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Scaling fine-scale processes to large-scale patterns using models derived from models: meta-models

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Introduction

Ecologists and natural resource managers face a common scaling dilemma in many applications. Our conventional knowledge base is rather fine-scale, but many of the issues that now face us are of much larger extent, often played out at landscape to regional scales. As an extreme example, consider the potential effects of anthropogenic climatic change on forests. Our best mechanistic understanding of the effects of temperature, moisture, and CO_2 on tree growth is at the level of plant ecophysiology (i.e., leaves, seedlings, and perhaps single trees; see Strain and Cure, 1985; Bazzaz, 1990), while assessments of these effects are typically addressed at regional or even global scales (e.g., Smith and Tirpak, 1989; IPCC, 1996; Walker and Steffen, 1996). Other applications, while less extreme, do not escape this fundamental scaling mismatch. For example, forest managers now integrate their activities at the level of ecosystems and at scales of entire forests (i.e., landscapes), yet we still work most comfortably at the scales we know best; that is, stand-level prescriptions carried out on individual trees.

Ecologists are increasingly savvy about scale (Delcourt *et al.* 1983; Wiens, 1989; Levin, 1992). The basic scaling rule that trades off spatial resolution and detail for spatial extent is appreciated: detailed fine-scale studies are carried out on small study areas, while studies of much broader extent necessarily sacrifice details to emphasize coarser-resolution patterns. This trade-off comes at some expense; applications at disparate scales are divorced from one another empirically and sometimes conceptually. For example, many models that address forest dynamics at the scale of the stand (*ca.* 1–10 ha) simulate the behavior of individual trees (Botkin *et al.*, 1972*a*,*b*; Shugart, 1984; DeAngelis and Gross, 1992) or are based on field measurements of individual trees (e.g., FVS: Wykoff *et al.*, 1982; Dixon, 1994). At intermediate scales, point models are often implemented to represent "average stands" (e.g., PnET: Aber and Federer, 1992; Century: Parton *et al.*, 1987). These point models are in fact scale-indeterminate, but are typically interpreted as if they represent homogeneous stands (a few m^2 for grasslands, 10s to 100s m^2 for forests). At a still larger extent, global vegetation simulation models used in climate-change research simulate plant functional types, cover types, or other abstractions of forests, and include dynamics that are analogies for plant demography (e.g., VEMAP, 1995). These differences in state variables and dynamics are appropriate as a strict scaling rule, yet as a result these classes of models do not share a common empirical basis; nor, in some cases, do they even share a common conceptual model of how vegetation responds to environmental forcings.

Our goal is to devise a modeling approach that can bridge disparate scales while preserving a common empirical and conceptual basis across scales. Our approach begins with a fine-scale model (in this case, a gap model), and then uses it to derive new models as statistical abstractions of the fine-scale model. The derived models operate at coarser resolution and hence over larger spatial extent, but they retain those finer-scale details needed for larger-scale applications. Because the derived models are statistically derived from the gap model, they are in a sense models of the fine-scale model: meta-models.

In the following sections an overview is provided of the general approach to scaling a gap model up to landscapes, and then three models are presented as illustrations of the meta-modeling approach. Some of the methodological issues of parameterizing and testing such models are discussed, and the chapter closes with a prospectus of where this approach seems to be leading.

Scaling from trees to landscapes: three approaches

Several approaches can be used to extend a fine-scale model to applications at larger scales. Two of these approaches are rather intuitive: a sampling approach such as used in distributing a point model over a wide range of parametric conditions; or using a bigger computer to simulate larger areas. It is instructive to review these intuitive approaches to point out their strengths as well as some shortcomings that argue against their general use.

A sampling approach

A straightforward way to represent a heterogeneous landscape is simply to simulate each of the environmental conditions on a case-wise basis. This approach is well established with point models (e.g., Solomon, 1986; Burke *et al.*, 1990). In this, a set of parametric combinations is assembled as, perhaps, a factorial stratification over the parameters that drive the model. Each parameter set is then simulated separately, and the output of all cases is aggregated to provide a "landscape scale" integration of the model.

Importantly, this approach is entirely consistent with the way landscapes are sampled in field studies, for example, by stratifying sample quadrats across a study area to represent the possible range of combinations of topographic position, soil type, and so on (witness the huge literature on gradient analyses e.g., Whittaker, 1956, 1967).

The chief advantage of this approach is simplicity; it requires no special modifications to the basic model. The drawback is that the approach is not truly spatial. Stratified field samples cannot discover the effects of local spatial context except via sophisticated statistical techniques (e.g., Legendre and Fortin, 1989); models distributed as stratified points cannot address these issues at all. Thus, forest dynamics that reflect nearby conditions, such as upslope area contributing surface runoff to the water budget, cannot be simulated in this way. Similarly, the spatial effects of contagious processes such as seed dispersal or disturbance (e.g., fire, pests) are lost to the sampling approach. A model that merely samples a landscape removes forest dynamics from their spatial context.

Brute force

Another approach to modeling large areas is to get a bigger computer. Indeed, it is instructive to trace the recent history of gap models from this perspective. The original gap model, JABOWA (Botkin *et al.*, 1972*b*) was undertaken partly as an experiment in high-performance computing with the sponsorship of IBM. The model simulated a single plot, 10 m × 10 m in area, that could support as many as 100 individual trees. A forest stand was aggregated statistically by simulating several independent plots and averaging their output. By contrast, the gap model used today, Zelig version Facet (see below), simulates a forest stand as an interactive grid of as many as 2500 plots; the model runs on a UNIX workstation but is well within the computational reach of today's PCs. Using a distributed queuing system on a UNIX network (see below), hundreds of model grids are run routinely in the time it originally took JABOWA to run a single plot: computing muscle has increased by a factor of $\sim 10^5$.

An alternative to brute force is to use a bit more finesse in applying more powerful computers to the scaling issue. One especially promising approach is to reformulate the model to take advantage of parallel processing (Schwarz, 1993). Because many ecological applications can be framed as parallel problems, this approach is a compelling means of scaling a model to simulate large areas while retaining fine-scale details: the application of what we might term elegant force.

Meta-models

A third approach is to derive new models to operate at larger scales – but to do so in a manner that retains as much of the finer-scale information as required for the application of interest. Here this approach is illustrated by using a gap model to generate and parameterize new models that reproduce, as statistical constructs, selected behaviors of the gap model. The new models are themselves models of the gap model: meta-models.

There are two compelling features of this approach. First, because the meta-model is defined to reproduce the finer-scale model, the two models provide consistent results across scales. As will be illustrated, this is because they share the same empirical basis and conceptual foundations. Second, this approach provides a two-layered modeling package that allows the researcher to use the model that is best suited to the application. Although there will always be cases where the simplification implicit in the larger-scale model undermines the application, there is the finer-scale model to fall back on in these cases. Thus, the fine-scaled model is available when details are needed, and the coarser-resolution model is available when some simplification is desirable.

A general approach is described for using a fine-scaled model as a means to develop a larger-scale, coarser-resolution model (a meta-model). This approach is illustrated with the example of a cellular automaton, derived from the gap model Zelig and emphasizing contagious spatial processes as the interactions of interest at the landscape scale. The versatility of this general approach is then illustrated with two further examples: a semi-Markovian model that emphasizes transient successional dynamics, and a stage-structured model developed for applications involving timber management.

First, there will be an overview of the gap model, and a description of the approach developed to facilitate performing the large numbers of simulations required to generate a meta-model.

