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Landscape Modeling☆

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Glossary

Disturbances A disturbance is a relatively discrete event that results in mortality of plants or animals or an event that is uncharacteristically intense or long-lasting. Wildfire, tornados, and logging are disturbances that are generally stochastic in location and time. Floods or extended dry periods (droughts) are considered disturbances if they are unusually large or intense.

Endogenous process An endogenous process emerges from the biotic and abiotic interactions internal to the system of interest. Examples include vegetation growth and succession, dispersal of organisms within a landscape, and topographic influences on microclimate. Some human activities may be considered endogenous, for example, various crop rotation systems, if they are well established and responsive to local needs.

Exogenous process An exogenous process is external to the system of interest. For landscapes, exogenous processes would include climate change or species migration into the landscape. Human activities may be considered exogenous if they are novel, permanent (eg, housing development), or are driven by external forces (eg, the world market for timber).

Geographic information system A Geographic Information System (GIS) is a computational system for storing, managing, manipulating, and displaying spatial data. Because landscape models are inherently spatial, strong links to GIS are either built into such models or are required to interface with the model input and output data. There are many GIS, free and commercial, available for use with landscape models.

Resolution The resolution of the information represented within a landscape model has three primary components: spatial, temporal, and taxonomic. Spatial resolution refers to the smallest unit size or area represented (synonymous with "grain"). For vector data, resolution is the minimum mapping unit. For raster data, it is the cell size. Temporal resolution refers to the frequency at which various social or ecological processes operate. Common examples include hourly, daily, monthly, annually. Taxonomic resolution is the degree of aggregation of species information. The smallest unit is typically species-specific information although ecotypes and populations have been used. Taxonomic aggregations typically used in landscape modeling include species, functional groups, potential vegetation types, and successional states.

Scenario A scenario is a finite suite of assumptions regarding future drivers of landscape change that are subsequently fed into a landscape model or models. The list of assumptions often includes future climate(s), future disturbance regimes, and future management or land use policies. Multiple scenarios can be created to form a full factorial matrix that highlights experimentation and statistical rigor. Alternatively, fewer scenarios can be assembled into central "story lines" that highlight key management or policy options.

Stochastic process A stochastic process has one or more simulated events or rates whose values are derived in part from a probability distribution function (eg, Gaussian, Weibull, exponential, uniform random, etc.). Therefore, such events or rates are not "deterministic," rather they are constrained but unpredictable. Examples of simulated stochastic processes include the location of lightning strikes, daily maximum temperature, wind speeds, etc.

I Introduction

A sufficient understanding of the threats to biodiversity and the opportunities to preserve or enhance biodiversity requires an acknowledgment of the broader context within which the various components of biodiversity operate. Over the past several

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decades, managers have realized that consideration of only small watersheds or forest stands is not sufficient to maintain biodiversity (Hansson and Angelstam, 1991; White *et al.*, 1997; Foley *et al.*, 2005; Fischer and Lindenmayer, 2007; Lindenmayer *et al.*, 2008). Insufficient attention to the broader context within which biodiversity operates can lead to population decline, local extirpation, or catastrophic disruption due to uncharacteristic disturbances (den Boer, 1981; Tilman *et al.*, 1994; Huxel and Hastings, 1999; Brashares, 2010; Spencer *et al.*, 2011). This broader context can be considered the "functional landscape": an area large enough to capture all of those processes that maintain or reduce biodiversity and large enough to provide sufficient habitat for viable populations. A functional landscape is typically smaller than a biome and several times larger than the maximum disturbance size (Baker, 1989a; Dunning *et al.*, 1992; Turner *et al.*, 1993, 1995; Forman, 1995).

Functional landscapes ("landscapes" henceforth) are an intuitive unit for studying and managing biodiversity. By encompassing most of the processes influencing biodiversity, landscapes afford the opportunity to practice inclusionary management that is more holistic and considerate of all relevant processes and elements (the individual components of a landscape, eg, forest patches, stream corridors, grass or shrub fields, etc.). However, landscapes pose distinct challenges for ecologists and managers. Because of their size, they are inherently non-replicable (Hurlbert, 1984) and significant change at the landscape-scale typically occurs over many decades: changes to species composition, structure, or function emerge more slowly when averaged across large numbers of each landscape element. Such large sizes and long durations are not commensurate with experimentation to determine the optimal management approach. For management, these concerns are particularly acute because trends occurring at a landscape-scale are often difficult and expensive to reverse through restoration efforts. Borrowing a business aphorism, changing course at the landscape-scale is akin to turning a cargo ship around: it happens slowly at best. And managers are responsible for ensuring that an ecosystem does not run into the shoals of lost biodiversity or reduced ecosystem functioning.

