Comparing effects of fire modeling methods on simulated fire patterns and succession: a case study in the Missouri Ozarks

Jian Yang, Hong S. He, Brian R. Sturtevant, Brian R. Miranda, and Eric J. Gustafson

Abstract: We compared four fire spread simulation methods (completely random, dynamic percolation, size-based minimum travel time algorithm, and duration-based minimum travel time algorithm) and two fire occurrence simulation methods (Poisson fire frequency model and hierarchical fire frequency model) using a two-way factorial design. We examined these treatment effects on simulated forest succession dynamics and fire patterns including fire frequency, size, burned area, and shape complexity of burned patches. The comparison was carried out using a forest landscape model (LANDIS) for a surface fire regime in the Missouri Ozark Highlands. Results showed that incorporation of fuel into fire occurrence modeling significantly changed simulated dynamics of fire frequency and area burned. The duration-based minimum travel time algorithm produced the highest variability in fire size, and the dynamic percolation method produced the most irregular burned patch shapes. We also found that various fire modeling methods greatly affected temporal fire patterns in the short term, but such effects were less prominent in the long term. The simulated temporal changes in landscape-level species abundances were similar for different fire modeling methods, suggesting that a complex fire modeling method may not be necessary for examining coarse-scale vegetation dynamics.

Résumé : Nous avons comparé quatre méthodes de simulation de la propagation du feu (complètement aléatoire, percolation dynamique, algorithme du temps minimum de propagation basé sur la dimension et algorithme du temps minimum de propagation basé sur la durée) et deux méthodes de simulation de l'occurrence des feux (modèle de fréquence des feux de Poisson et modèle hiérarchique de fréquence des feux) à l'aide d'un plan factoriel à deux facteurs. Nous avons étudiés les effets de ces traitements sur la dynamique simulée de la succession forestière et le comportement des feux, incluant la fréquence des feux, leur dimension, la superficie brûlée et la complexité de la forme des parcelles brûlées. La comparaison a été effectuée à l'aide du modèle de paysage forestier (LANDIS) pour un régime de feux de surface sur les hautes terres des monts Ozark au Missouri. Les résultats montrent que l'introduction des combustibles dans la modélisation de l'occurrence des feux modifie de façon significative la dynamique simulée de la fréquence des feux et des superficies brûlées. L'algorithme du temps minimum de propagation basé sur la durée a produit la plus forte variation dans la dimension des feux et la méthode de percolation dynamique a produit les formes des parcelles brûlées les plus irrégulières. Nous avons aussi observé que différentes méthodes de modélisation des feux ont grandement affecté le patron temporel des feux à court terme mais ces effets étaient moins marqués à long terme. Les changements temporels simulés dans l'abondance des espèces à l'échelle du paysage étaient semblables avec différentes méthodes de modélisation des feux, ce qui porte à croire qu'une méthode complexe de modélisation des feux n'est peut-être pas nécessaire pour étudier la dynamique de la végétation à une échelle grossière.

[Traduit par la Rédaction]

Introduction

Fire disturbance plays an important role in shaping ecosystem dynamics and vegetation patterns in many forested landscapes (e.g., Romme 1982; Miller and Urban 1999; Ehle and Baker 2003). Small and large fires of varying intensities create a mosaic of burned and unburned patches, affect tree species composition and age classes, and generate spatially heterogeneous fuel beds. The resulting fuel heterogeneity in turn influences the spatial pattern of subsequent fires (Turner and Romme 1994). The dynamic interaction of fire and vegetation at landscape scales is further complicated by other important ecological drivers such as tree species dispersal, successional recovery of disturbed landscapes, weather and climate shifts, and land management (Bessie and Johnson 1995; Schoennagel et al. 2004).

Simulation modeling is a valuable tool for studying the complex interaction of fire, vegetation, climate, and human activities over large areas and long time periods (Keane et al. 2004). A large variety of forest landscape fire succession models have been developed for various research purposes, such as reconstructing the historical range and variability of landscape patterns (Boychuk and Perera 1997; Keane et al. 2002; Wimberly 2002), examining human influence on fuel heterogeneity and fire patterns (Sturtevant et al. 2004), and

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Table 1. The eight fire modeling methods varied by the way fire occurrence and fire spread are simulated using a two-way factorial design.