The gap model

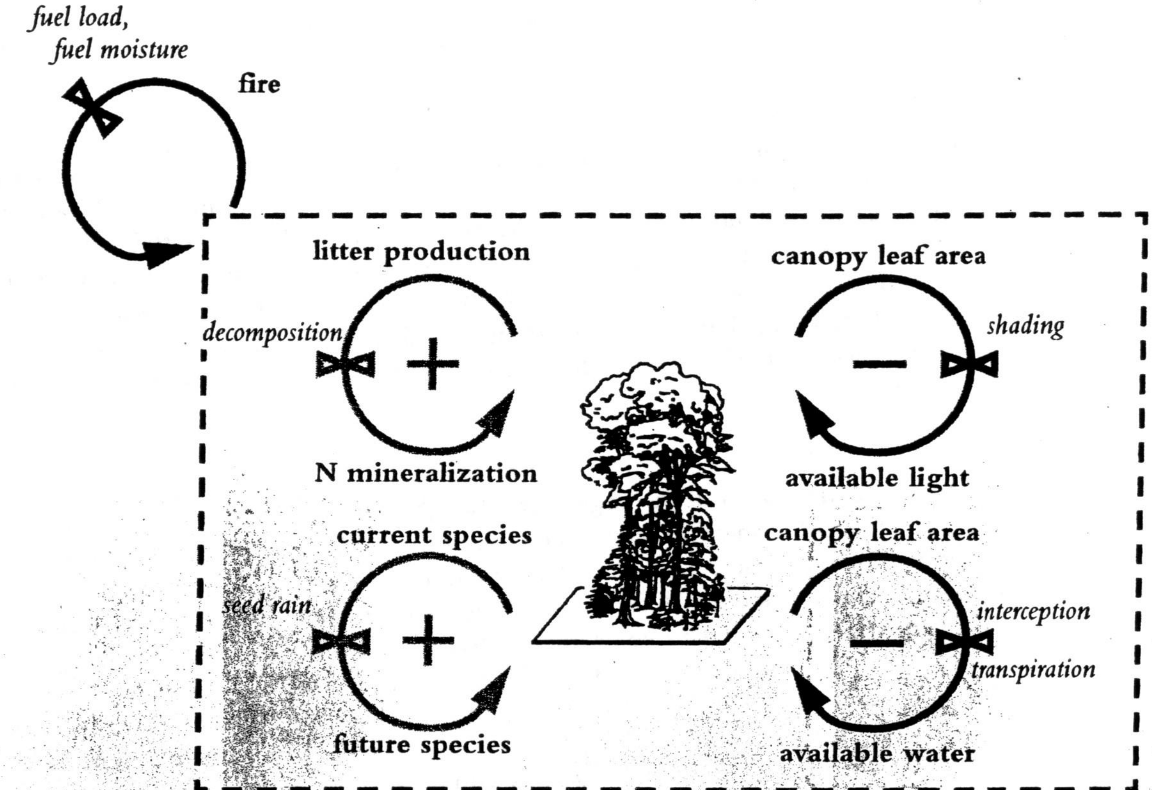
As the base model for our meta-modeling efforts, we use the gap model Zelig version Facet (Urban and Shugart, 1992; Miller and Urban in press, Urban *et al.* in review). Facet is so named because climatic variables are adjusted for topographic position. The functional unit is the slope facet (Daly *et al.*, 1994), which is defined in the model as a grid of homogeneous slope, aspect, and elevation. As a research tool, the model is continuously evolving; the examples presented here are based on version 97.3 of the Facet model, or FM 97.3.

Model structure

All versions of Zelig (there are several) simulate a forest stand as a grid of tree-sized cells. Each cell corresponds to a conventional gap model plot (Botkin *et al.*, 1972*a*,*b*, Shugart and West, 1980; Shugart, 1984; Urban and Shugart, 1992). The grid is underlain by a raster soils map, with each cell assigned a soil type. Zelig models allow the grid cells to interact in that trees on a grid cell may shade or be shaded by trees on nearby cells. This zone of interaction depends on tree height and latitude (sun angle), but for temperate forest may range over 5–6 cells or more. Typical applications simulate grids that are 10 × 10 to 50 × 50 cells, corresponding to stands on the order of ~1–20 ha.

Forest ecosystems can be envisioned as coupled sub-systems, and gap models can be envisioned as coupled sub-models. There are five conceptual sub-models

Fig. 4.1. Schematic of system-level feedbacks as implemented in the full version of the gap model Facet. Each submodel tends to act as a positive (+) or negative (–) feedback on itself. The sub-models are coupled by physical relationships and by tree species life-history traits (see text).



to FM (Fig. 4.1). These sub-models tend to behave either as positive or negative feedbacks in the model. For example, as the canopy develops, shading increases and this retards canopy growth (a negative feedback). In contrast, canopy development increases litterfall which increases N (nitrogen) mineralization, which further increases forest growth (a positive feedback). The sub-models are coupled by physical relationships. For example, litter moisture determined in the soil moisture sub-model affects decomposition rates and also affects flammability in the fire model. The sub-models are also coupled by life-history traits encoded as species parameters. For example, many trees that are shade tolerant are also drought intolerant and have high tissue N concentrations, effectively coupling the light, soil moisture, and decomposition submodels. In the examples used here, the primary emphases are the light regime, the soil water balance, and the fire model. A seed dispersal module under revision is not used in the examples presented here.

The physical template

FM 97.3 simulates the physical environment in terms of temperature, available light, soil moisture, and nutrient (nitrogen) status. As a Facet model, FM adjusts temperature and precipitation for elevation using locally regressed lapse rates (Running *et al.*, 1987; Daly *et al.*, 1994), and adjusts radiation for topographic position using standard geometric and micro-meteorological methods (Nikolov and Zeller, 1992). Here, an overview is provided of the light, soil moisture, and fire submodels, because these illustrate the methods of simplification in devising meta-models.

Light regime

FM summarizes vertical heterogeneity as height profiles in leaf area and available light, at a resolution of 1 meter. The crux of the light regime is a leaf-area profile defined for each grid cell, constructed by estimating total leaf area for each tree on the plot and distributing this leaf area along each tree's live crown (after Leemans and Prentice, 1987). The tree height and leaf-area allometries are based on regressions local to a study area (e.g., Gholz *et al.*, 1979; Garman *et al.*, 1995).

throughout the course of a simulation as duff accrues through annual litterfall and subsequently decomposes.

The model uses a Priestley–Taylor estimate of potential evapotranspiration (PET: Bonan, 1989). Because the PET estimate is driven by radiation and this can vary with topography, the routine adjusts the water balance for stands of different slope and aspect. PET is partitioned into two components. Transpiration depends on leaf area index. The fraction of PET not partitioned to transpiration may be drawn as evaporation from the litter and surface mineral soil. Actual evapotranspiration (AET) may be reduced from PET for three reasons: (i) precipitation and soil

Establishment

Seedling establishment is strongly keyed to light available at ground level and to the moisture status of the topsoil. Establishment probability may also be affected by litter depth (some species fare better on mineral soil). Each species has a maximum possible establishment rate, and in each simulation year species are filtered by light, temperature, and soil moisture multipliers that reduce the optimum rate. An environmentally filtered cohort of seedlings is then planted and tracked for a number of years until the seedlings become eligible to be established as trees.

Growth

Tree growth is modeled deterministically via a function that describes the maximum diameter increment that could be achieved by a tree of a given size under optimal environmental conditions. This function is itself driven by leaf area, with the result that a tree that prunes under shading naturally exhibits slower growth.

The optimal growth increment is further reduced to reflect the effects of shading, soil moisture, soil fertility (N), and temperature. Shading is modeled by integrating a shade response function over a tree's canopy, using the light regime computed as described above. Soil moisture affects tree growth by slowing growth as a species-specific maximum drought-day index is approached. Nutrient response is simulated in terms of the ratio of N supply to N demand for the plot. N supply is accounted as N mineralized as C is respired in the decomposition of litter and woody debris. If N supply is adequate, trees are unconstrained; otherwise, the growth of all trees is reduced accordingly.

The temperature response in this model assumes that there exists a cold temperature at which species response is low for physiological reasons, and that this occurs at reasonably cold temperatures (i.e., at high elevations in our systems). Conversely, at this latitude the effect of high temperature is largely expressed through its effect on the water balance – masking any direct effect on tree physiology. Thus, a one-sided temperature response curve is used that is disabled at warmer temperatures, where the soil moisture constraint becomes operative.

