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Forest landscape models: Definitions, characterization, and classification

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Abstract

Previous model classification efforts have led to a broad group of models from site-scale (non-spatial) gap models to continental-scale biogeographical models due to a lack of definition of landscape models. Such classifications become inefficient to compare approaches and techniques that are specifically associated with forest landscape modeling. This paper provides definitions of key terminologies commonly used in forest landscape modeling to classify forest landscape models. It presents a set of qualitative criteria for model classification. These criteria represent model definitions and key model implementation decisions, including the temporal resolution, number of spatial processes simulated, and approaches to simulate site-level succession. Four approaches of simulating site level succession are summarized: (1) no site-level succession (spatial processes as surrogates), (2) successional pathway, (3) vital attribute, and (4) model coupling. Computational load for the first three approaches is calculated using the Big O Notation, a standard method. Classification criteria are organized in a hierarchical order that creates a dichotomous tree with each end node representing a group of models with similar traits. The classified models fall into various groups ranging from theoretical and empirical to strategic and tactical. The paper summarizes the applications of forest landscape models into three categories: (1) spatiotemporal patterns of model objects, (2) sensitivities of model object to input parameters, and (3) scenario analyses. Finally, the paper discusses two dilemmas related to the use of forest landscape models: result validation and circular reasoning.

Keywords: Forest landscape models; Spatially explicit; Spatially interactive; Definitions; Model characterization; Model classification

1. Introduction

Scientists and managers face limitations conducting field experiments to assess large-scale, cumulative effects of forest management and disturbance when the temporal dimensions are long (e.g., 10^2–10^3 years) and the spatial extents are large (e.g., 10^3–10^6 ha). Temporally, some management effects are abrupt but long-lasting (10^1–10^3 years), often beyond the capacity of field observation, whereas other management effects may go undetected after a short period of time (<10 years). Spatially, when a study is expanded to the order of 10^3–10^6 ha, experimental studies become limited and additional complexities such as environmental heterogeneity and natural disturbances may further complicate the study. Thus, computer models become useful tools for landscape scale experiments (Mladenoff, 2004; Shifley et al., 2006). With modeling techniques, knowledge of physiological factors and their effects on the modeled processes and interactions within a particular system can be explicitly represented using mathematical equations and logical sequences. Those data can then be used in models to deduce results, especially at broad spatial and temporal scales, that cannot otherwise be investigated (Baker, 1993; Turner et al., 1995; Mladenoff and Baker, 1999; Urban, 2005).

Over the last 15 years, we have seen rapid development in the field of forest landscape modeling, fueled by both technological and theoretical advances. Forest landscape models have benefited greatly from technological advances, including increased computing capacity, the development of GIS, remote sensing, and software engineering. Ecological processes and their interactions in forest landscape models can be represented by well-designed computer software (He et al., 1999, 2002a). The core of landscape ecology provides a conceptual basis for forest landscape modeling from a theoretical perspective: the interaction of spatial patterns and ecological processes under various spatiotemporal scales, theories of disturbance, and equilibrium and non-equilibrium approaches to vegetation and

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ecosystems. The general background of forest landscape model developments has been reviewed by Sklar and Costanza (1990), Gardner et al. (1999), Mladenoff and Baker (1999), and recently by Mladenoff (2004).

Forest landscape models share common features, including: simulating (1) forest vegetation response at large spatial and temporal scales (e.g., in excess of 100,000 ha and 100 years) and (2) the outcomes of repeated, stochastic spatial processes (e.g., seed dispersal, fire, wind, insects, diseases, harvests, and fuel treatments). Depending on the model's purpose and design limitations, they may differ in the key ecological processes incorporated, the extent to which mechanistic details are simulated for each process, and the type and scope of applications.

Baker (1989) reviewed landscape models when they were to be developed. He provided definitions of whole, distributional (e.g., gap models and Markov chain models), and spatial landscape models that use location and configuration. Gardner et al. (1999) were the first to classify landscape models, particularly landscape fire simulation models. In their study, six broad model categories were identified: (1) theoretical, (2) exploratory, (3) physical, (4) probabilistic, (5) shape, and (6) statistical. The classified models in Gardner et al. (1999) exclusively belong to the spatial landscape model, according to Baker's definition. Gardner et al.'s classification is qualitative and criteria for each category were not given. However, the classification did summarize the techniques used to study relationships between forests and disturbances by fire, and it provided a framework for modelers to compare among landscape fire models and modeling techniques.

Keane et al. (2004) presented a comprehensive effort to quantitatively classify landscape fire succession models (LFSM), while also providing guidelines in model selection and interpreting differences for both modelers and users. They compared 44 models by ranking the degree of stochasticity, complexity, and the mechanisms for algorithms used in simulating fire ignition, fire spread, fire effects, and vegetation succession. The effort provided a quantitative basis, as compared to the Gardner et al. (1999) study, despite subjectively determining the degrees of stochasticity, complexity, and mechanism based on expert opinions. The classification was done using ordination techniques in three dimensions. It is difficult to qualitatively compare models since clear numeric distinctions among classes are not available with such a system. This problem is compensated by a second classification, constructed using keywords and results published for each model (Keane et al., 2004). The second classification is independent of the first one. It provides additional information that may be used to guide users and modelers in model selection. Perry and Enright (2006) classified landscape models into two general classes: analytical models and simulation models. Analytical models are mathematical models, such as regression-based models of landscape change. Simulation models are either large scale, spatially explicit landscape models (SELMs) or gap models. According to Baker (1989), SELMs are spatial landscape models and gap models are distributional landscape models. Perry and Enright (2006) discussed SELMs according to the complexity and mechanisms representing ecological processes, development, and applications. Unlike Keane et al. (2004), they did not use complexity and mechanisms to further classify SELMs.

Scheller and Mladenoff (2007) used three criteria to classify forest landscape models. They are (1) including/excluding spatial interactions, (2) static/dynamic communities, and (3) including/excluding ecosystem processes. Compared to the above efforts that generally provide grouping, or one level of classification, for landscape models, Scheller and Mladenoff's work led to a dichotomous classification. The classification criteria are strongly tilted towards selections of ecological processes at site-levels and landscape processes and key model design criteria (e.g., scale) are not considered. This leads to different kinds of models being classified into the same group. For example, LANDIS-II is a member of the LANDIS model family (Mladenoff and He, 1999; He et al., 1999). However, based on this classification, it is separated from LANDIS and classified into a group with FACET and FIRE-BGC. In fact, FIRE-BGC (Keane et al., 1996a) is not a single model. It uses FIRESUM, a gap model, and FARSITE, a mechanistic fire behavior model (Finney, 1998) to simulate fires at stochastic and fixed intervals. In the FIRE-BGC modeling framework, methods used to scale FIRESUM result in the simulated landscape not being spatially explicit. This treatment is very different from that of LANDIS and LANDIS II. FACET is a gap model that has improved ecological mechanisms and spatial interaction compared to the earlier JABOWA-FORET types of gap models. It considers interaction of directly neighboring plots when simulating seed dispersal (Urban et al., 1999), but it operates at much smaller extents (e.g., ~10 ha) than those (e.g., 10^3–10^6 ha) designed for LANDIS and LANDIS II.