Due to these spatial and temporal challenges, scientists and managers increasingly rely on landscape models to understand and project landscape change and its consequences for biodiversity. A landscape model is a mathematical and logical representation of a functional landscape that includes the subset of exogenous and endogenous processes necessary to explain coarse-scale spatial and temporal variability. A typical landscape model will include a representation of vegetative change (techniques for doing so described below) and one or more stochastic disturbances. The types of disturbances depend on the landscape: wildfire, forest management, flooding, landslides, drought can all be considered stochastic disturbances: they are not "deterministic," rather they are constrained but unpredictable. As with all models, a foundation of empirical data is necessary to derive the mathematical and logical abstractions of the real system.

Landscape models differ from other ecological models in that they are spatially explicit, depicting the composition, arrangement, and geographic location of the various landscape elements. In practice, this means that they are dependent upon sufficient spatial information. Model results are often provided via maps of species or biodiversity or other conditions of interest, allowing an intuitive assessment of spatial variation. Maps or other visual representations (eg, animations or virtual environments) are particularly valuable for communicating landscape change (although accompanying maps of model uncertainty are seldom provided).

Landscape models also typically include spatial processes. Spatial processes facilitate the lateral transfer of information, matter, or energy (Reiners and Driese, 2001). Movement of matter and energy includes the lateral transport of water and dissolved nutrients. The transfer of matter and energy may also be generated through disturbances. Wildfire is an archetypal spatial process because it is releasing and transferring energy and the size and duration of wildfire is highly dependent upon the spatial configuration of fuels and topography (Hargrove *et al.*, 2000; Finney *et al.*, 2007; Sturtevant *et al.*, 2009). The lateral transfer of information is synonymous with shifting species distributions and communities; information is transferred across the landscape through dispersal and migration. Similar to wildfire, dispersal is often highly dependent upon landscape configuration and fragmentation (Miller *et al.*, 1997; King and With, 2002; Higgins *et al.*, 2003b; Iverson *et al.*, 2004; Scheller and Mladenoff, 2008). Without spatial processes and interactions – or if these interactions are weak – landscape models could be reduced to a collection of individual units (eg, patches) and these units could be multiplied by their representative area. Further consideration of when spatial processes are necessary is provided below.

By representing the dominant processes at a scale relevant to understanding and managing biodiversity, and representing the spatial configuration and interactions across a landscape, landscape models allow empirically-derived knowledge to be extrapolated to larger spatial and temporal domains. Doing so, we can begin to engage in meaningful *ecological forecasting* (Clark *et al.*, 2001), providing managers and policy makers tools for enhanced decision-making that incorporates knowledge about the future, however limited (Pielke, 2003).

Landscape models are frequently paired with scenarios. Scenarios can be relatively simple narratives about future policies or conditions, for example, the Millennium Ecosystem Assessment (2005). Scenarios can also be framed within an experimental design with multiple factors along one or more gradients (eg, three levels of fire rotation period × three levels of harvest intensity in a full factorial design) (Thompson *et al.*, 2012). Each individual scenario is then used to project landscape change given the associated suite of assumptions about the frequency and intensity of the constituent processes (Carpenter, 2000). Typically, the results from each scenario are then compared against each other and with empirical data when available (more about validation later). By comparing results among scenarios, the need for absolute accuracy is reduced as the *relative* merits of different policies or assumptions can still be assessed (eg, Creutzburg *et al.*, 2016).

