causes A, experiments to test if A causes B will often be confounded. In addition, we clearly cannot perform direct controlled experiments on large ecosystems and human systems at the landscape scale.

One solution (the one we pursue in this book) is to build complex, dynamic models of the systems under study that can incorporate the fundamental characteristics of complexity mentioned above. These models themselves then represent "complex hypotheses" more in keeping with the complex nature of the systems under study. Testing these complex hypotheses is not a simple Popperian falsification exercise, however. Complex models fit reality to some *degree,* which is usually not zero, but is never perfect. We can never say that a complex model is "false" as we can with some simple hypotheses. We can only estimate the degree to which a particular model fits a particular reality—the better the fit, the better the model. Thus "complex hypotheses testing" implies devising ways to quantify the degree of fit of complex models to a complex reality. New methods to test and optimize the fit of complex models under the heading of the Model Performance Index (MPI) are described in Chapter 4.

1.10 Overview of the Book

We start with several chapters that describe the essential tools and steps that are required to build a simulation model of a spatially explicit system using the landscape modeling approach.

In Chapter 2, Maxwell et al. describe the Spatial Modeling Environment (SME), the software package that can be used to put together the local descriptions of processes and models into a spatial framework. This is a fairly technical chapter that also walks the reader through an example of a simple spatial model and explains the whole process in much detail. The development of SME went through a whole series of versions, starting from the early implementations on Macintosh computers to the latest more sophisticated SME3 that runs in a variety of operating systems (UNIX, Linux, Windows) and includes a Java-based user interface. The overall concept remained the same: The SME provides the functionality to translate the models formulated in user-friendly modeling packages, such as STELLA, into a compilable programming language (C, C++) and to link the local descriptions with spatial data and algorithms. A Modeling Collaboratory is described (i.e., a collection of hardware and software tools that can be used for the exploration of collaborative modeling techniques and the development of process-based spatial models, as well as for transparent access to high-performance computing facilities. This infrastructure is expected to open the simulation arena to a much wider set of participants and facilitate the application of computer modeling to the study and management of natural systems.

In Chapter 3 Voinov with coauthors describes how the unit model, the spatially uniform building block of a spatial model, can be constructed. Fitz et al. (1996) have previously developed the General Ecosystem Model (GEM). Here, this approach is further extended and generalized. An even more flexible modular structure is created that can be modified and adapted to suit the requirements of particular case studies and applications with minimal redundancy. The modular approach takes advantage of the Spatial Modeling Environment (described in Chapter 2) that allows integration of several unit models (which can be created in user-friendly modeling environments such as STELLA) with C++ user code. The modules are archived into a Library of Hydro-Ecological Modules (LHEM), which is available over the Web and includes modules that simulate hydrologic processes, nutrient cycling, vegetation growth, decomposition, and so forth both locally and spatially. Using the LHEM, the Patuxent Landscape Model (PLM) (see Chapter 8) was built to simulate fundamental ecological processes in the watershed scale driven by temporal (nutrient loadings, climatic conditions) and spatial (land use patterns) forcings. Local ecosystem dynamics are replicated across a grid of cells that compose the rasterized landscape. Different habitats and land use types translate into different modules and parameter sets. Spatial hydrologic modules link the cells together. They are also part of the LHEM and define horizontal fluxes of material and information.

In Chapter 4, Villa et al. discuss the calibration problem. Solving the problem of calibrating large, spatially explicit ecological models to known data and hypotheses is a challenge to the computing power of the fastest workstations and to the sophistication of the best optimization algorithms. The authors present a method that considers the problems of calibrating unit models to data at different sites using different formulations of the Model Performance Index (MPI) in a multistage procedure, to identify regions of increasing feasibility in the parameter space. The method uses an evolutionary algorithm to optimize the MPI. The result of the process is a hierarchically inclusive set of regions in the multidimensional parameter space where the model's behavior satisfies increasingly stringent calibration constraints.