Except Gardner et al. (1999) who focused on spatial landscape models, Keane et al. (2004) and Perry and Enright (2006) included both distributional and spatial landscape models in their classification. Scheller and Mladenoff (2007) included models from non-spatial gap models to biogeochemical models that operate at continental scales. This has made it difficult to focus on forest landscape models. It is apparent that the development of model classification frameworks is still evolving and it is becoming increasingly difficult to develop a framework that classifies all landscape models. Thus, a classification framework under a set of clearly defined terms for forest landscape models is needed.

It is therefore the objective of this paper to provide a framework of classifying and characterizing forest landscape models. Compared to previous studies, this classification has the following characteristics: (1) the classification criteria are selected based on the basic definitions of forest landscape models, and (2) the classification builds on previous studies in selecting criteria key to model design (e.g., complexity and mechanisms). I opted to use a set of qualitative criteria to classify forest landscape models in different groups. Each group is also characterized by these criteria and by doing so, generalizations can be made for each model group. The paper further summarizes the model applications in three general categories: (1) spatiotemporal patterns of model objects, (2) sensitivities of model objects to input parameters, and (3) scenario analyses. Finally, the paper discusses two dilemmas facing those using forest landscape models: result validation and circular reasoning. Forest landscape modeling is a rapidly evolving field. This work may provide a basis for model comparisons as well as help managers and researchers in model selection in their respective work.

2. Definitions

To facilitate the discussion in this paper, definitions and explanations of some key terms commonly used in forest landscape modeling are provided, followed by a brief review of the evolution of forest landscape models.

Model entity is the basic modeling unit. In spatial models, it is usually in the form of pixels, plots, or polygons, pertaining to certain spatial information. In a non-spatial model, it is in the form of modeling classes, such as vegetation types. For example, with the wildland fire behavior and fuel model, BEHAVE, a non-spatial model, a model entity is one of the 13 standard fuel models (types), which can spatially relate to the vegetation types in the study landscapes. The *model object* is the target being modeled, such as wildlife species, vegetation, fuel load, fire disturbance, wind, insect populations, diseases, and harvest. It is often interchangeable with a modeled process, which refers to the dynamics of the above model targets (He et al., 1999; Barrett, 2001). A model may have more than one model object, and each object has both general model parameters, which set the modeling premises, and its own set of parameters. Model parameters can be in the form of numeric values (e.g., probability or sizes), categorical types, or nominal classes. Model output variables are usually a different set of parameters from the model input parameters. From a modeling perspective, using model output parameters to check against model input parameters and the built-in model relationships (formulations) is a process called *result verification*. If model outputs meet the expectations, the built-in model relationships are validated. This process is also known as *model validation*. Result verification and model validation are sometimes not separated in a validation effort. Model validation ensures that the theories and assumptions underlying the model are correct, or at least justifiable. Model validation, however, is not equivalent to *result validation*, which requires independent data to check against the model-derived results (Rykeil, 1996).

"*Spatially explicit*" suggests that spatial reference to the coordinates of the modeling entities is required in modeling. Spatially explicit does not necessarily require direct use of geographic coordinates of the modeling entities. Many models (e.g., regression models of vegetation distribution) only require using spatial references to establish the relationships between model object*s* (e.g., tree species) and variables (e.g., environmental data). However, to use those relationships to make predictions for the model entities where no previous data exists, explicit coordinates (either geographic coordinates or relative pixel locations) are often required (Cajo and Braak, 1987). It is important to note that spatially explicit is not equivalent to spatially interactive (cf. Scheller and Mladenoff, 2007) in forest landscape models. *Spatially interactive* suggests that a simulated entity is a function of neighboring, or spatially related, entities. *Non-spatial processes* are processes that are spatially independent, such as tree growth, age increment, and longevity-caused mortality, which are usually modeled as spatially independent processes (e.g., Botkin et al., 1972; Shugart, 1984). *Spatial processes* are a set of spatially contagious processes, such as fire spread, windthrow, seed dispersal, insect outbreak, disease propagation, forest harvest, and fuel treatment. These occur in spaces often larger than the simulation plots and require a spatial context to simulate.

A *general definition of forest landscape model* is a model that predicts changes in spatial characteristics (distribution, shape, abundance, etc.) of model objects. Under this general definition, analytical models (cf. Perry and Enright, 2006) such as gradient-based, mathematic models that predict distributions of tree species are forest landscape models. These mathematical models, however, do not usually account for temporal dynamics, and they are not simulation models. *Simulation models* are models that derive the model objects of time t from the model objects of time $t-1$, thus explicitly considering temporal dynamics. Simulation models characteristically work in situations where model objects are affected by many variables and interactions between the variables and objects are complex. Thus, the way to derive model objects is through computer simulations using defined relationships that reflect current understanding of the model objects.

A *specific definition of a forest landscape model* is one that simulates spatiotemporal characteristics of at least one recurrent spatial process in a spatially interactive manner. Compared to the general definition, a forest landscape model under the specific definition has the following characteristics: (a) it is a simulation model, (b) it simulates one or more spatial processes repeatedly, and (c) it operates at a large spatial and temporal extent that is adequate to simulate the spatial process. The following discussion of forest landscape models will be based on this specific definition.

There are two general approaches in ecological modeling: physical approaches and empirical approaches. *Physical approaches* use mathematical equations to link the physical variables to the resulting phenomena deterministically. *Empirical approaches* synthesize the modeled processes using aggregated parameters generalized from physical parameters. Ecological models generally fall in two seemingly exclusive categories: deterministic models and stochastic models (Fig. 1). *Deterministic models* produce the same outcomes for each run, while *stochastic models* produce different outcomes for each run. Although both types of models are exclusive, stochastic models may often have deterministic components, and deterministic models may sometimes have stochastic components. In general, deterministic models are tactic and predictive, while stochastic models are strategic (Fig. 1).

3. Evolution of forest landscape models

Spatial modeling of forest types and tree species distribution can be traced back several decades (Press and Wilson, 1978;

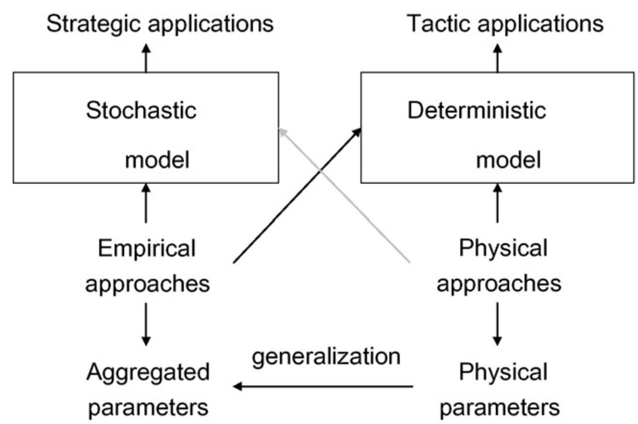

Fig. 1. Ecological models generally fall in two seemingly exclusive categories: deterministic models and stochastic models. Either category of model can use physical or empirical approaches or a combination of both. Physical approaches use mathematical equations to link the physical variables to the resulting phenomena deterministically. Empirical approaches synthesize the modeled processes using aggregated parameters generalized from physical parameters.

van de Rijt et al., 1996). It was not until the 1970s that computers were developed, making computer simulation possible. Forest stand dynamics models or gap models were the first generation computer simulation models. Gap models were largely developed during the 1970s and 1980s, although some modeling efforts were extended into the 1990s (e.g., Bugmann, 1996). Gap models use empirical relationships of tree species establishment, growth, competition, and mortality to model stand dynamics and are among the most effective tools for simulating stand composition and structural change at plot scales (Botkin et al., 1972; Shugart, 1984). The empirical relationships can be validated from observed or measured data. Some gap models require plot coordinates as a direct input while others do not. In either case, the results from the modeling entity (a plot) are often extrapolated to represent a much larger area in the landscape within which the plots are located. Since, theoretically, they can be applied to a set of plots that cover the entire landscape, gap models fall within the general definition of a forest landscape model.