While serving the purpose of extrapolating knowledge to larger spatial and temporal domains and forecasting change, landscape models also enable a synthesis of knowledge that is otherwise impossible. As knowledge about biodiversity expands and the threats to biodiversity multiply, the requisite number of processes that must be integrated and managed to preserve biodiversity has grown quickly. Forested landscapes are complex adaptive systems as there are feedbacks among species and among human and natural components (Messier *et al.*, 2015). However, the human capacity to synthesize the effects of many processes, each operating at unique and often disparate scales, is limited. Landscape models allow the representation of many different processes operating within and interacting across a landscape. Novel patterns will emerge ("emergent behaviors") that could not be anticipated using studies of isolated processes or intuition alone (Gustafson, 2013).

Because landscape models incorporate multiple stochastic and spatial processes, they are also well suited for partitioning the total uncertainty of a landscape projection into its components: parameter, model, and inherent uncertainty (Haag and Kaupenjohann, 2001; Higgins *et al.*, 2003a; Millar *et al.*, 2007). Parameter and model uncertainty are artifacts of the modeling process and represent the current limits of knowledge about the system. Inherent uncertainty is the accumulated effects of all remaining non-deterministic variation. For example, seed dispersal has significant inherent uncertainty as we can never know exactly how far an individual seed may travel. The exact time and location of lightning that ignites a fire is similarly unknowable. Inherent uncertainty may seem to deflate ambitions for ever increasing model accuracy. Nevertheless, even if the accuracy of a given model projection is weak or unknown (as is the case for all projections of the deeper future), knowledge about the sources of uncertainty (eg, Allen *et al.*, 2000; Xu *et al.*, 2009) can be extremely valuable to the management of biodiversity. If a system has relatively low inherent uncertainty, management for biodiversity will be relatively more effective. If the opposite is true, caution is warranted before investing considerable resources into attempts at guiding landscape change.

Finally, landscape models also provide an important heuristic function. The process of formulating, parameterizing, calibrating, and validating a landscape model requires the synthesis of multiple sources of data and models (eg, data assimilation, sensu Luo *et al.*, 2011). A landscape model typically requires vast quantities of data that are processed in advance of conducting any simulations. For example, even the simplest landscape model requires remotely sensed data that are classified to a spatial and taxonomic resolution that are congruent with the questions at hand. More complex landscape models may require additional edaphic or topographic data or more detailed taxonomic data. In addition, formulating how the various processes will interact across space and time requires a deep understanding of the ecology of the system (landscape modeling efforts generally involves teams of scientists). Existing representations of processes may need to be altered or discarded if they were developed for a scale substantially different from the other model components. Validation requires more data still and is difficult or impossible to obtain for long-term projections. In total, the modeling process is dominated by data synthesis and analysis with a relatively small amount of time devoted to actual simulations.

II Landscape Modeling Approaches

When is a landscape model useful or necessary? Landscape models are useful and necessary when the representation of exogenous and endogenous processes, represented within a geographic context and with spatial interaction among landscape elements, is required to project change and manage landscapes for biodiversity. These are also the criteria I used to select modeling approaches for review. There is an incredible diversity of landscape models, more than can be summarized here. These models span broad gradients of complexity, specificity, usability, and application. Many excellent reviews have been written summarizing the past and current state of landscape models (Baker, 1989b; Mladenoff and Baker, 1999; Keane *et al.*, 2004; Scheller and Mladenoff, 2007; Seidl *et al.*, 2011). More information about the mechanics of developing landscape models is also widely available (Maxwell and Costanza, 1997; Scheller *et al.*, 2010). Rather than an exhaustive and complete list, I instead focus on four of the most common approaches to formulating landscape models: state-and-transition models, process models, hybrid models and multi-modeling. I will highlight their respective strengths and limitations and the appropriate domain of application for each.