Moving from calibration of spatially uniform unit models to calibration of spatial models is yet another challenge. The MPI and other optimization techniques become inapplicable because of the enormous computer effort that would be required to run such optimizations over all of the cells in a spatially explicit model. Most of the calibration efforts in the spatial implementations are therefore still based on the trial-and-error approach, in which the skills and experience of the modeler becomes an intrinsic part of the calibration effort. By applying these skills and the "educated-guess" approach, we can considerably limit the parameter space and the number of model runs that would be required to fit the model to the available data. However, this fit is unlikely to be the *best* one; it will be just an approximation that can always use additional refinement.

Part II of the book is a collection of several diverse case studies, in which spatially explicit dynamic models have been created to resolve some very important ecological and management problems. All of the models employ the SME approach.

Chapter 5 examines habitat shifts in the Mississippi and Atchafalaya deltas in coastal Louisiana. Using spatial models, Reyes et al. examine land loss and yearly shifts of marsh habitats. The landscape model also served as a tool to analyze a series of weather scenarios under diverse sea-level rise rates. The landscape model integrated several individual modules at different scales. The physical module consists of a vertically integrated hydrodynamic model that moves and disperses salt and sediment. This was coupled with a process-based biological model of aboveground and belowground productivity and soil building. The coupling of spatial and temporal scales was a salient issue due to the size of the model. Resultant land elevation and habitat characteristics were updated annually and fed back into the hydrodynamic model. Simulations of land loss/creation and spatial variability of marsh types were validated against historical habitat maps. Future effects of weather and eustatic sea-level rise were evaluated for a 30-year projection starting in 1988. Results suggested that weather variability had the greatest impacts. The model strength lies in predicting the effects of regional management plans such as water diversions and structural-landscape-level changes.

In Chapter 6, Fitz et al. apply a similar approach to another predominantly wetland area—the Everglades in Florida. Water management infrastructure and operations has fragmented the greater Everglades into separate, impounded basins, altering flows and hydropatterns in these internationally recognized wetlands. This combination of altered hydrology and water quality has interacted to degrade vegetative habitats and other ecological characteristics of the Everglades. As part of a massive plan to "restore" the Everglades, simulation models are being applied to better understand the system's hydrologic and ecological dynamics, to help evaluate options for restoration. One such tool is the Everglades Landscape Model (ELM), a process-based, spatially explicit simulation of ecosystem dynamics across this heterogeneous 10,000-km^2 region.

The ELM model does an excellent job of reproducing the historical spatiotemporal dynamics of hydrology, surface-water and groundwater phosphorus, periphyton biomass and community type, macrophyte biomass and habitat type, and peat accumulation. Phosphorus loading throughout the Everglades system was then evaluated under two base scenarios. The 1995 base case assumed current management operations, with phosphorus inflow concentrations fixed at their long-term, historical average. The 2050 base case assumed future modifications in water management, with all managed inflows to the Everglades having reduced phosphorus concentrations (due to filtering by constructed wetlands). The ELM fills a critical information need in Everglades management and has become an accepted tool in evaluating scenarios of potential restoration of the natural system.

Chapter 7 is an application of the SME approach to an aquatic system by Behm et al. They investigate the role that estuarine processes play in altering the spatial distribution and abundance of eelgrass (*Zostera marina* L.) in the Great Bay Estuary, New Hampshire, USA. A unit model was developed to simulate interactions of eelgrass with environmental variables and other organisms. These variables include epiphytic algae, phytoplankton, macroalgae, detritus, consumers, and nutrients. A spatial simulation model was then used to simulate the annual as well as the spatial production of eelgrass habitats. A hydrology model developed by the University of New Hampshire Ocean Engineering Center was linked to the spatial model to drive the transfer of materials from adjacent cells. Using data obtained for river inputs of nutrients, the authors were able to simulate the seasonal and spatial variation in eelgrass production. Model results showed that both light attenuation and nutrient supply have a significant impact on eelgrass distribution. The spatial model was manipulated to test the effects of nutrient loading on interactions of eelgrass with other variables.