During the late 1980s and 1990s, forest modeling was characterized by the development of ecosystem process models (Running and Gower, 1991; Rastetter et al., 1991; Aber and Federer, 1992). Differing from gap models, ecosystem process models do not track individual trees (but see Friend et al., 1993). Rather, they tend to use generalized physical approaches to model the mass and energy fluxes that control key ecological processes. Although ecological process models can be applied to a plot, many of these models, such as FOREST-BGC and PnET, are designed to operate on an array of plots using satellite imageries and GIS data sets as direct input. The simulation results can be assembled pixel by pixel for the whole simulated area. Thus, some ecosystem process models also fall within the general definition of forest landscape model.

Gradient-based models or analytical models (e.g., Iverson et al., 1999), gap models, and ecosystem process models are spatially explicit, but they are not spatially interactive in their simulations. They are also not equipped to simulate spatial processes (He and Mladenoff, 1999a).

Fire is a spatial process, and fire ignition, spread, and effects occur in a spatial context. Fire is an important component of forest landscape modeling. Fire behavior models that simulate fire growth using physical approaches have been a focus of many fire studies since 1970s (Rothermel, 1972, 1983; Albini, 1976; Burgan and Rothermel, 1984; Andrews, 1986; Finney, 1998, 2001). Rothermel (1972) pioneered the physical approaches of fire behavior modeling based on controlled, landscape-scale experiments. Findings from those experiments are often summarized as empirical equations (Fig. 1) that are programmed in non-spatial models, such as BEHAVE (Andrews, 1986; Andrews and Chase, 1989) and FVS-FFE (Beukema et al., 1999; Crookston et al., 1999). They are used to estimate key fire parameters, such as intensity, duration, flame length, and spread rate. In the mid-1990s, advances in mathematics and computing made it possible to mechanistically simulate wildfire growth in a spatial context. This is represented by a physical fire growth model, FARSITE, which integrates component models for surface fire, crown fire, fire acceleration, spotting, and fuel moisture (Finney, 1998, 2001). FARSITE was developed to make projections of fire growth patterns and rates under natural and anthropogenic conditions.

Physical fire growth models typically focus on a single event over the length of an individual fire, because a vegetation simulator that models post-fire vegetation response is not usually included in this these models. They are most suitable for predicting fire growth once an ignition occurs or is hypothesized. They are not designed to simulate the recurrence of fire disturbance or multiple fire events over long time spans, where stochastic approaches become important. The stochastic approaches use probabilities in combination with random number generators in simulating fire. They have evolved from the pioneering work of Heinselman (1973) in dating historical fires to derive boundaries by studying forest patch age distribution. That research showed that as a spatial process, fire regime (size, return interval, and intensity) can be successfully described through study at large temporal scales (10s–100s years) with probability distributions of fire size and frequency. The theories of fire frequency and probability summarized by Van Wagner (1978) and Johnson (1992) provide the basis for many later landscape fire models.

Since the 1990s, a new realm of forest landscape models has been developed that uses stochastic approaches to examine the relationship between fire regimes and landscape heterogeneity, as well as fire-affected landscape changes over time (Green, 1989; Baker et al., 1991; Turner et al., 1994; Keane et al., 1996a; Roberts, 1996; Gardner et al., 1996; Mladenoff et al., 1996; Urban et al., 1999; Mladenoff and He, 1999). These models are developed to simulate the repeated patterns of the spatial processes in a spatially interactive manner. They are suited to examine the long-term effects of spatial processes such as harvest, insect, disease, and wind disturbances. The new generation of landscape models tends to use empirical relationships to aggregate detailed dynamics in succession. However, the current trend has shown that physical details are increasingly being incorporated in these stochastic models (Li et al., 2005; Cary et al., 2006).

4. Classification and characterization of forest landscape models

4.1. Forest landscape models vs. other forest models

The criteria at and near the root level of the dichotomous tree reflects the specific definition of forest landscape models. The first criterion is similar to that proposed in Scheller and Mladenoff (2007). Models that are non-spatial and those that are spatially explicit but are not spatially interactive are separated from other forest landscape models (Fig. 2). This group includes a variety of forest models that are not the focus of this study, such as gap models, ecosystem process models, and analytical models. Fire behavior models, including BEHAVE (Andrews, 1986; Andrews and Chase, 1989; Andrews and Collin, 1999), fuel and crown consumption and smoke production models (CONSUM) (Ottmar et al., 1993), the Vegetation Dynamic Development Tool (VDDT) (Beukema et al., 2003), a fuel characteristic classification system (FCCS) (Ottmar et al., 2003), the fire regime condition class (FRCC) (Hardy et al., 2001; Schmidt et al., 2002), and FVE-FEE (Beukema et al., 1999; Reinhardt and Crookston, 2003) are also in this group.

The second criterion separates physical fire growth models (e.g., FARSITE) from the rest of the forest landscape models that simulate the recurrence of at least one spatial process. One may argue that fire growth models can also simulate recurrent fires. However, this is rarely true because post-fire vegetation response is usually not included in this type of model.

The remaining criteria are general but fundamental to model design, modeling approaches, and consequently the scope of model applications. Regardless of diverse model objects (individual species, vegetation types, fire, fuel, insect, disease, or harvest), landscape modelers make conscious efforts to (1) design landscape models that balance the integration of ecological processes across different spatial and temporal scales, (2) that are able to simulate large areas over long time spans, and (3) that operate within current and foreseeable computational capability. The most fundamental decisions they have to make include selection of model temporal scales, the number of spatial processes included, and the method of simulating site-level succession.

4.2. Temporal scales and temporal resolutions

Temporal scales here refer to temporal resolutions or model time steps, not temporal span or the number of iterations of model simulation. Simulating the recurrence of spatial processes implies using multiple iterations or long temporal spans for all forest landscape models. Temporal resolution is selected as a model classification criterion because it is usually related to the mechanistic details of modeling. The level of mechanisms has been considered in previous model classifications (Gardner et al., 1999; Keane et al., 2004; Perry and Enright, 2006).