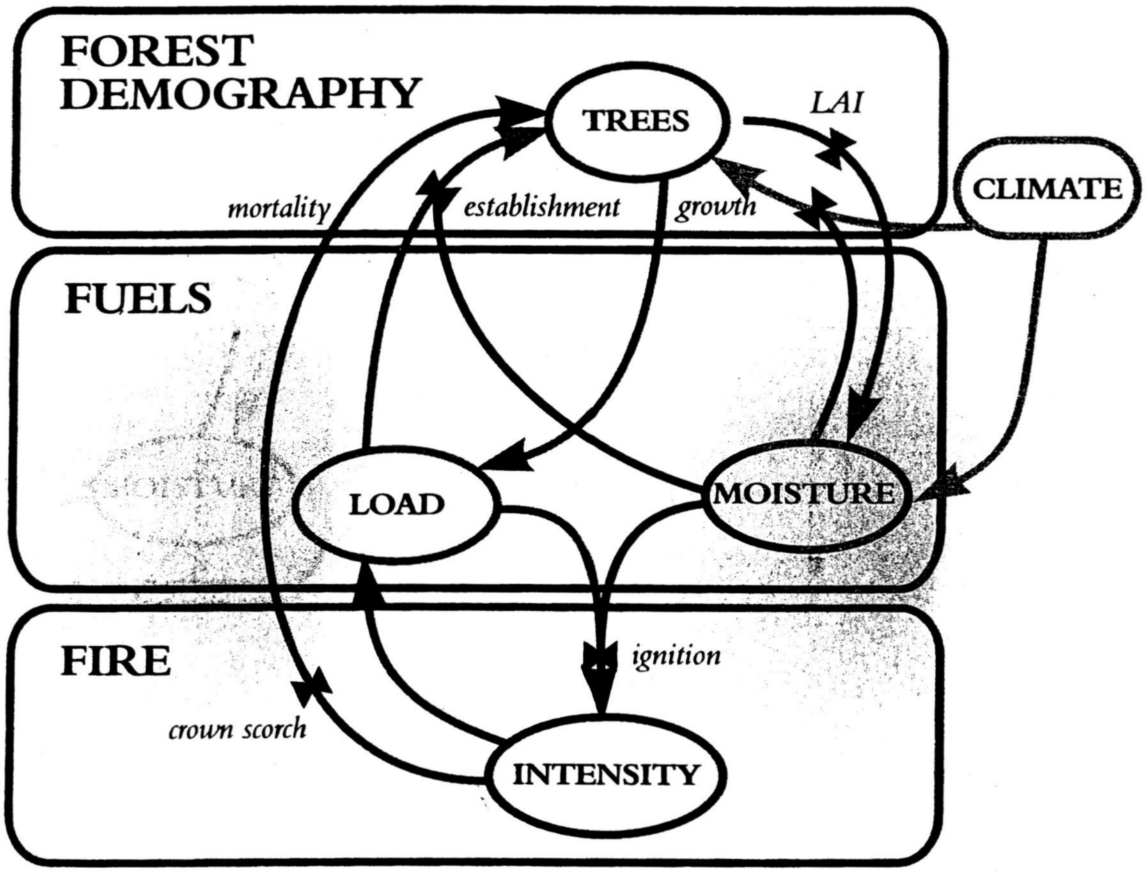
Environmental factors interact to constrain tree growth. An interaction is assumed between above- and below-ground constraints, but it is assumed that moisture and nutrients are so tightly interrelated that they are inseparable for our purposes. Thus, the overall constraint is the product of the temperature, light, and below-ground factors, where the below-ground factor is the minimum of moisture or nutrients.

Mortality

Trees may die for three reasons in the model. There is a low baseline rate of purely stochastic mortality that is estimated from expected species longevity; this annual probability is age and size independent. A second cause of mortality is lack of vigor, which is invoked when a tree fails to achieve a minimum growth threshold for more than two successive years. Trees of any size may be subjected to chronic drought stress on severe sites, or acute drought on any site in an extreme year.

Temperature effects are largely chronic rather than acute, and are a dominant

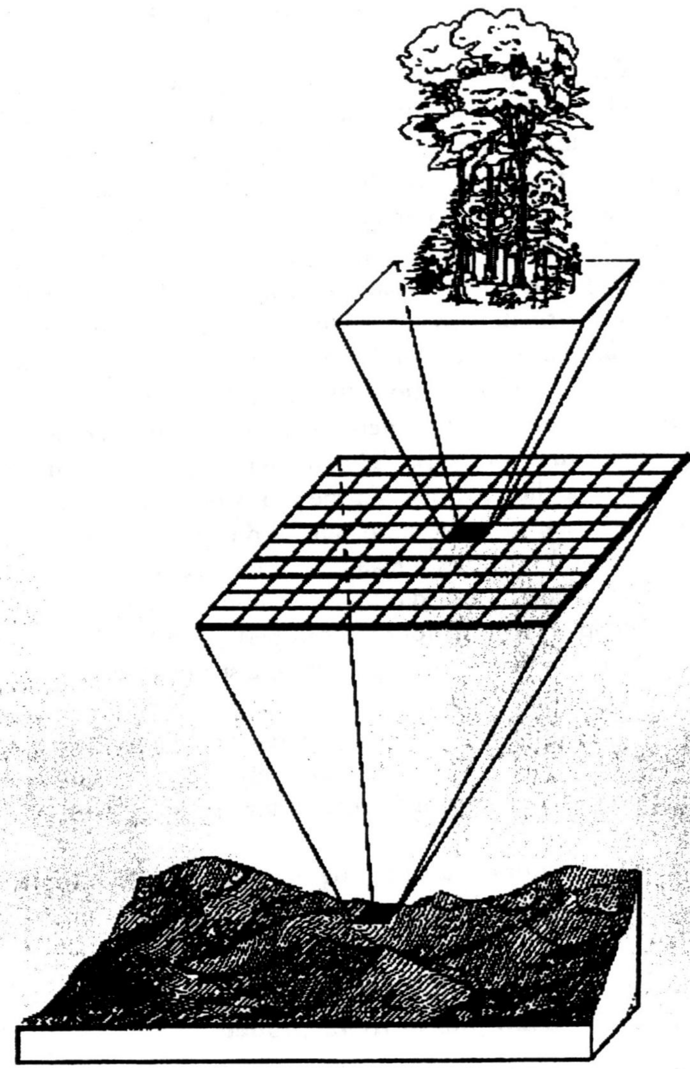
Fig. 4.2. Schematic of the fire model in FM, emphasizing couplings among forest condition, fuels, and fire behavior as governed by climate. Fuel loads reflect forest condition because litterfall is a function of tree demographics. Fuel moisture is computed from the soil water balance, thus coupling fire with climate. Fire frequency is internally generated by the model, with fire occurrence and fire intensity being functions of this fuel moisture and fuel load. Fire then affects forest condition via crown scorch (which might be lethal) and seedling establishment.



Extending the gap model to landscapes

There are two steps in our approach to extending a gap model to the landscape scale. The first step is implicit in the structure of the Facet model, which adjusts the grid for topographic positions defined by slope, aspect, and elevation (Fig. 4.3). The second step involves performing the large number of simulations needed to characterize the range of environmental heterogeneity represented within a landscape. For this, a distributed queuing system has been developed.

Fig. 4.3. Scaling the gap model ZELIG version Facet from the model plot (grid cell), to a forest stand (grid), to a slope facet on a landscape. Climatic drivers in the model are adjusted for slope, aspect, and elevation using locally regressed lapse rates for temperature and precipitation, and geometric models for radiation.



The distributed queuing system

A distributed queuing system (DQS) distributes simulations (jobs) to a number of client workstations in a network. Our system uses the Tcl/Tk tool command language toolkit (Ousterhout, 1994) to present the user with a series of three graphic user interfaces that pre-process the session, perform the actual simulations, and then post-process the collective output. In the first session, the user defines the combination of driving parameters for a set of simulations. A single simulation is defined by a combination of run-time parameters that include input Driver files (species parameters, climate and soils data), topographic position (slope, aspect, elevation, and a soils map for the grid), the number of years to simulate, and which output files to save. Run-time parameters may be held constant or varied according to a variety of sampling designs (uniform, stepwise incremental, or gaussian). The parameters are typically distributed, based on empirical distributions estimated from data in a geographic information system. This initial session results in the generation of a run list, which is a set of combinations of run-time parameters for each of a user-specified number of simulations (typically 100–500).

The second session with the DQS then distributes the runs across any number of client workstations in a network. The master server program on the host machine sends a job to a client, and when the job is finished the client copies the selected output file(s) back to a common output directory on the host machine. Client machines can be selected individually, or scheduled to avoid particular times of the day (run in background mode during office hours, resuming at night). Using a network of 15 Sun Sparc workstations we can perform 500 simulations in a few hours' clock time. This performance improves almost monthly as faster hardware becomes available.