From wetlands and aquatic systems we then move to mostly terrestrial landscapes. In Chapter 8, Voinov et al. describe the Patuxent Landscape Model (PLM), which was designed to simulate fundamental ecological processes on the watershed scale. It has also been linked to an economic model that generated possible scenarios of land use change. The PLM was assembled based on modules from LHEM. Different habitats and land use types translate into different parameter sets. The model describes the 2352 km^2 of the Patuxent River watershed in Maryland and integrates data and knowledge over several spatial, temporal, and complexity scales, and it serves as an aid to regional management. In particular, the model addresses the effects of both the magnitude and spatial patterns of human settlements and agricultural practices on hydrology, plant productivity, and nutrient cycling in the landscape. The spatial resolution is variable, with a maximum of 30 m $\times$ 30 m tested on several subwatersheds. The finer resolution allows adequate depiction of the pattern of ecosystems and human settlement on the landscape. The temporal resolution is different for various components of the model, ranging from hourly time steps in the hydrologic sector to yearly time steps in the economic land use transition module.

A modular, multiscale approach was used to calibrate and test the model. Model results show good agreement with data for several components of the model at several scales. A range of scenarios with the calibrated model shows the implications of past and alternative future land use patterns and policies. The 18 scenarios analyzed include (1) historical land use in 1650, 1850, 1950, 1972, 1990, and 1997, (2) a "buildout" scenario based on fully developing all the land currently zoned for development, (3) four future development patterns based on an empirical economic land use conversion model, (4) agricultural "best management practices" that lower fertilizer application, (5) four "replacement" scenarios of land use change to analyze the relative contributions of agriculture and urban land uses, and (6) two "clustering" scenarios with significantly more and less clustered residential development than the current pattern. Results indicate the complex nature of the landscape response and the need for spatially explicit modeling.

In Chapters 9 and 10, SME was closely integrated with Geographic Resources Analysis Support Systems (GRASS)—another open source, public-domain software package. GRASS is a geographic information system that provides a wealth of functionality for instantaneous spatial data analysis and processing. SME adds dynamics to the model. The marriage of the two software systems offers much power and promise for complex spatial modeling.

In Chapter 9, Trame-Shapiro et al. use the SME modeling approach to describe the population dynamics of two endangered bird species: the vireo and the warbler. The studies are performed at Fort Hood, an Army training installation in central Texas. The Fort Hood Avian Simulation Model (FHASM) is a dynamic, spatially explicit model of ecosystem processes and population dynamics. The model simulates changes in vegetation and avian populations across the installation ($\sim$ 88,000 ha) over 100-year intervals (although shorter or longer runs are easily accommodated). The user designates management policies for each simulation run.

The Fort Hood Avian Simulation Model (FHASM) was used to generate probabilities of extinction for Fort Hood populations of the vireo and warbler under various scenarios, in a procedure known as population viability analysis (PVA). To do so, portions of FHASM were eliminated, and the resulting, simplified model became FHASM-V. Two applications are described here. First, FHASM-V was compared to a 1996 model designed for use in population viability analyses workshops of the vireo and warbler. Demographic variables of the two models were matched as much as possible. Second, a comparison was made among projected long-term probability of survival of the two species under three different habitat protection policies, using FHASM-V alone. Results furnished additional information for endangered species policy on Fort Hood while providing an interesting comparison to calculations using the 1996 model.

Chapter 10, by Aycrigg et al., is about spatial landscape simulations used to access impacts on another endangered species, the desert tortoises (*Gopherus agassizii*) in the Mojave Desert, California. This model was also developed at the U.S. Army Construction Engineering Research Laboratories (USACERL), Champaign, Illinois, to assess the impacts of military training across time and space. The desert tortoise was designated as federally threatened in the Mojave Desert in 1990. Its patchy distribution over very large areas makes population-density estimates difficult to obtain. It is a long-lived animal that does not reproduce until about 15 years old, making it highly susceptible to perturbations in the environment.

The spatially dynamic habitat model and the desert tortoise model were developed to evaluate the potential response of tortoise density and habitat suitability to changes in the intensity, location, and timing of military training. The model includes mathematical, logical, and stochastic processes. The initial conditions are seeded by the use of a snapshot of the system at some real or artificial start time. Various types of input data are used to seed the model including raster images, vector data, point information, and object status and location. Differences between the output and the seed values reveal the simulated changes within the landscape associated with various land management schemes.