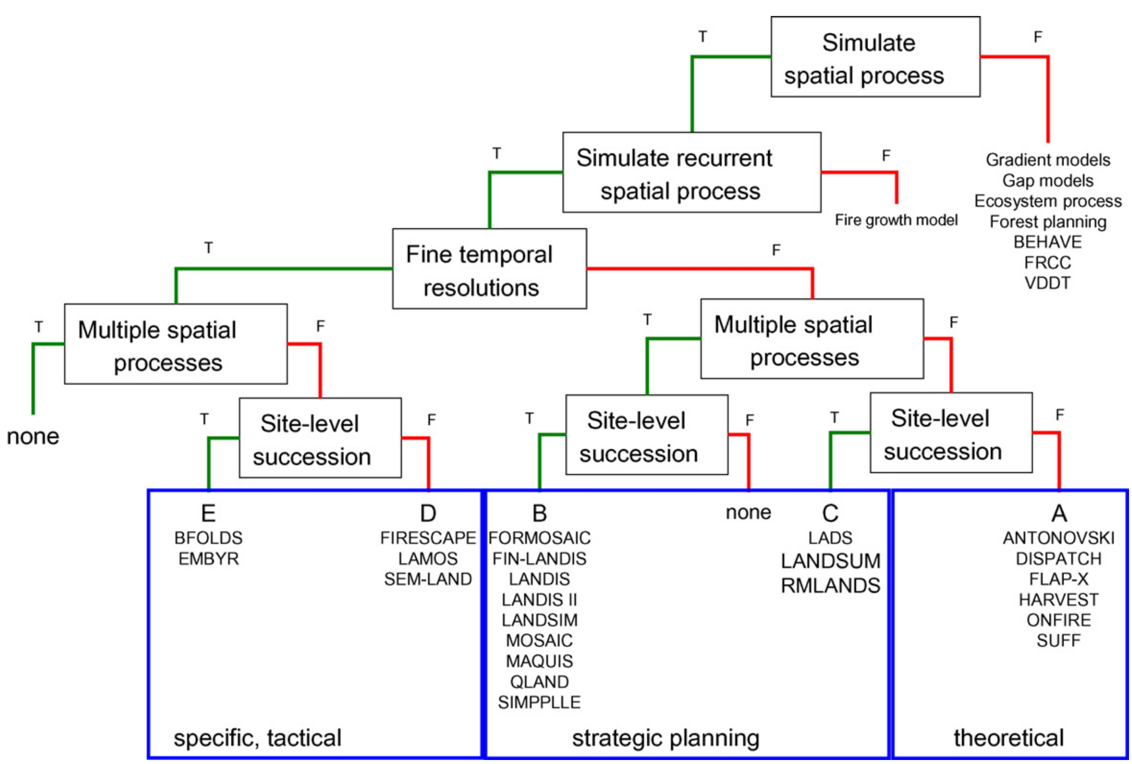

Fig. 2. A classification of forest landscape models using key characteristics. The figure shows that forest landscape models have been developed using diverse approaches. In general, fire temporal resolution models (groups D and E) are more suitable to tactical and specific objectives, coarse temporal resolution models (groups B and C) that simulate site-level succession are more suitable for strategic planning, and coarse temporal resolution models (group A) that do not simulate site-level succession are more suitable for theoretical studies.

Temporal resolutions for forest landscape models are not as obvious as spatial resolutions, which are explicit in raster models. The obvious temporal resolutions are those linked with model iterations, the simulated length of a time step, which is usually specified as a model parameter. Succession is often simulated via age increment over each model time step (e.g., by 1, 5, or 10 years) and is synchronized with model iteration. A landscape model can have multiple temporal resolutions, since there is usually more than one model object (process) simulated and each process may have its own temporal resolution. For example, fire spread is a process operating in the order of minutes to hours, while succession is often simulated using longer time steps. However, within a given model iteration, other model objects, such as fire spread, seed dispersal, and harvest, may often have unspecified temporal resolutions that are obviously finer than the model time step.

BFOLDS simulates vegetation change at 1-year time steps, but once fire ignition occurs, the model simulates fire spread on an hourly basis using the Canadian Forest Fire Behavior Prediction System (Yemshanov and Perera, 2002). FIRESCAPE operates at a daily time step that switches to hourly whenever fire ignites (Cary, 1998). For many forest landscape models, temporal resolutions that drive fire spread are not specified. For example, SEM-LAND operates at 1-year time steps that change to a much finer time step (unspecified) when simulating fire spread using daily weather data (Li et al., 2005; Li, 2000). LANDSUM operates at 1-year time steps for succession dynamics. It simulates fires using predefined fire sizes randomly drawn from the historical distribution. Thus, it is not necessary to specify a temporal resolution for its fire spread (Keane et al., 2002). Similarly, LANDIS 3.0 operates at 10-year time steps. It uses predefined fire sizes from historical distribution. Fire in LANDIS 3.0 spreads from the ignited pixel outward until the predefined fire size is met. Fire spread interacts with fuel (amount) and vegetation, which operate in decadal resolution. Thus, no temporal resolution for fire spread is specified (He and Mladenoff, 1999b). LANDIS 4.0 uses burning times to simulate fire spread based on FARSITE (Yang et al., 2004). Burning times and their standard deviations are derived from the historical fire data record and are in the order of hours; thus, the temporal resolutions for fire spread is in the order of hours or minutes. For some models, temporal resolution is a variable. For example, HARVEST simulates one time step per model run (Gustafson and Crow, 1994, 1996, 1999). The length of time represented by the model run is input by the user.

Temporal resolutions are usually determined at the model design stage. Once chosen, they may dictate the modeling approaches for each object. Fine temporal resolutions (e.g., in hours, days, seasons, or less than 1 year) entail choosing physical variables and using physical approaches in model simulations. Thus, the output parameters are mechanistically derived. A physical simulation of fire spread, for example, may involve using variables such as wind speed and intensity, terrain, and weather. The outcomes of such simulations may include fire frequency, size, and intensity. Coarse temporal resolutions (e.g., 1 year or larger) often entail using empirical approaches and generalized parameters in model simulation. In models of coarse temporal scales, fine scale processes are integrated across temporal scales not by simulating them physically but by representing them as aggregated spatial and temporal phenomena, such as predefined fire size or harvest allocation.

Increasingly, however, physical approaches are used in coarse temporal scale models and empirical approaches are used in fine temporal scale models. For example, LANDIS 4.0 simulates vegetation dynamics in 1 or 10-year time steps. However, a highly physical approach based on FARSITE is used to simulate fire growth. LANDSUM is a polygon-based model with relatively coarse spatial scales (resolutions), but it uses fine resolution rasters to simulate fire spread with greater physical details. On the other hand, empirical and stochastic treatments are sometimes needed in many models of fine temporal resolution. FIRESCAPE and BFOLDS, for example, use hourly weather data to simulate fire ignition and fire spread. Since instant weather data is not available, they need to be either generated using a computer program or drawn from historical weather data series, both involving empirical and stochastic treatments.