The final session with the DQS consists of post-processing the collated output. UNIX awk scripts, generated internally by the post-processor, cull user-selected output variables to a new file which is formatted for use with graphics or statistics packages.

The DQS thus facilitates our conducting the many simulations needed to represent a landscape. More to the point here, this also allows us to perform the range of simulations needed to build and fully parameterize a meta-model.

Examples of meta-models

To illustrate our approach to building meta-models, the approach begins by "building" the cellular automaton MetaFor. A brief overview is then provided of the other two models, as a contrast to MetaFor and to provide some notion of the range of possibilities for meta-models.

MetaFor: a cellular automaton

A cellular automaton simulates dynamics in a raster grid by positing that the future condition of a given grid cell depends on its current state and the state of its neighbors (Hogeweg, 1988; Green, 1989). Neighbors are typically specified to include the four cells adjacent in the cardinal directions to the focal cell or eight neighbors (including also the diagonal neighbors); in fact, there is no reason why the neighborhood cannot be defined by whatever rules make sense for the application. Cellular automata are well suited for applications where the behaviors of interest are contagious processes or neighborhood interactions.

Table 4.1. *Structure of the cellular automaton MetaFor, as state variables, system dynamics, and parameterization scheme*

Component	Definition	Derivation
State variables	Cover type	Dominant tree species
	Age class	Simulation timestep (a counter)
Input map files	Elevation	Digital elevation model (DEM)
	Slope	From DEM
	Aspect	From DEM
Input data files	metaSpecies	Parameters derived from Facet
	metaSite	Climate coefficients (from Facet)
Processes	Establishment	Automaton; plus environmental constraint (from Facet)
	Mortality	Age-related or disturbance (from Facet)
	Fire	Automaton; conditioned on age and moisture (from Facet)

Structure and dynamics

MetaFor represents a landscape as a grid wherein each cell is assigned a cover type

The physical template

The climate and soil moisture routines in Facet operate at monthly or submonthly timesteps, and require as input information on minimum and maximum temperature, precipitation, and radiation, as well as canopy leaf area, and soil texture for all layers in the soil profile. Long-term patterns in temperature and soil moisture are summarized by saving a temperature index (growing degree-days) and a moisture index (drought-days) from long-term (100-yr) simulations with a stand-alone version of the gap model's climate and soil moisture routines. These data are then used in a regression analysis, to build functions that predict the indices from topographic data stored in MetaFor. Growing degree-days are predicted from multiple regression on elevation, slope, and aspect. To incorporate stochastic interannual variability in temperature we also include the standard deviation of degree-days, which is predicted from the mean. Each simulation timestep, a random (gaussian) amount of variation in temperature is added to the mean degree-day index predicted for each grid cell. Thus, there is spatial as well as temporal variability in temperature in the landscape model.

Predicting soil moisture is confounded somewhat by the fact that temperature and moisture are themselves correlated: temperature decreases while precipitation increases with elevation in mountainous terrain; temperature is also a main component of evaporative demand. To attend this, degree-days are used for a given year (i.e., with the stochastic variation added) to partially predict drought-days. Another random deviate is then applied to add stochastic variation in drought-days that is unrelated to temperature (i.e., that due to year-to-year variation in precipitation). These relationships are derived by partial regression and used to generate temperature and soil moisture surfaces from the DEM files used as model input.

Demographic processes

Cell-based analogs of tree demography include the assignment of a species type to each unoccupied cell (establishment), the "aging" of these cells simply by accruing timesteps since establishment, and the clearing of cells after mortality (age-related or through disturbance). In MetaFor the processes of aging and mortality are quite simple; establishment is somewhat more complicated.

The colonization of an unoccupied cell by a species is conditioned on two factors: the physical environment and existing species composition within the neighborhood of the cell. The physical environment is specified as the cell's degree-day and drought-day indices, as computed each timestep with some stochastic variation. Species response functions on [0,1] are used to modify establishment probabilities; these functions are taken directly from Facet. Each species has its "environmental probability" of establishment calculated as the product of the temperature and moisture multipliers. A cell with an inhospitable environment (e.g., a cold alpine site or xeric outcrop) is likely to be unoccupied and will persist as a gap. The neighborhood effect on establishment, used to mimic seed dispersal, is estimated by tallying the proportion of the cells in the neighborhood that are occupied by each species (including "gap" cells that are unoccupied). The neighborhood is specified by the user and can consist of 4, 8, 12, or 24 cells. The inclusion of "gap" as a species in the neighborhood forces large gaps such as those created by fires to be colonized mostly by encroachment from the edges, rather than being recolonized immediately and entirely the year following a fire. Actual establishment probabilities are computed as the normalized product of the environmental constraints and neighborhood influences.

In effect, the dynamics of the landscape are rather straightforward after initial establishment: each cell either "ages" one timestep or it is cleared by mortality or disturbance.

Disturbance itself is a contagious process that is conditioned on site condition, specifically soil moisture (a proxy for fuel moisture) and time since establishment (a proxy for fuel load). At each timestep, fires may be ignited at stochastically selected points (cells). Fires spread from these ignition points probabilistically. Each neighboring cell has a probability of burning that is computed as the product of the moisture and stand age functions. A uniform-random number on [0,1] is drawn and the cell either burns or does not; if it burns, it is added to an array of cells comprising the current fire (a cluster of cells). This process is recursive and continues until a maximum fire size is reached (a computational check) or until no burnable cells can be found adjacent to the current fire.

Illustrations

The automaton generates realistic patterns in vegetation cover (Fig. 4.4, left: see color section). In this example, the landscape is a ~47 000-ha sample of Sequoia National Park in the Sierra Nevada of California, as a 1024 × 512 grid of 30-m cells. The model is capable of simulating much larger areas, but in this case we are limited by the availability of climate data (lapse rates are poorly defined east of the topographic divide).

The question naturally arises, "How well does this match the actual vegetation in the park?" This question is frustratingly difficult to answer in a straightforward way. It is known that the gap model matches field data, at least insofar as reproducing elevational and topographic trends in species basal area (Miller and Urban, in press; Urban *et al.*, in review). And, because the automaton is defined to reproduce the gap model, it is easy at one level to claim that the automaton thus also matches our data. But, in fact, only one image of the Park's vegetation is available, a map classified from a combination of satellite imagery, air photos, and ground data (Fig. 4.4, right). This map is flagrantly different from the predicted map, and yet any comparison of the two is misleading; neither map is a particularly valid picture of reality. The modeled map represents potential vegetation in the absence of any recent fires and with no other disturbances. The "real" map is a highly aggregated and interpolated composite of subjective cover types; the apparent homogeneity of huge expanses of the Park is clearly an artifact of the classification scheme used in generating the map. This broaches a quite general issue in landscape models, which is deferred to a later discussion.

Mosaic: a semi-Markov patch transition model

Another common way to model landscape dynamics is to simulate the transitions among discrete patch types, for example seral stages or land cover types (Johnson and Sharpe, 1976; Weinstein and Shugart, 1983; Baker, 1989). A Markov chain is a well-studied formalism for such models (Usher, 1992). In a first-order Markov model, the transitions depend only on the current state (i.e., history does not matter). A more complex and realistic model includes time lags making the transitions dependent on history; this extension renders the model semi-Markovian. The gap model Zelig has been used to generate and parameterize various versions of a semi-Markov model called Mosaic (Acevedo *et al.*, 1995*a*,*b*, 1996).

The state space of a semi-Markov model is a set of *n* patch types; the state dynamics are transitions or conversions among these patch types. The heart of the model is the $n \times n$ transition matrix, the elements of which are the probabilities that a patch of a given type will undergo a transition to some other type. The transition will occur, however, after a time lag characteristic of each pair of states. In the aggregate, a Markov chain models the proportion of the study area that is in each of the states at a given time. For spatial applications, the model is implemented by applying the transition probabilities on a per-cell basis on a raster map. The result is a time series of new maps of the landscape, each map a stochastic realization of the model.

An issue in generating a semi-Markov model is how to estimate the transition probabilities and delays. If the number of patch types is large, or if some transitions are uncommon, it may be quite difficult to estimate these parameters. For complex transitions among landscape elements that undergo change over time scales of decades or longer, there may be no feasible way to measure these rates directly from readily available data. Our approach has been to use the gap model to estimate these parameters.

