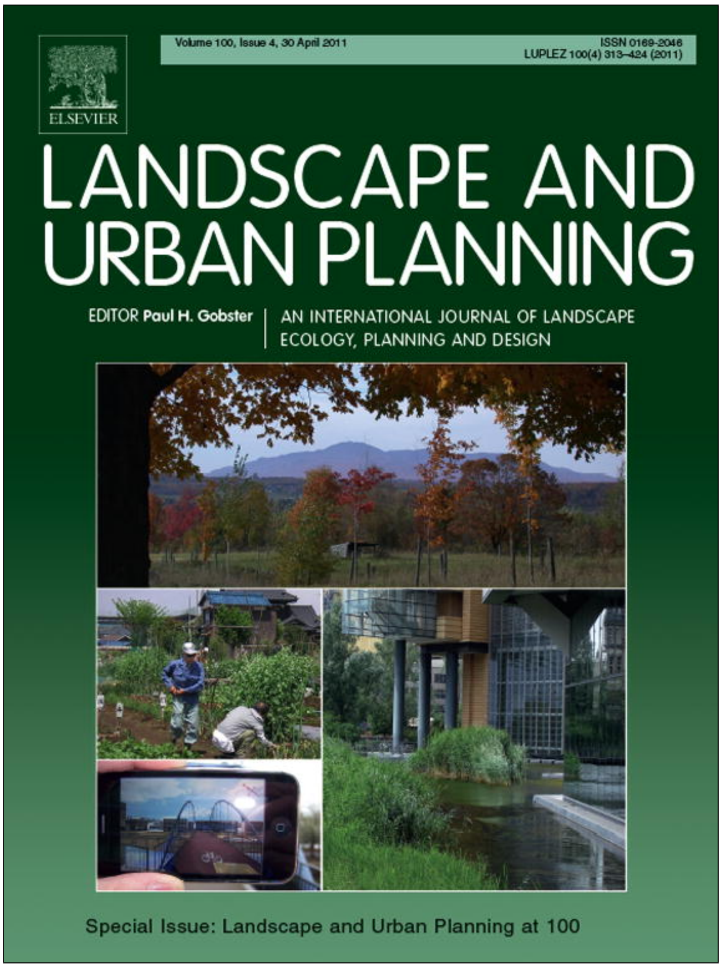

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Challenges of forest landscape modeling—Simulating large landscapes and validating results

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ABSTRACT

Over the last 20 years, we have seen a rapid development in the field of forest landscape modeling, fueled by both technological and theoretical advances. Two fundamental challenges have persisted since the inception of FLMs: (1) balancing realistic simulation of ecological processes at broad spatial and temporal scales with computing capacity, and (2) validating modeled results using independent, spatially explicit time series data. The paper discusses the current status and future directions regarding these two challenges.

1. Introduction

Forest landscape processes are natural and anthropogenic spatial processes such as fire, wind, insect outbreak, disease spread, seed dispersal, tree harvest, and other silvicultural treatments. These processes operate across a range of spatial (10^3–10^7 ha) and temporal (10^1–10^3 years) scales and interact with non-spatial, site-level processes such as succession. For large spatial and long temporal scales, controlled field experiments designed to study the effects of these processes are not possible. Thus, forest landscape models (FLM) are important tools for investigating landscape processes and their effects on species composition, age structure, and spatial pattern. Over the past 20 years, FLMs have been used increasingly to assist forest management planning and assess long-term, large-scale, cumulative effects of forest landscape processes.

Two fundamental challenges have persisted since the inception of FLMs: (1) balancing realistic simulation of ecological processes at broad spatial and temporal scales with computing capacity, and (2) validating modeled results using independent, spatially explicit time series data.

2. Balancing realism and computing capacity

FLMs necessarily simplify or omit certain details of site-level dynamics in order to make landscape-scale analyses computationally tractable. For example, models of forest stand dynamics simulate individual tree growth and survival on gap-sized forest plots (e.g. 0.01–10 ha in size). Direct applications of these models to large forest landscapes in which each cell (pixel) corresponds to a plot have been unsuccessful, primarily because the computational load increases exponentially with the number of pixels, as governed by the Big O Notation (He, 2008). In order to simulate large landscapes, FLMs track coarser vegetation characteristics for each cell such as vegetation type, and presence or absence of tree species groups by age cohort. Early forest landscape models developed two decades ago were able to simulate raster grids of 100 cells × 100 cells, which were used to model spatial extents of 10^3–10^4 ha, depending on the land area associated with each cell. Those models represented a remarkable advance compared to non-spatial models, but the maximum landscape that could be simulated was a limiting factor for addressing spatial heterogeneity generated by most landscape processes (e.g., fire disturbance). Fortunately, computer memory and processing speed have increased exponentially over the last two decades. Now it is common for FLMs to work with raster grids as large as 1000 cells × 1000 cells. Consequently the size of landscapes that can be simulated at a resolution of 30 m (0.09 ha, the resolution of widely used Landsat TM imagery) has now increased to 10^5 ha.