4.3. Single vs. multiple spatial processes

Many forest landscape models simulate one spatial process, typically fire (e.g., ONFIRE, Li et al., 1997, FIRESCAPE, Cary, 1998). The HARVEST model simulates the effects of timber harvest allocations as the only spatial process (Gustafson and Crow, 1994). Models that simulate multiple spatial processes include MOSAIC (Green, 1989), one of the earliest models, followed by LANDSIM (Roberts, 1996) and the models of the LANDIS family, including FIN-LANDIS (Pennanen and Kuuluvainen, 2002), QLAND (Pennanen et al., 2004), LANDIS 3.0 (Mladenoff and He, 1999; He et al., 1999), LANDIS-II (Scheller et al., 2007), and LANDIS 4.0 (He et al., 2005). LANDIS simulates fire, wind, harvest, insect, disease, and fuel treatment as spatial processes. It is a raster-based model, allowing multiple spatial processes to interact at cells where they overlap. SIMPPLLE also simulates multiple spatial processes, including fire, insect, disease, and harvest disturbances (Chew et al., 2004). It is a polygon-based model that uses the current state of each neighboring polygon to adjust the probability of insect and disease processes in the next time step. In SIMPPLLE, fire spreads from polygon to polygon within a time step, with fire spread influenced by vegetation, elevation, and suppression assumptions. LANDSUM also simulates fire, insect, disease, and processes. However, only fire is simulated as a spatial process while insects, diseases, and harvests are treated as non-spatial processes. FORMOSAIC is a model that simulates timber harvest, wind, and pig damage (similar to deer browsing) as spatial processes (Liu, 1998). It is a raster model, but within each cell FORMOSIAC also tracks the location of individual trees. This model is highly customized for tropical forests and plantations in Southeast Asia, but the design is quite unique.

4.4. Site-level succession and Big O notation

Site-level succession dynamics are vegetation dynamics at each model entity (cell or polygon). As discussed previously, stand dynamics models or gap models are best developed to simulate site-level dynamics. Spatial applications of gap models were of interest in many modeling efforts, such as FIRESUM (Keane et al., 1989), SORTIE (Pacala et al., 1996; Pacala and Hurtt, 1993), ZELIG (Urban and Shugart, 1992), FACET (Urban et al., 1999), and more recently, NORTHWDS (Bragg et al., 2004). These models have incorporated more spatial interaction than the earlier JABOWA-FORET types of gap models. FACET considers interaction of directly neighboring plots when simulating seed dispersal (Urban et al., 1999); SORTIE tracks individual tree locations and simulates seed dispersal using mean dispersal distances and seedling density defined for each species (Ribbens et al., 1994). But even with state-of-the-art computers, these models are limited to simulating relatively small sections of landscapes (e.g., <10 ha, Pacala et al., 1996; Caspersen et al., 1999) because the computational loads of forest landscape models follow the Big O Notation that measures the computational loads.

If Algorithm A is to be an order of $f(N)$, which is denoted as $O(f(N))$, $f(N)$ is called the algorithm's growth rate function. Because the notation uses the capital letter O to denote order, it is called Big O Notation. If a problem of size N requires time that is directly proportional to N, the problem is $O(N)$, that is, order N (Carrano, 1995), which increases exponentially with the N^2 relationship for landscape models, where N is the number of model entities (pixels or polygons). If a landscape model uses a gap model to simulate site-level dynamics, the computational load is n^4N^2, where n is the number of species (trees) tracked by the gap model, and n^4 represents the computational load for simulating growth, birth, mortality, establishment, competition and others simulated in the gap model. In general, the computation loads for spatial application of gap models are 2–5 orders of magnitude higher than the simplified approaches currently used in landscape models (discussed below). In other words, if a simulation takes 5 h to complete using a landscape model, it will take 500–5000 h to complete using a gap model embedded in a landscape model. Thus, to be able to simulate large areas using these models, spatially inexplicit scaling-up is needed (e.g., Keane et al., 1996b; Acevedo et al., 1996; Urban et al., 1999).

Most forest landscape models employ simplified approaches in simulating site-level succession on the premise that fine scale, site-level vegetation dynamics can be aggregated while modeled landscape-scale objects are relatively less affected (Rastetter et al., 1992). In forest landscape modeling, three simplified approaches are used in processing site-level succession dynamics: (1) using spatial process as surrogates, (2) using succession pathway approaches, and (3) using species' vital attribute approaches. Each approach represents a solution that reduces the computational load at site scales (Fig. 3). In this study, models are classified based on no site-level succession or simulating site-level classification. This reasonably sorts various models into similar groups. Thus, no attempt was made to further classify models based on approaches used to simulate site-level succession.

4.4.1. No site-level succession—spatial processes as surrogates

This approach does not explicitly simulate site-level succession. Rather, variables from simulated spatial processes are used as a surrogate for site-level succession dynamics. Time since last fire, for example, is a variable for many models that simulate landscape fire and fuel dynamics, is used to represent stand age in DISPATCH (Baker et al., 1991) and ONFIRE (Li et al., 1997) as well as the amount of fuel accumulated in FIRESCAPE (Cary, 1998). Time since last harvest is used to represent stand age in HARVEST (Gustafson and Crow, 1996), while the actual site-level succession is not simulated. These models are either highly conceptual (e.g., DISPATCH and HARVEST) or tend to work in the systems where spatial processes may override site-level succession dynamics. In many boreal forest ecosystems (Li et al., 1997), western coniferous forests in the U.S. (Romme and Despain, 1989), chaparral shrub lands in southern California (Franklin et al., 2005), and Eucalyptus ecosystems in Australia (Gott, 2005), fires tend to be stand leveling, for example, and once they occur, they can reset succession to the initial stage.

With site-level succession not simulated, the computational loads simply follow nN^2 where $n = 1$, since the site-level process is reduced to traverse each model entity to update disturbance history (e.g., time since last disturbance). Such a process requires only one operational step ($n = 1$) of computer processing. Computationally, this approach can be 5 orders of magnitude less than using gap models (Fig. 3).

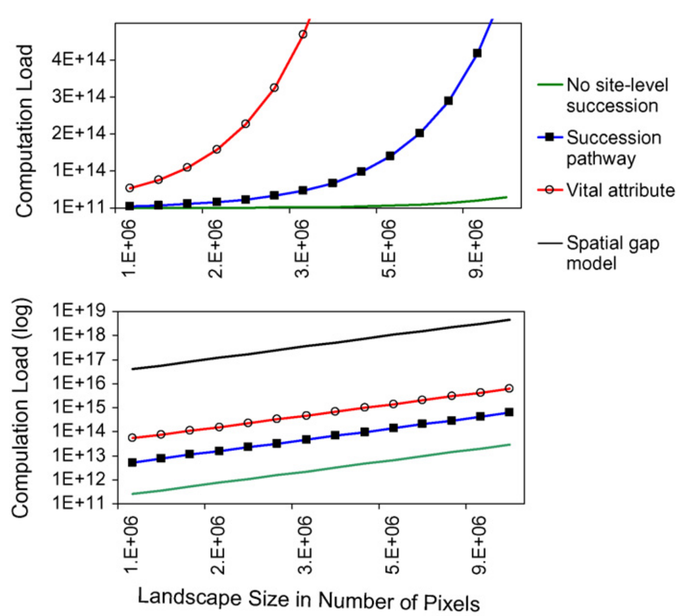

Fig. 3. Computational load estimated using Big O Notation for landscape models using no site-level succession, successional pathway, vital attribute, and spatial gap model approaches. In general, the computation loads for spatial application of gap models are 2–5 orders of magnitude higher than the simplified approaches currently used in landscape models.