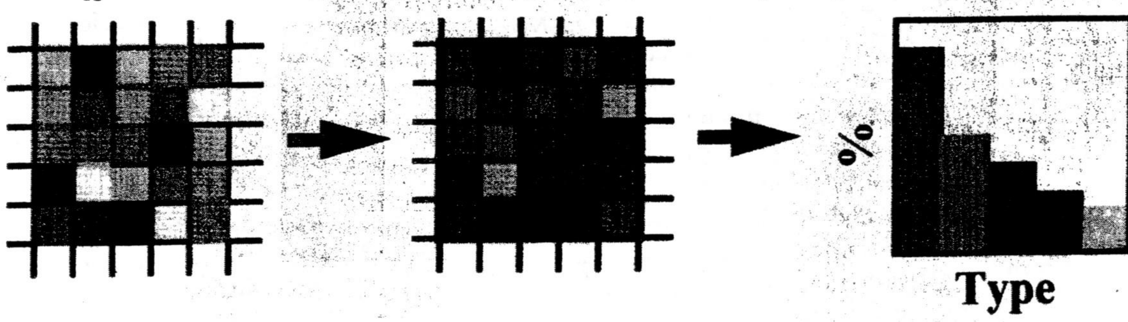
Structure and dynamics

The Mosaic models used are structured by defining a mosaic tile on the landscape as a homogeneous unit of arbitrary area (~1–10 ha). The state variable for the tile is not its dominant patch type, but rather, a frequency distribution of gap-sized elements within that tile that are in each patch type (Table 4.2). For example, a 1-ha tile would have 100 gap-model cells of 10 m $\times$ 10 m within it. The state dynamics of the model are the changes in the frequency distribution of within-tile types through time. Thus, some information is tracked on the within-tile heterogeneity of forest stands but without tracking the location of each gap-scale element within the larger tile (Fig. 4.5).

Table 4.2. *Structure of the semi-Markov model Mosaic, as state variables, system dynamics, and parameterization scheme*

Component	Definition	Derivation
State variables	Frequency distribution of cover types within tile	Classified by user (application specific), typically dominant species and/or age (size) class
Input map files	Elevation	Digital elevation model (DEM)
	Initial conditions	From GIS coverages, imagery
Input data files	Transition probabilities and transition delays	Fitted parameters (from Facet)
Processes	Establishment, succession	Semi-Markovian; biased by environment (from Facet)
	Mortality	Age-related or disturbance (transitions to 'gap') (from Facet)

Fig. 4.5. Schematic of the structure of the semi-Markov model Mosaic. Continuously varying species composition and age structure are classified to discrete cover types for each gap-scale element (cell) within a larger, 25-cell mosaic tile (in bold); the frequency distribution of these types within each mosaic tile in the landscape comprise the state of the system.



Parameterization

Building a semi-Markov model consists of defining the patch types, and then inserting a "patch type classifier" into the gap model. In the models we use, the types have been variously defined: by dominant species only (Acevedo *et al.*, 1996), or by combinations of dominant species in each of two height classes (Acevedo *et al.*, 1995*a*). The gap model is then run, and at every timestep each model plot is classified to patch type. As any model plot changes from one type to another, the transition is tallied. In the simple case of a first-order Markov chain and one model plot, these tallies can be used to derive the transition matrix directly. For semi-

Markov models, the calibration is more complicated. In the models developed, transitions may have fixed lags (latencies) concatenated with distributed delays, thus providing more realistic successional dynamics. This requires the estimation of several parameters for each transition (duration of the latency, if any, and parameters of the delay density function). These parameters are estimated by statistical analysis, including non-linear estimation procedures.

Illustrations

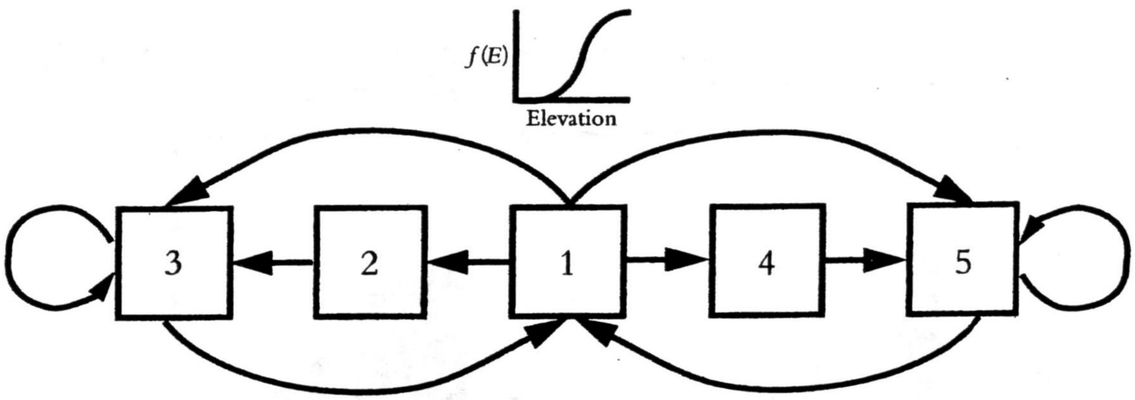
The first version of Mosaic was based on functional roles of trees, and was motivated in part by a desire to develop a tropical forest model that incorporated dynamics similar to that of a gap model while conceding that there was a lack of the life-history data to be able to parameterize a simulator as detailed as a gap model (Acevedo *et al.*, 1996). This example is less applicable to landscape-scale applications, but it does highlight an important consideration for meta-models: if the model is sufficiently simple, there may be a tractable analytic solution. Indeed, Acevedo *et al.* (1996) illustrate a progression of models ranging from the detailed (and complicated) gap model, to a semi-Markov model that can simulate realistic successional dynamics but that also yields a concise analytic solution.

A second example of the semi-Markovian approach is a more complicated version of the model, with patch types defined as two-layered combinations of dominant species in the over- and understory (Acevedo *et al.*, 1995*a*). This version of the model was implemented for the forests in the Pacific Northwestern United States, where old-growth issues are often framed in terms of the vertical structuring of forests. In this version, the transition probabilities are also conditioned, on elevation recognizing a major ecotone between lower elevation forest characterized by Douglas-fir and western hemlock, and high-elevation forests dominated by true firs (Fig. 4.6). The model reproduces patterns in species distribution across this ~6300-ha watershed in the central Oregon Cascades, in this example illustrating the dominance of the western hemlock plant association at lower and middle elevations (Fig. 4.7: see color section).

ZelStage: a stage-structured model

ZelStage was developed to investigate the effects of forest management and natural disturbances on stand dynamics and landscape patterns in the Oregon Cascade and Coastal mountain ranges. An important consideration in the development of this model was the ability to realistically simulate long-term stand dynamics for landscapes under alternative forest management practices. This argued for a modeling approach that tracked stem densities by species (the common currency of forest management), but further required an approach computationally modified for efficient, simultaneous simulation of multiple stands over a landscape.

Fig. 4.6. Transition diagram for forests in a Pacific Northwestern version of the semi-Markov model Mosaic (after Acevedo et al., *1995*a*). Patch types are (1) gap, (2) young Douglas-fir/hemlock, (3) mature Douglas-fir/hemlock, (4) young true fir, and (5) mature true fir. The function of elevation,* f(E), *splits the model into two domains.*



Structure and dynamics

ZelStage is a deterministic model made up of a stage-structured framework, statistical functions of growth and mortality, and algorithms taken directly from the gap model. The stage-structured component is the basis for tracking stems. Instead of dealing with individuals, ZelStage tracks the number of stems per hectare of each species in 3-cm diameter growth stages (size classes). This simplification reduces both storage requirements and amount of processing with only a nominal reduction in detail given the small size-class interval (Fig. 4.8).

Growth of stems among size classes is modeled using transition functions derived from simulation experiments with the gap model (Table 4.3, and see below). Transition functions formulated as linear and non-linear regression equations predict the proportion of stems advancing from one size class to another given the current size class, crown ratio, and cumulative leaf area index above the base of the crown. Mortality functions determine the proportion of stems that die from natural causes during a time step. Ingrowth is calculated using an approach similar to the gap model, but is deterministic.