In Chapter 11, Deal et al. develop a spatially explicit model to examine the dynamic spread of fox rabies across the state of Illinois and to evaluate possible disease-control strategies. The ultimate concern is that the disease will spread from foxes to humans through the pet population. Variables considered, including population densities, fox biology, home ranges, dispersal rates, contact rates, and incubation periods, can greatly affect the spread of disease. The spatial modeling technique used was a grid-based approach that combines the relevant geographic condition of the Illinois landscape (typically described in a georeferenced database system) with a nonlinear dynamic model of the phenomena of interest in each cell, interactively connected to the other appropriate cells (usually adjacent ones).

The resulting spatial model graphically links data obtained from previous models (fox biology, rabies information, and landscape parameters) using various hierarchical scales. It makes it possible to follow the emergent patterns and facilitates experimental data collection techniques. Results of the model indicate that the disease would likely spread among the native healthy fox population from east to west and would occur in epidemiological waves radiating from the point of introduction, becoming endemic across the state in about 15 years. It was also found that although current hunting pressures can potentially wipe out the fox in the state, some level of hunting pressure can be effectively utilized to help control the disease.

Finally, in Chapter 12, Seppelt and Voinov explore how optimization can be performed using spatial models. In the other chapters, models were mostly used to run scenarios (i.e., the user first identifies a set of forcing functions or initial conditions) that are then translated into system behavior by applying the models. Optimization procedures allow one to formulate certain goals that we wish the system to achieve and then use the model to translate those goals into control variables and parameters that let us reach those goals. For a mainly agricultural region studied in this chapter, the goal, or the performance criterion, was formulated as a combination of economic and ecological factors, which combine economic aspects, such as farmer's income from harvest, with ecologic aspects, such as nutrient flow from the watershed into the estuary. The task was to find optimum land use patterns and rates of fertilizer application to maximize the performance criterion.

Optimization in spatial modeling is usually prohibitive because of the high computational complexity. The authors developed a framework of procedures for numerical optimization in spatially explicit dynamic ecosystem simulation models that overcomes some of these difficulties. The results were tested using Monte Carlo simulation, which used stochastic generators for the independent control variables. Gradient-free optimization procedures (genetic algorithms) were used to verify the simplifying assumptions. Parts of the framework offer tools for optimization, with the computation effort independent of the size of the study area. As a result, important areas with high retention capabilities were identified and fertilizer maps were set up depending on soil properties. It was shown that optimization methods, even in complex simulation models, can be a useful tool for a systematic analysis of management strategies of ecosystem use.

1.11 Prospects and Challenges for the Future

Key areas for future development include the following:

- Using the modeling process to build a broad consensus among stakeholders
- Developing sufficient databases of historical landscape changes to allow better calibration and testing of landscape-change algorithms
- Linking process and agent-based models from several disciplines with geographic data at several different time and space scales
- Better understanding the relationship between resolution and predictability in landscape modeling to allow a more "optimal" resolution to be chosen for specific modeling problems

Our experience with spatial modeling indicates that complexity is one of the major challenges. As spatial resolution increases, the models become more difficult to build, require more number-crunching power from the computing platforms, and require more sophisticated datasets. They also become much more difficult to interpret and analyze. Some standard output from a spatial model may look like a series of spatial coverages over, say, a 1000-km^2 area during, say, a 1-year time period. Assuming that we are modeling some 10 variables at a daily time step and 1-km^2 spatial resolution, this will result in 3,650,000 numerical values coming out of just 1 model run. It is difficult to grasp and process all of the information generated, and there are not many methods to wrap this information in meaningful indicators that would still preserve the spatial and temporal information needed.