4.4.2. Simulate site-level succession—succession pathway approaches

The succession pathway approaches use state-and-transition models to represent succession by linking vegetation types or development stages to the transition time. Along pathways, succession will ultimately reach a climax, or stable vegetation types. Succession pathway approaches are deterministic, but stochastic characteristics such as transition time and transition probability can be simulated using Markov modeling (e.g., Gardner et al., 1999; Hargrove et al., 2000). It is possible to incorporate a spatial process of different forms (e.g., fire with different intensities) or multiple spatial processes (e.g., fire, insect, disease, and harvesting) into succession pathways. Spatial processes can interact with the pathway by advancing or rewinding succession stages, and interactions between spatial processes and succession pathways are predefined and deterministic. Single pathway models are associated with one model object (spatial process), as in EMBYR (Gardner et al., 1996; Hargrove et al., 2000). In EMBYR, vegetation is interpreted as fuel types and updated per iteration via a predefined transition probability. Multiple pathway models are associated with multiple model objects, or with one model object with multiple forms, as in LANDSUM (Keane et al., 2002), SIMPPLLE (Chew et al., 2004), and LADS (Wimberly et al., 2000). In LANDSUM and LADS, fire can have multiple forms in terms of intensity, such as stand replacement fire (high severity) and non-lethal surface fire (low severity). Vegetation can have multiple predefined pathways under these fire severities. SIMPPLLE divides vegetation continua into a suitable number of states based on the knowledge available and the resolution needed to address management issues. It is assumed that the likelihood and intensity of disturbance processes can be associated with these discrete vegetation states based on the interaction of vegetation with fuel loads, life history characteristics, dispersal interactions, and resource availability. Each combination of dominant species, size-class/structure, and density by habitat type group that can represent an existing vegetation unit is identified as a potential vegetation state within SIMPPLLE.

The succession pathway approach is highly empirical, while the transition time and direction can often be quantified from extensive field work. Succession pathways can be as simple as vegetation development stages (e.g., seedling, sapling, young forest, and old forest) or as specific as major vegetation types of different seral stages, such as those developed by Keane et al. (2004) for mountain pine beetle.

The computational loads for forest landscape models that use succession pathways follow $nN + N^2$, where n is the number of pathways that need to be determined. Computationally, this approach can be 3–4 orders of magnitude less than using gap models to simplify site-level succession (Fig. 3).

4.4.3. Simulate site-level succession—vital attribute approaches

Vital attributes are defined as a set of autecological characteristics necessary to predict a species' behavior in environments of recurrent disturbance (Nobel and Slatyer, 1980). The vital attributes generally pertain to the means of species succession (longevity, sexual maturity, sprouting), competition (shade tolerance), dispersal, and tolerance to disturbance. They can be defined either for individual species or for species' functional groups. In vital attribute approaches, site-level succession is a competitive process driven by species' vital attributes, and the process is based on empirical rules (Roberts and Betz, 1999). The species' competitiveness is a function of that species' longevity, maturity, and seeding capability. Without disturbance, more shade tolerant species will out-compete less shade tolerant species to reach climax, a stable state. Species' vital attributes can also interact with disturbances. Post-species response is a competitive process driven by a combination of species' longevity, maturity, seeding capability, sprouting capability, and environmental adaptability. Roberts (1996) first implemented the vital attribute approach in LANDSIM, a polygon-based model. The approach is adopted by models of the LANDIS family (Mladenoff, 2004). Compared to succession pathway approaches, vital attributes approaches are more mechanistic, less deterministic, and require more computation (Fig. 3). They are more flexible in incorporating multiple species (e.g., 30 species) than succession pathway approaches, which typically define succession pathways for one or a few vegetation types. Another unique feature for models that use the vital attribute approach is that they can effectively simulate seed dispersal, a spatial process that is important in many systems (He and Mladenoff, 1999b). Of special note is a model developed by Perry and Enright (2002) that both uses succession pathways and also simulates seed dispersal.

With forest landscape models that do not simulate site-level succession, the computational loads simply follow $nmN + N^2$ where n is the number of species or functional types and m is the number of vital attributes involved. Computationally, this approach can be 3 orders of magnitude less than spatial applications of gap models (Fig. 3).

4.4.4. Simulate site-level succession—model coupling approaches

Bettinger et al. (2005) present a spatial modeling framework (LAMPS) for forest landscape planning in Oregon's Coast Range, USA. LAMPS simulates timber harvesting as the only spatial process on both private industrial and public lands. They used ORGANON, an individual tree-based growth and yield model or ZELIG, a gap model based on theoretical ecological relationships to simulate the dynamics of stand age and stand composition for site level succession. LAMPS groups pixels of similar terrain and vegetation into basic simulation units, which are aggregated into management units whose sizes are appropriate for logging systems. The management units can be further aggregated temporally for similar treatments, such as clear cutting and thinning. A finite number of stand conditions are simulated using ORGANON or ZELIG independently to serve as look-up tables for LAMPS. This model coupling approach presents a unique solution to simulate large landscapes (e.g., 5 million pixels) with stand-level information.

4.5. Syntheses

Forest landscape models have been developed using diverse approaches largely driven by the research or applications modelers have. In the dichotomy tree, this is represented by the fact that almost all end nodes contain a group of models. It is apparent from this classification that landscape models that operate at coarser temporal resolutions are largely separated in two groups, with group A simulating one spatial process and group B simulating multiple spatial processes (Fig. 3). Models that simulate multiple spatial processes (group B) always simulate site-level succession. Vegetations modeled at individual sites serve as the media with which multiple spatial processes interact, while some models directly simulate the interactions of spatial processes. In LANDIS 4.0, fire, wind, and harvest activities can affect both fine and coarse fuel loads, which in turn affect fire intensity once an ignition occurs (He et al., 2005). Models that simulate one spatial process (group A) usually do not simulate site-level succession, except for those in group C, which includes LANDSUM, RMLANDS[1], and LADS. LANDSUM requires site-level succession because it simulates fire and other landscape processes (harvest, insects, and disease). Group C models represent a unique approach that combines spatial and non-spatial simulation for multiple landscape processes. Currently, LADS only simulates fire. Without a major modeling intake, however, additional succession pathways can be defined to simulate the effects of other landscape processes, a fact which demonstrates the flexibility of succession pathway approaches.

The classification tree also illustrates that models of fine temporal resolutions usually simulate only one spatial process (Fig. 3). These models either simulate (e.g., BFOLDS and EMPYR in group E) or do not simulate (e.g., FIRESCAPE, LAMOS, and SEM-LAND in group D) site-level succession. Models that do not simulate site-level succession (group D) use variables of the spatial process (typically time since last fire) to substitute for vegetation stages. Models that simulate site-level succession can directly derive vegetation dynamics as a result of the interaction between fire and vegetation. LANDIS 4.0 simulates multiple spatial processes. However, only fire is currently simulated at fine temporal resolutions.

Group A includes some of the earliest landscape models, such as DISPATCH (Baker, 1991), HARVEST (Gustafson and Crow, 1996), and ONFIRE (Li et al., 1997). These models are theoretical and empirical (Gardner et al., 1999). They are designed for conceptual use and are generally not suitable for tactical forest management issues, nor for the specific characteristic of the single spatial process simulated. However, the models of group A provided exploratory examples for which later models were developed. The later models made improvements in the following aspects: (1) including site-level succession (e.g., groups B and C), (2) including multiple spatial processes (group B), or/and (3) including additional mechanistic details (groups D, E, and F). Compared to models in group A, models in groups B and C are strategic models. In other words, they are scenario models and suited to evaluate the effects of alternative forest management plans or other change scenarios. Many of them have been used to assist in the planning of national forests (Gustafson et al., 2004; Zollner et al., 2005; Bettinger et al., 2005; Shifley et al., 2006; Thompson et al., 2006). Groups D and E models are designed to address more specific needs. Compared to models in groups A–C, they are tactical. For example, SEM-LAND was used to investigate the response time of fire suppression (Li et al., 2005). FIRESCAPE was used to investigate the effects of the annual treatment level of prescribed[1] fires (King et al., 2006).