Ideally, a model is no more complex than necessary to answer the given question. Given the enormous additional complexity introduced by the inclusion of spatial processes (Shugart Jr., 1998; Strayer *et al.*, 2003), it is critical to decide when spatial processes – and therefore the need for a landscape model at all – is justified. All ecosystems contain spatial interactions. The question is whether the policy, management, or ecological question can be answered with a simpler non-spatial model or whether the additional complexity is necessary. There are no absolute answers, however, general criteria can be outlined based on the strength of spatial interactions at the chosen model resolution and extent (Strayer *et al.*, 2003). If a spatial process is occurring at a resolution much finer than model resolution, the process is often considered "noise" that can be safely averaged without loss of important information. For example, when modeling the effects of climate change on terrestrial systems at regional or continental systems (eg, Medvigy *et al.*, 2010; the inclusion of the effects of competition among neighboring trees or fine-scale seed dispersal would be unlikely to reduce uncertainty over the near term (<20 years). Inclusion of the effects of tree species migration via dispersal may, however, be required if substantial range shifts are expected over longer durations. Similarly, if a spatial process naturally occurs across extents far greater than the focal extent, the process can be represented as a simple rate with change through time. For regional landscapes (or smaller), climate is often treated in this fashion even though we recognize that weather can he highly localized.

Table 1 Four general landscape modeling approaches, example questions, and strengths and weaknesses

Model approach	*Example question*	*Strengths*	*Weaknesses*
State-and-transition	How will the relative abundance of early seral forest change given increased logging	Relatively straightforward logic; easier to parameterize; simplification facilitates collaboration; reduced computational requirements	Less flexible responses to novel climates, introduced species, altered disturbance regimes; non-stationary landscape dynamics poorly represented
Process	How will net biome production change if wildfire increases with climate change?	Highly flexible; ability to represent non-stationary landscape dynamics; can represent changing ecosystem process rates	Steep parameterization requirements; requires specialized knowledge and therefore less suitable for stakeholder engagement; high computational requirements
Neutral	Are patch size location, or shape important determinants of population migration?	Assess strength of individual processes; location neutral and not context dependent; testing of multiple landscape configurations	The results are more abstract; artificiality may render results less applicable to actual threats to biodiversity; lack of place-based output maps reduce stakeholder engagement
Hybrid or multi-modeling	Do landscape-scale fire dynamics influence carnivore population viability?	Integration of multiple domains (eg, forests and animal metapopulations); integration across broader range of spatial and temporal scales; increased ability to assess sources of uncertainty.	High complexity can overwhelm modeler's ability to partition sources of variation; need to validate across multiple domains; communicating system behavior to non-technical audiences is challenging.

All models are compromises. The data available to parameterize and validate models are limited as are the resources (fiscal, computational, and time frame) available for developing and applying a model. Is it important that the model be able to run on a typical desktop computer? Is an intuitive user interface necessary for the intended user to be able to quickly implement the model? What is the need for detailed documentation? Each model developer must rank the priorities for resolving the question at hand.

Models must also compromise among the represented processes for the allocation of complexity. For example, a landscape model with a fire component that represents hourly growth of a fire and flame-lengths at a 1-m resolution necessarily devotes fewer resources to landscape processes that unfold over many decades (eg, tree species migration). If the model developer devoted most resources to developing a model of individual trees, the biogeochemical components may be simplified or lacking altogether. Each of the four types (**Table 1**) described below represent the compromises and sacrifices outlined above. None of these model types is appropriate for all situations and questions.

A State-and-Transition Models

State and transition models are typically used to address management questions for which distinct vegetative conditions or classes are readily identifiable and their relative abundance is an important biodiversity consideration. State and transition models place each landscape element into one of a limited number of states (eg, Cattelino *et al.*, 1979; Klenner *et al.*, 2000; Acevedo *et al.*, 2001; Monticino *et al.*, 2002; Pastor *et al.*, 2005). These states typically represent the vegetative condition at a given time. For example, in the eastern United States, a landscape element could be initially classified as "even-aged pitch pine" if satellite and field data indicate that the unit is dominated by *Pinus rigida* with an average age between 30 and 100 years (**Fig. 1**). The transition to a different pre-determined alternative state may occur either if a set amount of time has passed (succession) or if a transition is triggered by a disturbance event. The even-aged pitch pine may transition to "oak-pine mix" 70 years after initiation unless a fire is simulated, changing it to "early-seral pitch pine" or "uneven-aged pitch pine," depending on fire severity (**Fig. 1**).

Transitions among states may be triggered by disturbance (as above) or may be randomly chosen via a transition probability matrix (Logofet and Lesnaya, 2000; Yemshanov and Perera, 2002). In that case, a transition to one of many possible alternate states is based on a probability assigned to each alternate state. The combination of a fixed state and a transition determined in part by a stochastic process is considered a *semi-Markov* model.