Despite progress in computing technology and modeling techniques that have greatly increased the maximum spatial extent that can be addressed by FLMs, current modeling applications still struggle with the trade-off between greater spatial extent and finer spatial resolution. When modeling landscapes greater than 10^6 ha, current applications typically must use a coarser scale of resolution (e.g., 300 m × 300 m rather than 30 m × 30 m). The change of spatial resolution inevitably affects simulation results because landscape

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patterns and processes are scale-dependent and their response to changing scale is often non-linear (Wu et al., 2004). For example, with increasing cell size, rare forest types will be replaced by dominant forest types. Moreover, some important fine-scale processes such as selective harvesting and windthrow, which in reality result in critical changes to wildlife habitat, cannot be explicitly modeled (Shifley et al., 2008). Coarse spatial resolution may omit important aspects of ecological realism that are evident at finer scales. This is an area with little research to date.

In recent years, there has been a trend to add more detail to the modeled processes in FLMs. Qualitative attributes of a cell such as forest type are now deemed insufficient to capture the full picture of landscape dynamics. Consequently, quantitative attributes such as tree density and biomass are now incorporated in newer FLMs. Increasing the level of detail carried in the model can eliminate some adverse effects associated with coarse spatial resolution. For example, the original LANDIS model, a well-known FLM, tracks tree species by their presence/absence and age cohort within each cell. Without additional quantitative information, it is impossible to determine which species or age cohorts dominate each cell and which are rare. Further development of LANDIS has led to variants (cf. He, 2008) such as QLAND, LANDIS-II, and LANDCLIM, which track tree density or biomass by species and age cohort within each cell. These models provide richer information for each cell than the original LANDIS. However, due to the additional computer memory required to track density or biomass variables for every species and age cohort within each cell, these models can only be applied to relatively small raster grids (e.g., 10^4–10^5 cells in Schumacher and Bugmann, 2006; 10^4 cells in Scheller et al., 2011). Increasing cell size is the only realistic approach to modeling larger landscapes. But with larger cell sizes other landscape processes such as fire or harvest are underestimated when those disturbances affect only part of a cell. For these reasons applications of the newer FLMs designed to link forest stand dynamics with landscape processes typically report a maximum simulated landscape size of less than 10^4 ha. In terms of total modeled landscape size this represents little progress compared to a decade ago. Although advances have been made in model detail and realism, total simulated landscape area remains as a bottleneck for FLMs. If contemporary FLMs are to simulate larger landscapes (e.g., 10^5–10^7 ha) then either the stand level dynamics need to remain simplified or total spatial resolution must be sacrificed.

The trade-off between computational capacity and spatial extent is an inherent constraint in application of FLMs to address complex ecological and management questions. Increased computing capacity can help alleviate the conflict but does not eliminate it. Recently, FLMs have taken advantage of desktop computers with a 64-bit operating system and newer programming algorithms to expand simulation capacity while simultaneously increasing detail in simulated ecological processes. For example, the LANDIS PRO model employed efficient new data structures combining sorted linked lists and hash tables to record tree species and age. This new design shifts from cell-level memory compression to grid-level memory compression. This innovative design along with a 64-bit operating system makes it possible to simulate very large landscapes (e.g., $>10^8$ pixels) for the data structure of present/absence age cohort (LANDIS 5.0–6.0). With such technological breakthroughs, forest dynamics of an entire ecological section (e.g., 90,000 km^2) can be simulated at 30 m resolution. In LANDIS PRO 7.0, attributes such as trees per acre and quadratic mean DBH are tracked for each cell. Tree growth, mortality, seed dispersal and regeneration are simulated in conjunction with inter-tree competition and succession. With these attributes, aboveground forest biomass and carbon can be modeled as affected by forest succession, natural disturbances, and management (www.missouri.edu/~landis.htm).

3. Model evaluation

Evaluation of forest landscape simulation models is a complex process that has never been fully addressed for FLMs. Evaluation includes two integral components: (1) model verification—demonstrating that the ecological processes embodied in the model are adequately represented in the model's equations and algorithms and that they are correctly programmed; and (2) model validation—quantitative and qualitative comparisons of model predictions over time and space with observed forest landscape changes derived from independent field data (Shifley et al., 2009). Most FLMs achieve model verification, and sensitivity analysis is often a part of model verification. By systematically varying initial conditions and model parameters and examining the resultant outputs it is possible to understand the range of variation predicted by the model and obtain a qualitative understanding of predicted responses to a range of modeled disturbances. However, few FLMs have been able to validate their simulated outcomes against field data due to the lack of independent time series data at landscape scales and the inherent stochasticity of forest landscape processes. Some attempts to validate FLMs use data collected at the stand level. However, validation for FLMs must—at least in part—be conducted at landscape and land type scales. This requires the development of appropriate statistical procedures and independent validation data sets for these large landscapes.