ZelStage uses raster-based data layers to represent several levels of spatial organization of the forest as well as the environmental field for a landscape. An initial stand map indicates the stand code for each cell or group of cells of the landscape. This code is used as an index to the input stand table that designates the initial structure and composition of each stand. For forest management considerations, a harvest unit map is used to delineate aggregates of cells treated as unique management units. The spatial grain of input maps can be any size above 0.3 ha (this lower size is imposed for computational reasons explained below).

To implement forest management, ZelStage contains an event scheduler that allows the user to implement a range of stand-level treatments at any time during

Fig. 4.8. Schematic of the stage-structured model ZelStage, in which the state variables are 3-cm diameter classes for each tree species.

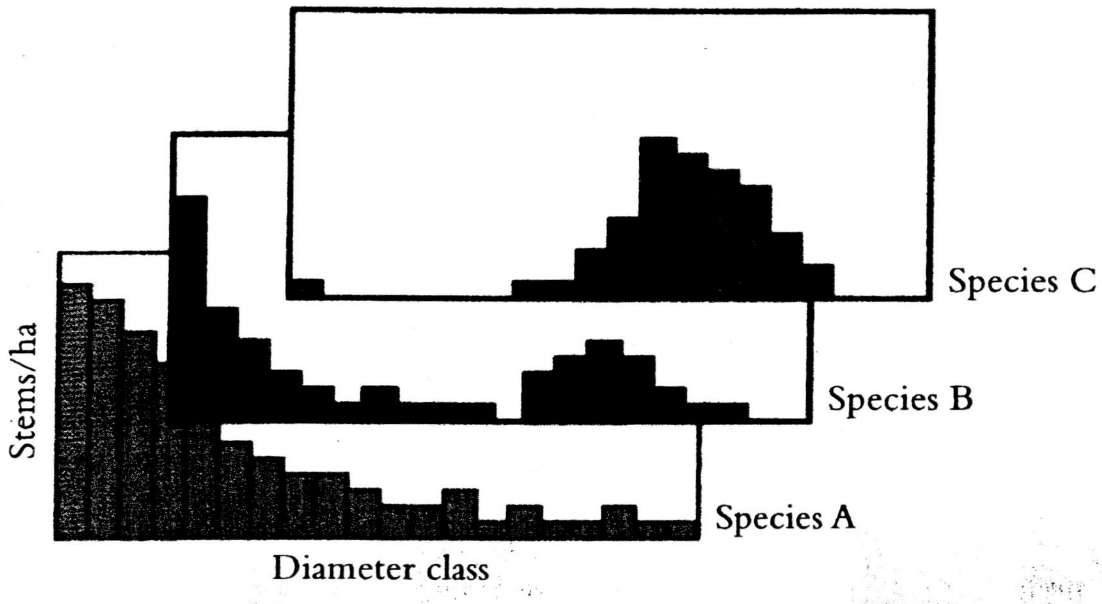


Table 4.3. *Structure of the stage projection model ZelStage, as state variables, system dynamics, and parameterization scheme*

Component	Definition	Derivation
State variables	Diameter frequency distribution by species	Binning continuous distribution into discrete classes
Input map files	Stand map	GIS database
Input data files	Environmental parameters	GIS-based models and coverages
	Stand condition	GIS-linked data tables
Processes	Establishment	Constrained by stand condition and climate (from Zelig)
	Growth to next size class	Regression (from Zelig)
	Mortality	Regression (from Zelig)

the simulation. Commands are read from an ASCII script, and specify the year, type, and parameters of an event. Event parameters define the removal and retention of basal area, volume, and density, and planting of stems. Command scheduling arguments specify the harvest unit or individual stand to be effected, the species and size classes to consider, and the retention/removal strategy (e.g., from top down, bottom up, or proportional to the existing size-class distribution). Additionally, basic algorithms were incorporated into ZelStage so that harvest units can be selected to simulate dispersed and aggregated harvest patterns (from the Cascade model, Wallin *et al.*, 1994).

Parameterization

Data for the generation of transition functions are derived from controlled simulation experiments with a modified version of Zelig. An initial requirement was the calibration of the gap model for the environmental conditions of the area of interest. Field data sets for over 2000 stands in western Oregon were used for calibration. A data base of weather conditions (monthly means, variances of precipitation, temperature, solar radiation) has been developed for all of western Oregon and was used to determine environmental inputs for a simulation area.

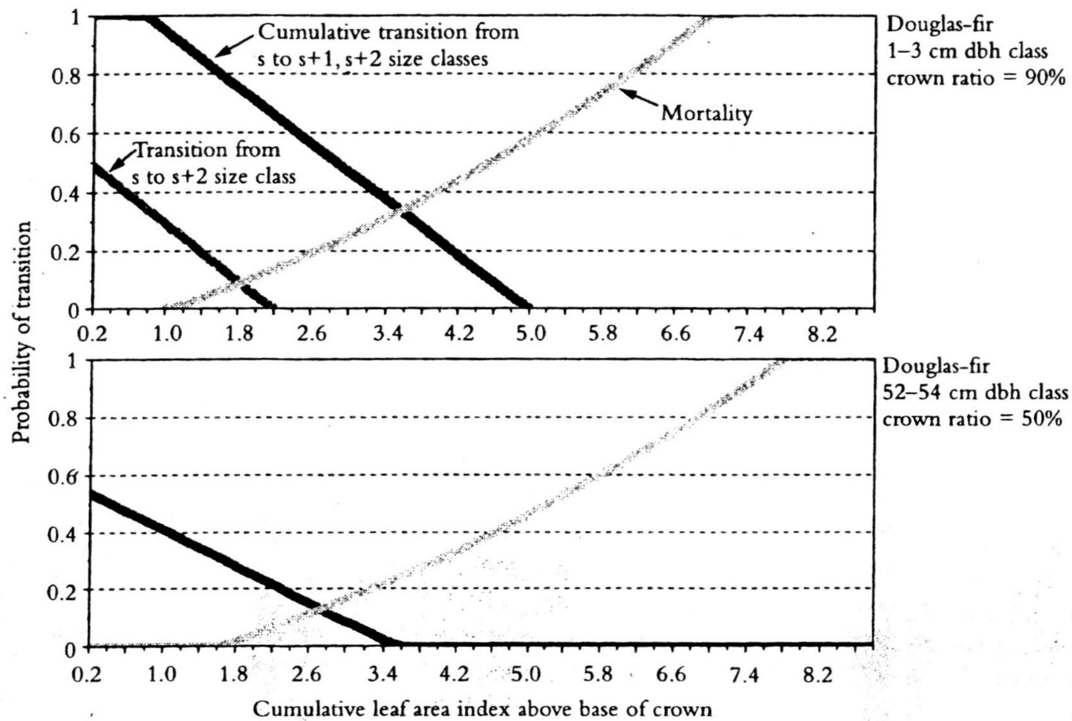
For a given environmental field, the modified gap model simulates annual diameter growth of a stem for a 5-year period, given an initial diameter, crown ratio, and cumulative leaf area above the base of the crown. Mortality and weather conditions are simulated as stochastic processes, thus annual variability of stem growth and mortality are taken into account. Because the model is stochastic, replicates are used to derive samples of potential growth and mortality. The weather information specified in the simulation essentially defines the environmental domain of the resulting transition functions. For a user-selected species, the gap model automatically simulates growth and mortality for stems over a broad range of diameters, crown ratios, and leaf area indices. The initial diameter, simulated 5-yr diameter increment, occurrence of mortality, initial crown ratio, and leaf area index are output for analysis. A post-processing program combines all replicates for a species and determines the initial 3-cm size class of a stem, the proportion of stems that grew into a larger size class and the corresponding 3-cm size interval, and the proportion of stems that died.

For each species, transition and mortality functions are derived from step-wise linear and non-linear regression analysis of the proportion tallies. Variables considered for inclusion in a model include first- and second-order terms of mid-point diameter, leaf area index, and crown ratio, and all possible two-way interactions (Fig. 4.9). Separate transition functions are derived for predicting advancement to one, two, and three size-classes, if necessary.