The number of states and their taxonomic resolution (eg, three classes of pitch pine vs. broader classes, such as "forest," "prairie," and "savannah"), and the number of transitions is dependent upon the objectives of the research or the management application. Simulations may alternatively focus more on transitions among major land uses and land cover types (eg, agriculture, forest, pasture, developed; Kepner *et al.*, 2012).

Because of the finite number of states (and therefore transitions), state and transition landscape models are conducive to rapid deployment and collaborative model construction. One of the most commonly used state and transition models, Vegetation Dynamics Development Tool (VDDT), has an intuitive graphic interface that allows groups of scientists and managers to quickly

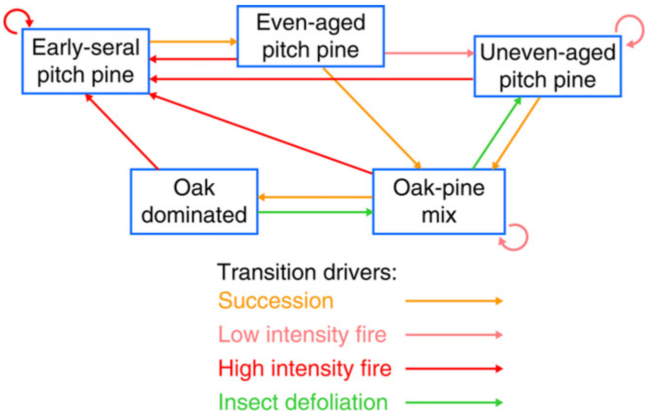

Fig. 1 Conceptual diagram of a mid-Atlantic pine barrens state-and-transition model.

visualize a model and focus their efforts on deliberatively constructing the states and transitions that best represent the dynamics of their system (Hemstrom *et al.*, 2001; Shifley *et al.*, 2008). This relative simplicity also maximizes transparency and can generate greater "buy-in" from local managers and stakeholders. This process of constructing state and transition models to engage a broader group of participants has been widely used by The Nature Conservancy in North America (Shlisky *et al.*, 2005).

At the same time, the finite states also limit the inferential power of state and transition models. Most landscapes around the world today are in part dominated by one or more *non-stationary* processes, meaning that their frequency or magnitude is changing through time. Consequently, many pre-defined states may cease to be significant components of their respective landscapes or the transitions among states may be substantially altered through time. Novel communities (states) may emerge due to climate change (Williams *et al.*, 2007) or invasive plant or animal species, for example, insects (Ward and Masters, 2007).

B Mechanistic Process Models

All landscape models represent one or more processes; what distinguishes these models is that all processes, including succession, are explicitly represented and there are no fixed states or transitions. Rather, structure and composition are emergent properties of the model. Depending on how vegetative change is represented and on the taxonomic resolution, plant community composition may be a function of disturbance intensity and type, plant competition for light or nutrients, seed dispersal, and other species life history attributes (Mladenoff *et al.*, 1996; Roberts, 1996). Because vegetation is more nearly continuous, all other processes can be formulated to be more sensitive to the effects of plant community composition, diversity, and structure. In particular, ecosystem processes (eg, aboveground net primary productivity, soil respiration) can more readily be incorporated as these generally require a tight coupling between vegetative composition, structure, climate and soils (Scheller *et al.*, 2011).

Such landscape process models therefore have much greater flexibility to deal with non-stationary processes, notably climate change. Novel communities can emerge from the interplay between stochastic disturbance processes (themselves responding to climate), species life history attributes, and ecosystem processes that will dictate other physiological constraints (eg, nitrogen availability, soil moisture, Scheller *et al.* 2011; **Fig. 2**). Such an approach is essential for projecting landscape capacity to sequester carbon and provide habitat further into the future (beyond 50 years).

The added flexibility does, however, come with a substantial cost. The data required to parameterize such models is orders of magnitude greater than for state-and-transition models. And the process of constructing and parameterizing mechanistic process models is at best a specialized skill and, at worst, hopelessly opaque to anyone outside of the discipline. Policy-makers, managers, and stakeholders can feel removed from the modeling process and are generally unable to assess the quality of the research. The important drivers which may emerge – eg, nitrogen deposition, litter chemistry – are not readily measureable by land managers and often only indirectly related to the task of managing for biodiversity.