Because FLMs simulate succession, disturbance, and their interactions, the modeling results should also be evaluated in the following three areas: (1) stand development under no disturbance conditions, (2) disturbance effects on stand development (e.g., fire-induced mortality, post-fire regeneration), and (3) spatial and temporal heterogeneity of disturbance patterns and interactions among disturbance agents. Ideally these characteristics should be validated using independent data sources, but when that is impossible sensitivity analysis is an option. Because succession is often simulated as a deterministic process in a FLM, succession should be less difficult to validate than other characteristics, provided there is a true spatial time series vegetation data at landscape scales. Disturbance effects have been widely studied at stand scales using the field observation data (e.g., Johnstone et al., 2010). These studies often show that tree mortality and seedling density on disturbed sites are determined by pre-disturbance vegetation, site physical factors, and disturbance severity and interval. The knowledge gained in these studies has already been applied in FLM validation at the cell level. However, few studies have actually validated disturbance effects on succession at landscape scales. The third evaluation aspect, spatial and temporal heterogeneity, is also difficult to validate. Most FLMs employ a distribution based approach to simulate disturbance. Thus, the size and frequency distributions of a disturbance process are used as model parameters. Although individual disturbance events are randomly simulated, landscape-level disturbance properties are set during model calibration. Therefore, simulated disturbance patterns at landscape scales can only be used to verify whether the model is implemented correctly. Recent development of fire disturbance simulation has more realistic representation of occurrence and spread using FARSITE fire spread algorithm (Yang et al., 2008), and thus may be truly validated with real fire occurrence and spread data.

Over time, landscape-scale data sets for FLM validation will become more readily available. Sources include repeated measures of U.S. Forest Service Forest Inventory and Analysis (FIA) data and long-term, landscape-scale manipulative experiments such as the Missouri Ozark Forest Ecosystem Project (Shifley and Kabrick, 2000). Advances in FIA data collection procedures make annual forest inventory data available. Annual FIA inventory provides necessary independent spatial-temporal data for FLM validation. Specifically, annual estimates of number of tree (trees/acre), basal area (ft^2/acre) and age distribution of each species can be derived for the simulated landscape as well as individual land types using FIA tree and area expansion factors (Woodall et al., 2010).

The general FLM calibration and validation procedure using FIA data may include the following steps: (1) initializing the FLM using FIA data for year A, (2) using the FLM to simulate change from year A to B, (3) comparing simulation results for year B (e.g., number of trees and basal area per species per area) with FIA estimates for year B at the land type and landscape scale, (4) re-calibrating FLM parameters and/or modifying component models of ecosystem processes (e.g., growth, mortality, and establishment rates) based on the discrepancies found in the prior step, (5) iterating steps 2–4 and modifying the FLM parameters or component models until a satisfactory match is met, and (6) using the revised FLM to simulate change from year A to C and comparing simulation results for year C with FIA estimates for year C, which provides model validation.

FIA data have a relatively short time span (e.g., 1985–2010 for Missouri and 1978–2010 for Arkansas) and thus temporal autocorrelation (Araújo et al., 2005) may limit the effective use of FIA data to validate vegetation change for long projection periods. Nevertheless, FIA data provide rare spatial time series that cover a wide area from which various forest successional stages across space may mediate the relatively short survey time span. Since each FIA plot records disturbances (e.g., fire, wind, or harvest), subsets of FIA plots corresponding to a given disturbance type can be used to evaluate post-disturbance vegetation succession and therefore provide finer-scale validation of disturbance regimes simulated by the FLM. The availability of FIA and other landscape-scale data sets will increase future opportunities for rigorous FLM validation.

4. Conclusion

Despite massive increases in computational capacity over the past two decades, only moderate increases have been made in the maximum spatial extent that can be simulated by FLMs. This is partially due to advances in the modeling capabilities and the associated computational demands of FLMs. However, to a great degree it is due to the trade-off between computational capacity and spatial extent that is an inherent constraint in application of FLMs. Recent developments in 64-bit desktop computers and newer programming algorithms make it possible to expand FLM simulation capacity while simultaneously increasing detail in simulated ecological processes. A new generation of FLMs in response to such technologies may emerge over the next a few years.

Greater access to large-scale, long term, spatially explicit forest inventory data such as those produced by FIA provides emerging opportunities for FLM validation. Change over time and space in number of trees (trees/acre), basal area (ft^2/acre) and age distributions of each species simulated in FLMs can be checked against observed values derived from FIA data at both the landscape and the land type scale and for specific disturbance regimes. However, FLM model validation is currently limited to relatively short time series. Rigorous, quantitative FLM validation based at least in part on spatial time series data is an emerging step toward improving the quality and credibility of FLM predictions.

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