No forest landscape model is entirely deterministic because the recurrence of spatial processes involves stochasticity. Repeated fire patterns are largely affected by climate, for example, whereas fire ignition and fire spread are mainly affected by the local weather conditions, fuel, terrain, vegetation, and other factors. Forest harvesting involves policy shifts as well as forest conditions affected by natural disturbances, such as windthrow, fire, insects, and disease. Both spatial processes involve a great deal of uncertainty in simulation. However, all landscape models use both deterministic and physical approaches in certain aspects of their model simulations.

5. Applications of forest landscape models

There are numerous applications using forest landscape models, and these applications are strongly related to model design. Applications of forest landscape models generally fall in the three categories: (1) spatiotemporal patterns of model objects, (2) sensitivities of model object to input parameters, and (3) comparisons of model simulation scenarios.

5.1. The spatiotemporal patterns of spatial processes

The direct outputs of landscape models are the spatiotemporal patterns of the model objects because the modeled spatial processes are stochastic and complex, and understanding their manifestations over space and time is necessary. Thus, the most effective method is to simulate spatiotemporal patterns of the model objects using built-in model relationships and parameters related to the model objects. Predominant studies in this aspect involve deriving estimated fire frequency and fire cycle from simulated fire events, (Ratz, 1995; Li, 2002) as well as reconstructing historical and natural fire regimes (Li, 2000; Wimberly, 2002; Keane et al., 2003; Nonaka and Spies, 2005; Thompson et al., 2006). Gustafson and Crow (1999) simulated rules of forest harvest over space and time and their effects on resulting landscape patterns. Bettinger et al. (2005) simulated harvesting policies of private industrial and public forests on the capacity of landscape to provide a wide range of services and products. The results from these studies are often in the form of a spatial pattern of the model objects over long timeframes.

The spatiotemporal patterns of the simulated model object (often fire or harvest) are usually further inferred to derive

[1] http://www.umass.edu/landeco/research/rmlands/rmlands.html.

vegetation dynamics using empirical relationships for models with one model object. The inferred vegetation dynamics may include stand age, seral stages, and level of fuels accumulation. Therefore, the modeled results can be directly related to ecological and management issues that forest managers concern. Li and Barclay (2001) studied fire disturbance patterns and their correspondent forest age structure in one example; Boychuk and Perera (1997) modeled temporal variability of different fire disturbance regimes and derived forest age-classes for the boreal landscape at various spatial scales in another.

For forest landscape models that have more than one model object, vegetation dynamics are usually directly simulated using one of the four approaches discussed in previous sections. More complex results such as interactions between vegetation and the other model objects can be derived from these models. He and Mladenoff (1999b) examined how disturbance and species dynamics interact across a large heterogeneous landscape with multiple land types having different species environments and varied fire return intervals. They were able to reveal temporal recovery stages of individual tree species under equilibrium and non-equilibrium conditions. Their study showed that it may take several centuries for certain species to recover from past human activities to approach their landscape compositional equilibrium. Wimberly (2002) used a spatial model of wildfire and forest succession to simulate historical forest patterns. He identified the proportions of old-growth forest on this historical landscape, concluding that both small and large patches of old forest have important ecological roles in an Oregon Coast Range ecosystem and that management efforts should consider the implications of altering these historical patterns. Scheller and Mladenoff (2005) estimated the combined effects of climate change, wind and fire disturbances, as well as species migration on a regional forest using the LANDIS-II model. They showed that spatial processes are important in affecting the above ground, live biomass and species composition, as well as that migration will be significantly reduced because of limitations with species dispersal.

The simulated spatiotemporal patterns of model objects can be further used to derive results such as wildlife habitat suitability. Gustafson and Crow (1994) modeled the effects of harvesting on landscape structure; the simulated spatial patterns were further assessed for a generalized neotropical migrant forest bird using a GIS model. Akcakaya et al. (2004) observed that demographic (metapopulation) models did not incorporate the temporal variations of spatial pattern (habitat). They linked a landscape model to a metapopulation model and demonstrated the use of such model coupling efforts in assessing forest management options (Akcakaya et al., 2004). Larson et al. (2004) demonstrated the application of a population viability model that is linked to realistic landscape simulations using a GIS-based habitat suitability index (HIS) model. The habitat suitability is derived from a landscape model simulation. They showed that combining landscape, habitat, and viability models in a single analysis provides benefits beyond those of the individual modeling effort.

5.2. Sensitivities and uncertainties of spatial processes to input parameters

Methods like sensitivity analysis are commonly used to evaluate forest landscape models. These methods attempt to analyze model behavior by ranking the parameters according to their contribution to the response of model objects. Sensitivity analyses are particularly insightful, revealing the important factors that influence model objects. Cary et al. (2006) compared the sensitivity of simulated burned area to environmental factors – namely, terrain (flat, undulating, and mountainous), fuel pattern (finely and coarsely clumped), climate (observed, warmer and wetter, and warmer and drier), and weather (annual variability) – for four independently developed landscape fire succession models. Their results demonstrated that all four models are generally more sensitive to variations in climate and weather than to terrain complexity or fuel pattern. Schumacher and Bugmann (2006) investigated the relative importance of several drivers (climate, natural disturbance, and management) that influence forest landscape dynamics in the Swiss Alps. They concluded that the effects of climate change are likely to have major consequences for mountain forests in their study area. Syphard and Franklin (2004) studied the sensitivity of simulated disturbance (fire) and species composition to increased pixel sizes. They found that systematic effects of aggregation on pattern, process, and species response suggested that modelers can detect ranges of resolutions for which parameters hold, helping to identify appropriate levels of spatial generalization for their research.

Uncertainty analysis assesses uncertainties in the model output as the results of error propagation through the model from the input data and uncertainties in the model itself. Uncertainties embedded in model parameters are often related to measurement, observation, and synthesis and are subjective uncertainties. Uncertainties due to random algorithms built in the model are stochastic uncertainties. When uncertainties are larger for stochastic processes than subjective processes, it suggests that input model parameters play little role in model outcome. Xu et al. (2004, 2005) studied cell-level uncertainties in the LANDIS model. They found that cell-level uncertainties increased with simulation years and reached an equilibrium state where initial data inputs had no effect on model outputs. They also found that at landscape scales, species percent area and their spatial pattern were not substantially affected by cell-level uncertainties, indicating the importance of landscape legacies.