C Hybrid and Multi-Modeling

An emerging trend is the combination of one or more modeling approaches to understand and project changing biodiversity. In particular, hybrid models and multi-modeling offer the opportunity to include processes or interactions across a broader range of spatial, temporal, or taxonomic resolutions than might be possible with a single modeling approach.

To better understand vegetation change, hybrid models have been deployed to represent finer-scale processes using a different modeling paradigm than is used to represent broader landscape process interactions. For example, competition among individual trees and subsequent growth may be simulated using an individual tree model (Robinson and Ek, 2003; Seidl *et al.*, 2012) or a gap model (Pastor and Post, 1988; Seidl *et al.*, 2005). These fine-scale models can be subsequently stitched together spatially to form a

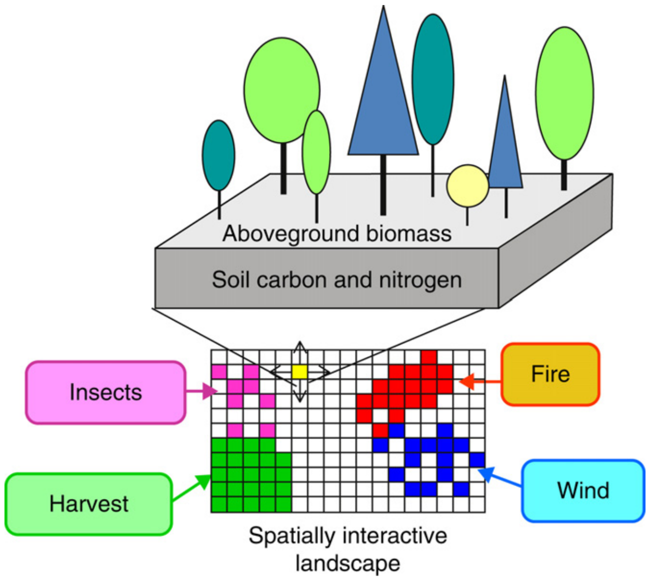

Fig. 2 Conceptual diagram of a process landscape model, emphasizing ecosystem processes and spatially dependent disturbances.

continuous landscape (eg, Urban *et al.*, 1991; Bragg *et al.*, 2004). Alternatively, individual tree data can be averaged using ecological field theory and scaled-up to allow for the efficient calculation of processes that operate at larger spatial or temporal scales (eg, Seidl *et al.*, 2012). The advantage of hybrid forest models is the inclusion of individual trees, their growth, and competition with neighbors. The challenge is the additional parameterization and data required. To date, these data are seldom captured via remote sensing and hybrid models have been limited to relative small landscapes (<10,000 ha).

Multi-modeling (or "model coupling") has also been extended to assessing animal population viability. The challenges of overlaying stochastic animal populations on top of the existing stochastic disturbance dynamics are considerable. However, advances in software and computer power have accelerated the ability to consider both changing habitats and changing populations simultaneously (Larson *et al.*, 2004; Akcakaya *et al.*, 2005; Shifley *et al.*, 2008). For example, to project changes in the population of fisher (*Martes pennanti*) in the southern Sierra Nevada, California, a landscape change model was coupled with a meta-population model (Spencer *et al.*, 2011; Syphard *et al.*, 2011). As a result, two of the largest sources of uncertainty were incorporated: wildfire and fisher dispersal. Doing so a more accurate estimate of inherent uncertainty was achieved (Scheller *et al.*, 2011).

D Neutral Models

Neutral models are not a model type in and of themselves but rather are a unique application of landscape models (Gardner *et al.*, 1987; With and King, 1997). Neutral modeling is the process of applying a landscape model to a strictly hypothetical landscape. In this case, the complexity inherent to parameterizing an actual landscape is jettisoned in favor of a focus on the processes themselves. A neutral modeling approach allows for much more precise testing of model sensitivity to landscape configuration and community composition than is possible on a real landscape. The goal of neutral landscape modeling is a more fundamental understanding of the processes that control landscape change across *all* landscapes rather than the narrower domain of a real landscape. Real landscapes simply never contain the full range of possible landscape configurations and species that may inform longer-range management efforts. As an example, Huxel and Hastings (1999) used neutral models to examine how the placement of restoration efforts (adjacent to existing habitat vs. random placement) could significantly influence habitat restoration success. Attempting to find a suitable suite of similar landscapes (with replication) for such experimentation would have been impossible.