Illustrations

An initial prototype of the ZelStage model was implemented for a mid-elevation, ~3000-ha watershed in the Oregon Coast Range. Transition functions for the four dominant tree species (three conifer, one hardwood species) were developed to handle growth and mortality of stems <120 cm in diameter. Average environmental conditions of the watershed were used to generate a single set of transition functions. Vegetative cover types of the watershed were derived initially from

Fig. 4.9. Examples of transition functions predicting the growth and mortality of stems in the stage-structured model ZelStage. Functions are species- and size-specific, and are modified further by leaf area and crown ratio.



Landsat Thematic Mapper imagery. For simplicity, classes were aggregated into six cover types using a minimum mapping unit of 0.3-ha, for a final total of 1200 individual stands. An existing harvest unit map was used to designate 218 management units. Structure and composition of each stand type was initialized from representative field-plot data. Simulations were run over a 60-year period under a dispersed harvesting strategy (Wallin *et al.*, 1994), with 10%, 20% and 20% of the harvest units treated at years 1, 25, and 50, respectively. Stand treatments consisted of two levels of basal area removal (20%, 60%) with preference for larger stems. At year 60, stands were classified into hardwood, conifer, or mixed hardwood-conifer and saved as output cover-type maps.

The simulated landscapes illustrate the model's ability to simulate effects of overstory thinning (Fig. 4.10: see color section). Compared to the 20% removal, the 60% treatment resulted in an increase in mixed stands due to more favorable conditions for hardwood species (i.e., more light, less competition from conifer species). In general, these results corroborate current understanding of thinning effects in coastal watersheds, and lends credence to the ZelStage approach. In future applications, our intent is to develop and use transition probabilities for the suite of environmental conditions across watersheds in order to simulate gradient responses to forest management practices.

Discussion

Thus far the general approach of deriving landscape-scale models from a more detailed, fine-scale model has been illustrated. Three different models illustrate the approach, each emphasizing specific aspects of forest dynamics that might be important for particular applications. The models have complementary strengths and weaknesses. The automaton is especially appropriate for contagious processes or neighborhood interactions, and is extremely fast. This comes at the expense of rather crude representation of demographic processes, and consequently rather crude temporal dynamics. The semi-Markov model, in contrast, provides transient dynamics that rival those of the gap model, albeit for discrete patch types. An additional benefit of the Mosaic model is the inclusion of within-tile variability as represented by the frequency distribution of gap-scale elements; this approach is in marked contrast to most landscape-scale models, which assume homogeneity at the scale of the larger mosaic tile. Within this format, simpler versions lend the powerful summary and interpretative guide of analytic solutions, while more complex versions provide ever more realistic behaviors (at the cost of analytic simplicity). The stage-structured model retains nearly all of the information contained in the gap model, and thus is capable of reproducing gap-model behavior with striking fidelity yet in a computationally convenient form. The cost of this is the added burden of parameterizing the model, which must attend every size class for every species, each modified by various combinations of leaf area and crown ratio, and environmental conditions. For each model, there are challenging parameterzation problems that limit the practical applications of these models. Developing efficient algorithms for model parameterization will streamline this approach greatly.

Parameterization issues

The onus of parameterizing these models poses a compelling challenge to the meta-modeling approach. It should be emphasized that parameterization presents both statistical and computational challenges, the latter due to the sheer number of simulations involved. For this reason, we are actively pursuing methods to automate the parameterization of meta-models. There are, of course, issues that are specific to each of the model forms we have illustrated.

Automata are largely governed by the rules that bias cell fate according to neighboring cells, and the specification of the rule set still remains as much art as science. An issue particular to the Sierran study site is that a model with states defined as cover types (species) cannot easily simulate surface fires typical of this area (i.e., fires that burn through an area and leave the canopy intact). We are currently developing an automaton capable of simulating surface fires (Chang and Urban, 1997).

The parameterization of a semi-Markov model strictly requires a matrix of transition probabilities that are unbiased by the antecedent conditions of a patch type. In practice, the parameters we have derived may be influenced by preceding seral stages. A convenient parameterization entails a set of simulations in which each patch type is initialized by itself (i.e., a pure stand of a single type) and allowed to undergo transitions from that pure state (Ablan, 1997). This is a much more complicated parameterization scheme and we are currently improving the approach.

The stage-structured approach suffers numerical distractions stemming from the discretizing of continuous phenomena. These include cases where a tree might "grow through" more than one size class in a single timestep, an occurrence that must be attended in the regressions of transition functions. At the other extreme, stems can become "stuck" within very large size classes due to insufficient growth over the 5-year timestep. Employing variable size classes or time steps is a possible solution, but would complicate the model further. Similarly, ZelStage must be properly scaled to avoid transferring partial stems; the model works in integer trees. Thus, the minimum spatial resolution of the model is dictated by the stand area that will support sufficient tree densities to prevent partial stem transfers.

While more automated and robust approaches to many of these issues are pursued, there remains a set of issues that are general to all approaches to modeling landscapes. One especially compelling issue is that of model testing.

Testing landscape models

It comes as a tautology that models derived to simulate landscapes are difficult to test. After all, these models are developed, in part, because sufficient data to pursue empirical studies at these scales is lacked. Very little has been presented in the way of formal tests of the models illustrated here, which broaches a problematic issue in landscape modeling.

Landscape-scale data are typically available in the form of maps of vegetation or cover types, often classified from satellite imagery, air photos, and limited ground data. The vegetation map of Sequoia–Kings Canyon National Park (Fig. 4.4, right panel) is a typical example. Two points must be observed of this figure. First, there is only one image. This presents the logical difficulty of comparing the result of a stochastic simulation model to a real map which also can be considered to be a unique realization of a stochastic process (reality). Thus, even a "perfect" model should not be expected to reproduce the real map. The likelihood that this might happen by chance is vanishingly small, and decreases further if there are appreciable influences from initial conditions (which we probably do not know), or inertia or legacy effects due to events that happened long ago. Thus, a point-to-point comparison of model to data is largely futile. Likewise, in cases where there is another map of the real landscape, representing a later time period, one might be tempted to project the earlier map with the model and test it against the latter map. But, again, if there is considerable stochasticity to the real landscape, there is no particular reason to expect the prediction to match reality. One way to avoid this pitfall is to test the model at a higher level of abstraction than that of the maps themselves. For example, it is logical to compare the statistics of the model output with the statistics of the real map. Appropriate metrics might include any of the myriad metrics of landscape pattern (e.g., O'Neill *et al.*, 1988; McGarigal and Marks, 1995; Riitters *et al.*, 1995). Using this approach, one might assess the spatial processes in an automaton by comparing the spatial autocorrelation in model output to that observed in real maps. While these metrics are readily available and the tests are straightforward in concept, landscape modelers have been slow to develop appropriate tests for these models.

A second point to be made from Fig. 4.4 is that the vegetation cover is classified evolve toward each other. For example, we might add spatial neighborhood interactions to Mosaic, or seed dispersal to ZelStage; or more realistic transients might be eked from MetaFor by incorporating elements of the other two models. Thus far this line of model evolution has been avoided. Instead, ways to build meta-models more efficiently and more robustly have been focused on. This entails, for example, devising automated and more streamlined schemes for model definition and parameterization. This, in turn, will allow more ready building of a greater number of variations on the models themselves; a larger family of meta-models geared to particular applications. Recognizing that each such model has its own strengths and weaknesses, variety allows us to choose the simplest model that will address the application at hand.