5.3. Scenario analyses

The lack of management experience with landscape scales and the limited feasibility of conducting landscape-scale experiments have resulted in increasing use of scenario modeling to analyze the effects of different management actions on focal forests and wildlife species. Model scenarios are created by altering input parameters to reflect changes in climate, disturbance, fuel and harvest alternatives. The built-in model relationships remain unchanged. Comparing results from different model scenarios provides relative measurements regarding the direction and magnitude of changes within the simulated landscape. Keane et al. (1999) simulated landscape patterns over 250 years under four scenarios for Glacier National Park, USA to study temporal patterns of ecosystem processes: (1) complete fire exclusion under current climate, (2) historical wildfire and current climate, (3) complete fire exclusion under a future climate, and (4) future wildfire and future climate. Their results show that fire influences landscape pattern metrics more than climate. He et al. (2002b) studied landscape change under forest harvesting and climate warming-induced fire disturbance. They used two simulation scenarios: (1) forest harvesting with current fire disturbance and (2) forest harvesting with increased fire disturbance under warming climates. They found that increased fire disturbance can accelerate the decline of shade-tolerant species and accelerate the northward migration of southern species. Also, they found that harvesting accelerates the decline of northern hardwood and boreal tree species. Nonaka and Spies (2005) used a stochastic fire simulation model to simulate pre-European settlement landscapes and quantify the historical range of variability (HRV) of landscape structures. They examined two alternative policy scenarios: (1) current management policies for 100 years into the future and (2) wildfire scenarios with no management. Their results showed that the current landscape was outside the HRV and did not return to the HRV in the 100 years under either scenario. Extensive forest harvesting and anthropogenic fires in the 20th century have severely altered on the landscape that could require centuries for recovery under wildfire scenarios. Wang et al. (2006) simulated the effects of reforestation on landscape burned by a large catastrophic fire in northeastern China. They included four reforestation intensities (the percentage of the landscape receiving tree plantation) in their modeling scenario and two spatial patterns of plantation (dispersed vs. aggregated planting). They found that 30% planting intensity with a dispersed planting method is most effective for forest recovery in that region.

Scenario analysis can also be coupled with a factorial design of simulation experiments (e.g., Sturtevant et al., 2004; Wang et al., 2006; Cary et al., 2006; Yang et al., 2007). Each simulation scenario represents an experiment that is independently simulated with an adequate number of replicates. The results of each experiment can be statistically analyzed using the response variables in a multivariate analysis of variance (MANOVA) to test the global null hypothesis that the alternative scenarios do not influence the mean value of each response variable. Pillai's Trace statistic can be used to test hypotheses because it is relatively insensitive to the heterogeneity of variance assumption in MANOVA (Zollner et al., 2005). In addition, the response variables can be decomposed into separate ANOVAs to examine each response variable's sensitivity to the alternative scenarios. Finally, the ANOVAs can be rerun so that Ryan–Einot–Gabriel–Welsch multiple range tests can be used to conduct multiple comparisons and examine the relative ranks of the scenario for each response variable (e.g., Zollner et al., 2005; Sturtevant et al., 2004).

6. Challenges of forest landscape models

There are two dilemmas facing those using forest landscape models: result validation and circular reasoning. Results of forest landscape models are the time series of model objects across space. Result validation in the traditional sense involves using independent data at a given time and space to check against model predictions for that time and space. If the checked results are valid, the results of continuing predictions bear the validity. Under no circumstance can all time series data from a forest landscape model simulation be validated in the traditional sense. If the entire time series could be validated, there would be no need for forest landscape models.

The dilemma regarding result validation of forest landscape models is that independent time series data across time and space is not available. Each real landscape is non-replicable and unique in nature. This difficulty renders the traditional model validation approach inapplicable to landscape models. Thus, for forest landscape models, result validations may involve the three following approaches. First, results from different simulation scenarios are compared, as suggested in Rykeil (1996). Such comparisons reveal the magnitude and direction of change, which can provide a degree of assurance regarding the correctness of the model results. Second, simulated results can be compared with those simulated from other independently developed models. This approach is used less often, since it requires expertise and efforts to understand and use other models, but findings from this approach are often rewarding (see Cary et al., 2006; Yang et al., 2007). Third, results can be qualitatively or semi-quantitatively compared with those from long-term landscape scale experiments or empirical knowledge that is based on ecological principles. The third approach is by far the most widely used for result validation in forest landscape modeling (e.g., He et al., 2002c, 2005).

In forest landscape modeling there are anticipated results and emergent results. The anticipated results are those expected through the predefined built-in model formulations (relationships). The emergent results are those not anticipated and emerge through the simulations of the interactions of complex relationships in the models. It is often difficult to separate expected results from emergent results. A caution against circular reasoning is the caveat often encountered in this situation, where researchers discuss biological or environmental forcing (causes) of their modeled results, whereas the forcing (causes) is actually built in the model formulation to derive such results. It should be pointed out that most model simulations do not lead to new understanding of the modeled processes themselves. The primary and subsequent results simply reflect the relationships used in building the models, which in turn reflect current understanding of the processes. The findings of these models are simply the spatiotemporal variations of the spatial process (discussed in Section 5.1), not the mechanisms that drive the potential changes of the spatial process. Emergent results are generally those resulted from the interactions and feedbacks of model objects.

Future development of forest landscape modeling is likely to be in the following areas. (1) Model development will move from the foci of theoretical and exploratory purposes to the foci of strategic and tactical purposes with increasing model realism, responding to the needs of forest management and planning. (2) Multiple spatial and temporal resolutions will be implemented for different processes as have been shown in LANDIS modeling family (Scheller et al., 2007; Syphard et al., 2007). (3) Standardized module components may emerge as handy utilities that are ready to be plugged into other models. Since component-based models provide non-developers or end users with access to model components, a component-based model can be more rigorously tested, evaluated, and modified than before, and thus, model development processes can be driven not solely by original developers, but by the broader scientific community (He et al., 2002a). (4) Synchronization of multiple ecological processes can be made possible with multiple computer processors. This will help deal with the limitation that ecological processes are simulated in a sequential order as determined by the executable program. (5) Model memorization will be improved so that a forest landscape model not only memorizes vegetation, disturbance, and management status at the current and previous model iteration, but also the entire temporal sequence. This would allow more effective studies of legacies of forested landscapes responding to various disturbance and management activities.

7. Conclusions

Model classification criteria in this study are as arbitrary as in previous classification studies. For this classification, I used temporal resolution rather than spatial resolution as a model classification criterion. One may argue that spatial resolution may be more important than temporal resolution. This argument is valid since, for example, a 200 m resolution can create much different results than a 30 m resolution in a model application. Many forest landscape models can accept a range of spatial resolutions. The common range is from 30 to 200 m (e.g., Keane et al., 2002; He et al., 2005; Li et al., 2005; Thompson et al., 2006). Spatial resolution equal to or larger than 500 m (in some cases 1 km) is usually used in biogeographical or biogeochemical models, which are designed to simulate at continental scales and is not suited for landscape processes. Spatial resolution is generally related to input data for landscape models whereas temporal resolution is related to model design, which is more fundamental than input data.

There is no perfect classification of forest landscape models. The classification presented in this study is not based on applications in which models of fire and harvest may be classified into different groups. Rather, the classification is based on scientific definitions of forest landscape models and criteria key to model design. One group of models often bears the characteristics of another group. A model classified in the specific, tactical category can be considered theoretical depending on applications and purposes, and vice versa. Forest landscape modeling is a rapidly developing field. Model classification will continue to evolve with new development and applications.

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