Although further removed from the immediacies of landscape management, neutral models could inform managers about potential biodiversity risks or opportunities that are not immediately apparent from an examination of current conditions (Huxel and Hastings, 1999; With *et al.*, 1999; King and With, 2002). The risk is further detachment from management relevancy: maps of actual landscapes and geographically grounded projections of landscape change remain extremely powerful tools for communicating the science of landscape change.

III Conclusions

The limitations to landscape models are similar to that of all models, with one important caveat. All models are limited (or strengthened) by the empirical foundation upon which they are built: the data underlying their formulation, the data available to parameterize a model in a novel setting, the computational limits to complex simulations, and the software limitations to managing complex algorithms and architectures. These limitations also apply to models of any complex system.

Landscape models, like climate forecasting models, are further limited by the ability to validate results. When projecting more than a few years into the future, validation of model results – the cross-check against reality that has made weather forecasting so successful – requires the continual collection of spatially explicit data through time (Rastetter, 1996; Rykiel, 1996; Haag and Kaupenjohann, 2001; Gardner and Urban, 2003). If projecting more than 10 or 20 years, validation would require patience and funding not typically afforded scientists and managers. In addition, because of stochastic events, the actual observed landscape is but one of many possible outcomes that could have occurred. A single model simulation will never match reality. Thus, even assuming that spatial data are collected, validation should be against confidence intervals generated by running the model many times (ie, model replication).

Complete validation may be the gold-standard of modeling (as double-blind experiments are to medicine) but it is only one route to building confidence in the knowledge gained from models. Other avenues for building confidence in landscape model results include the validation of individual processes, model documentation, model transparency (eg, closed vs. open source), and repeated application across diverse systems. Deploying a rigorous software engineering process during the development stage can maximize model verification (sensu Aber, 1997) and has become increasingly important as model complexity increases (Scheller *et al.*, 2010).

It is incumbent upon those who build and apply landscape models to follow a few general principles: (1) Quantify model sensitivity. There is little value obtaining precise leaf nitrogen estimates if wildfire explains 90% of the variation in species composition. Conversely, if leaf nitrogen is the controlling variable, more effort can be placed obtaining empirical estimates. (2) The inability to validate the complete landscape doesn't preclude the validation of individual processes. Often available knowledge about individual processes (tree growth rates, wildfire spread, logging patterns) is large and should be rigorously utilized. (3) Replication is essential. The existence of inherent uncertainty in reality, and the incorporation of stochastic processes into models, ensures that no single model simulation will precisely match reality. (4) Communicate uncertainty. Although maps of projected landscape change are powerful tools for communication, it is essential that the underlying uncertainty be expressed through time series with replicate standard errors, probability surface maps, or similar approaches.

Similarly, it is incumbent upon the managers and policy makers to be aware of these principles and to recognize those model applications that do or do not adhere to them. Unfortunately, many managers and policy makers instinctively distrust model results and do not engage in the process. This is perhaps in part due to inadequate education and outreach on the part of those conducting modeling research (Pielke, 2003). It is also true that model results have often been presented as *predictions*, which imply a high level of accuracy, and the degree of uncertainty has been under-represented. Model application needs to include a clear articulation of what managers can learn from models while acknowledging that we live in a highly uncertain ("black swan" Taleb, 2007) world.

As the collective challenge to preserve biodiversity increases, tools that enable learning about the future are increasing valuable. Landscape models – in conjunction with well formulated scenarios – offer a route to understanding and managing biodiversity across large areas and long durations. The relentless increase in spatial data (particularly from remote sensing), computing power, and the sophistication of landscape models has enabled scientists and managers to look further into the future and with greater accuracy than ever before. Continued success and improvement is possible, dependent upon the ability of scientists to provide a transparent, collaborative, and rigorous system that maximizes learning while acknowledging uncertainty.

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