In order to realize the goals of the modeling effort, it is crucial to determine the amount of complexity (both spatial, temporal, or structural) that is justified. The

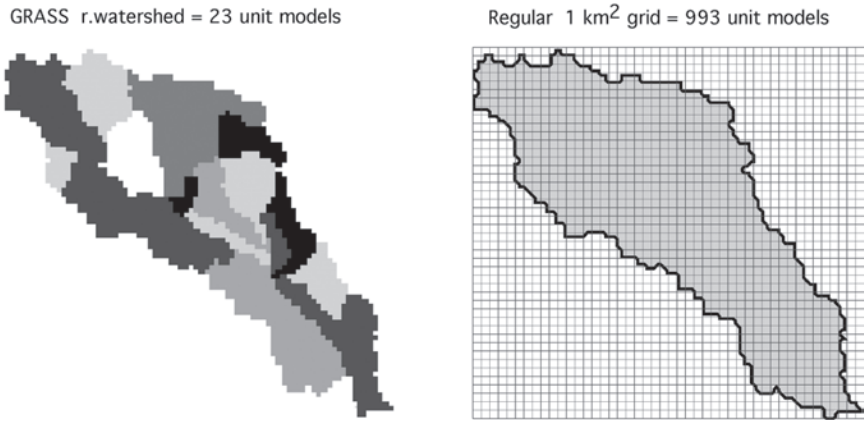

FIGURE 1.3. Raster cell-based approach versus lumped patch or polygon-based approach. The higher complexity of the cell-based approach adds flexibillity and versatility to the simulations.

raster grid-based approach that we assume in most of models described here may be treated as the ultimate spatial representation for modeling. It is always important to decide what is the smallest spatial unit that we model as a spatially homogeneous entity. Comparing the so-called lumped spatial models with the grid-based ones (Fig. 1.3) we can see that the number of spatial entities that are to be considered increases quite dramatically when we switch to uniform cells of the same size from larger spatial units, such as subwatersheds [in the HSPF model (Donigian et al., 1984)], hillslopes [TOPMODEL (Beven and Kirkby, 1979)], hydrologic units [SWIM (Krysanova et al., 1999)], patches [RHESSys (Band et al., 1991)], and so forth. As the number of spatial entities increases, so does the overall complexity of the model and the amount of effort to build, maintain, and analyze it. There should be a good reason to do that.

In most cases, it is the flexibility of the spatial representation that justifies the grid-based approach. With this approach, there is no fixed geometry of spatial units that the model has to maintain; at any time during the simulation, one can modify the landscape template over which the model is built. If the pattern of land-use changes (as in the PLM model described in Chapter 8), a new map can be fed into the simulation at any time and one does not need to recalculate new model geometry, new hydrologic units, or new patches. For example, the ELM model of the Everglades (Chapter 6) can model habitat succession as a function of water quality, hydroperiod, and climate. The spatial pattern can actually change within the model. In addition, because the representation is spatially explicit, we can pinpoint quite precisely the changes in the spatial characteristics of landscapes or habitats and where exactly future changes are to be expected.

Of course, in certain cases, this degree of spatial detail may not be required and then a more spatially aggregated model may work just as well. However, with the rapid development of remote sensing techniques, there are more spatial datasets becoming available at high degrees of spatial resolution. Managers and decision makers are keen to use these data and incorporate the newly available spatial knowledge in their practice. In addition, as the human impact on the environment becomes more severe, there is growing interest in understanding the intricate spatial patterns involved in integrated socio-economic and ecological dynamics. One wants to know exactly where the effects will be the most sever and precisely where they were caused. As a result it is likely that grid-based models that are closely associated with remote sensing-based raster data sets will be in increasing demand in the future. The challenge then is to learn how to wrap the avalanche of spatio-temporal output from these models into meaningful indicators that can be presented to stakeholders, which they can understand and use in their decision-making.

It is also likely that we will see hierarchies of models that will operate over several spatial manifolds and will integrate information both from raster coverages (grid-based models) and vector coverages (patch-based models). The latest version of the Spatial Modeling Environment (SME)—the software framework that we use in the applications in this book—already provides functionality that is essential to build such multilayer models. Some processes and modules can then run over larger patches, especially those that are characterized by more aggregated datasets—say, the socio-economic processes mostly described for census blocks, counties, townships, and so forth. These modules can be dynamically linked to modules operating on a grid basis and depicting information that is collected in raster format—say, via remote sensing. Certain elements of this raster–vector interplay can already be found in models presented in this book (e.g., the canals in the ELM, Chapter 6).

Overall, spatial landscape modeling (as described in the case studies in this book) has provided significant new insights into how landscapes function. As more data and computer power become available, applications of the techniques described here should become more common and more useful to a wide range of stakeholders.

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