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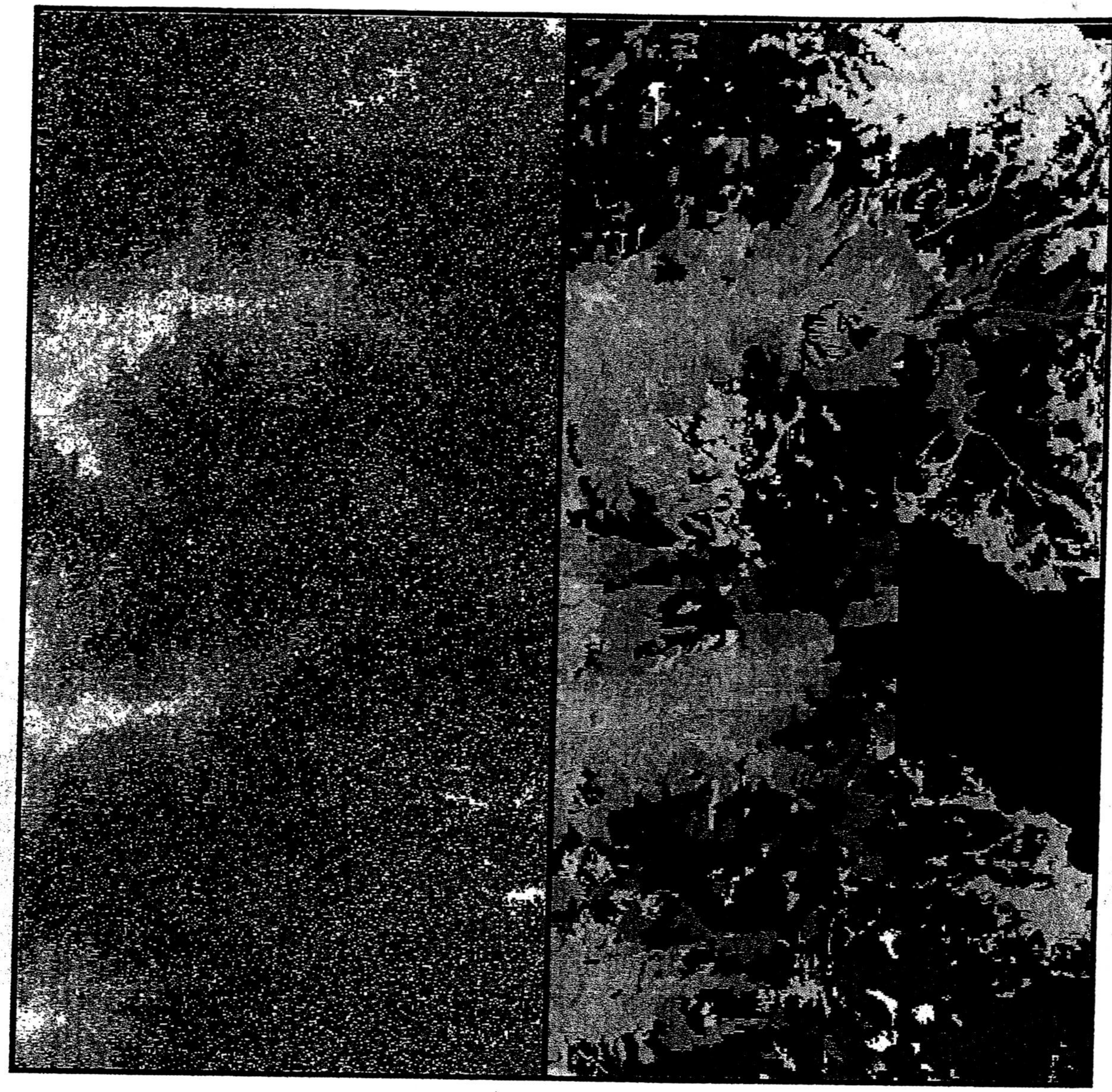


Fig. 4.4 Sample of Sequoia – Kings Canyon National Park as simulated at 30-m resolution by [illegible]

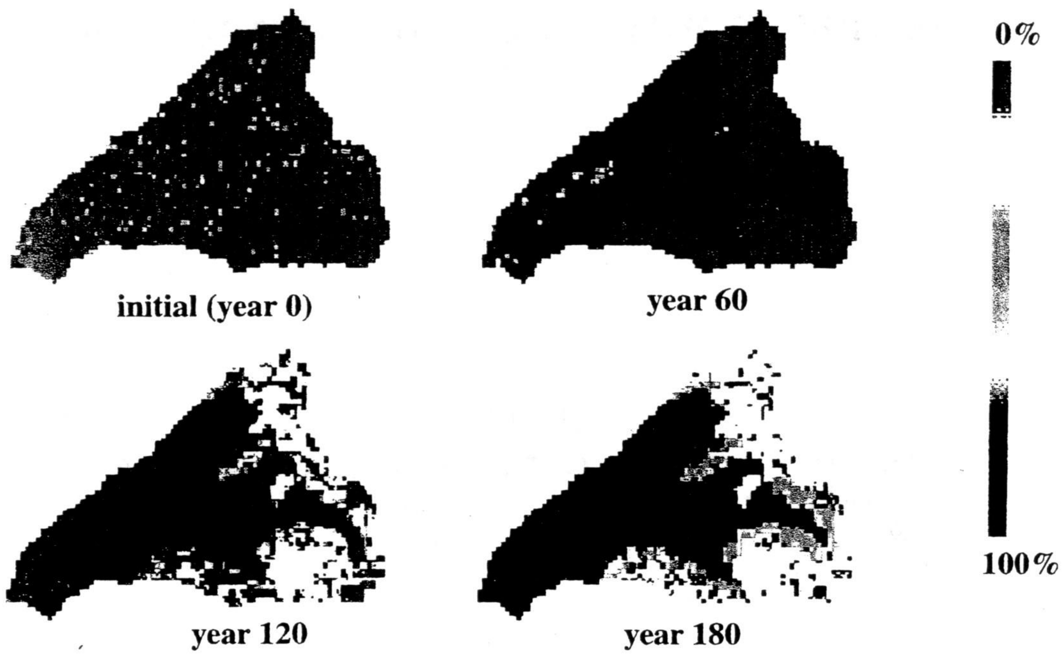
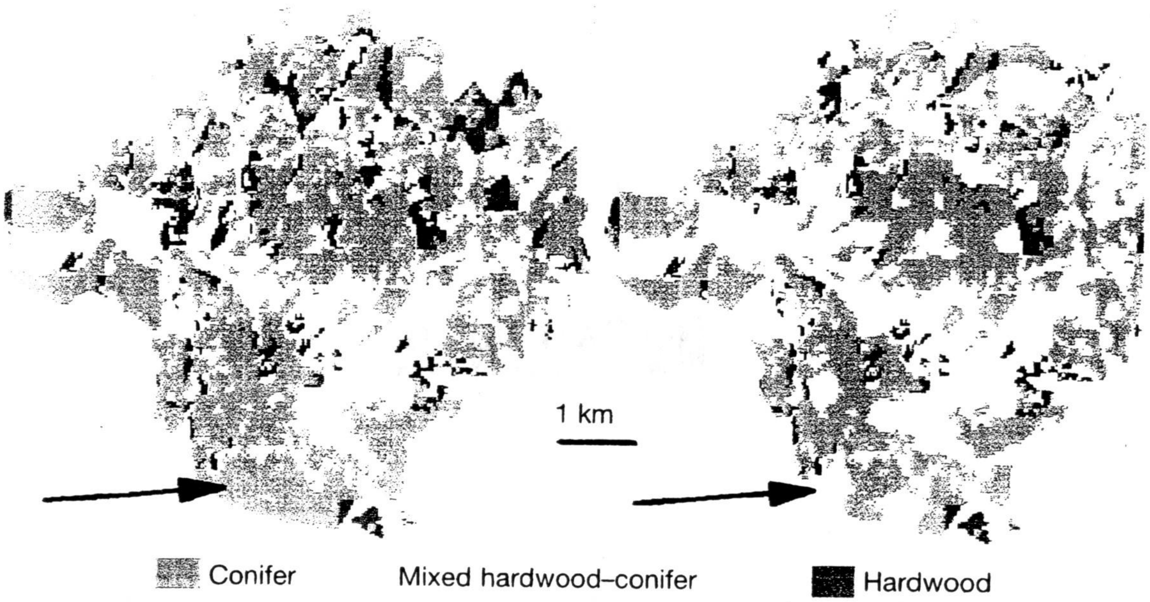


Fig. 4.7. Example simulations of the H.J. Andrews Forest, a ~6300-ha watershed in the central Cascades of Oregon, as simulated with the Mosaic model (from Ablan, 1997).

Fig. 4.10 Simulated conditions 60 years from the present, for the Horse Creek Watershed located in the central Oregon Coast Range. Ten, 20, and 20% of the harvest units were treated at years 1, 25, and 50, respectively, using a dispersed harvest strategy. Stand-level treatments consisted of removing 20% (left panel) or 60% (right) of the overstory basal area. Arrows indicate the tendency of different removal levels to favor conifers (left, at 20%) or hardwoods (right, at 60% removal).



Spatial modeling of forest landscape change: approaches and applications

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