	Factor I (fire occurrence simulation method)	
Factor II (fire spread simulation method)	Poisson fire frequency model (P)	Hierarchical fire frequency model (H)
Completely random (CR)	PCR	HCR
Dynamic percolation (DP)	PDP	HDP
Size-based minimum travel time algorithm (SM)	PSM	HSM
Duration-based minimum travel time algorithm (DM)	PDM	HDM

evaluating forest management alternatives and fire suppression plans (Gustafson et al. 2004). These models use different methods to simulate fire occurrence and fire spread and are implemented with varying levels of ecological detail. Because of the prevalence of forest landscape fire succession models and the diversity of simulation methods, it is important to understand the premise and behavior of various fire modeling methods.

Fire modeling methods used in forest landscape fire succession models are different from those used in fire growth simulation models (e.g., FARSITE; Finney 1998). Fire growth models focus on the simulation of a single fire event in great detail with fine (e.g., hourly) time resolution. The purpose of these models is to predict the movement of fire fronts within a short time scale (usually a fire season). In contrast, forest landscape fire succession models simulate multiple fire events over long time scales (e.g., 1000 years) with coarse (e.g., yearly or decadal) time resolution. Their purpose is to simulate broad-scale fire patterns such as statistical descriptions of fire frequency and fire size (Li et al. 2008). Our study focused on fire modeling methods for forest landscape fire succession models.

Efforts have been made to classify landscape fire succession models. For example, Keane et al. (2004) classified landscape fire succession models in terms of the gradient of stochasticity, complexity, and mechanism inherent in the each of the four simulation components (i.e., succession, fire ignition, fire spread, and fire effects). The classification schemes provide formal descriptions for objectively comparing a forest fire simulation model with others but do not provide much information about how different fire modeling methods lead to different simulated fire and succession patterns. There are only a few published papers that compared simulated fire patterns across different methods. Li et al. (1997) compared mean interval between successive fires simulated with four fire probability functions to investigate modeling effects on simulated temporal patterns of fire disturbance. Cary et al. (2006) assessed the sensitivity of four existing models (EMBYR, FIRESCAPE, LANDSUM, and SEM-LAND), in terms of area burned, to variation in environmental factors and complexity of model formulation. Their studies laid groundwork for examining the effects of different modeling methods on fire patterns. However, these examinations were not comprehensive because there are other important aspects of fire patterns besides fire interval and area burned.

Our study examined effects of fire modeling method on simulated vegetation dynamics and a wide range of measures of fire patterns, including fire frequency, fire size, burned area, and shape complexity of burned patches. A fire modeling method consists of three fundamental components: fire occurrence, fire spread, and fire effects (Keane et al. 2004). Method for simulating fire effects was fixed in this study and we focused solely on fire occurrence and fire spread simulation methods. We hypothesized that certain aspects of simulated fire patterns are most likely affected by fire occurrence simulation method (e.g., fire frequency) and others are more affected by fire spread simulation method (e.g., fire size and fire shape). Interactions may also exist between fire spread and fire occurrence. For example, different fire spread simulation methods produce different fire shapes, resulting in different fuel patterns, which may later modify simulated fire frequency.

Our research questions include (*i*) how do different fire modeling methods affect fire patterns, (*ii*) do different fire spread simulation methods influence fire occurrence patterns and vice versa, and (*iii*) how do different fire modeling methods affect simulated vegetation dynamics? To answer these questions, we compared simulated fire and succession patterns across a spectrum of fire spread simulation methods (from simple statistical methods to complicated physical methods) under two fire occurrence process scenarios (fire hazard being constant and being dependent on fuel). All of these fire modeling methods were implemented in one single spatially explicit and stochastic forest landscape model (LANDIS 4.0; He et al. 2005) that is capable of simulating the interaction of fire, fuel, and succession dynamics. The comparison was conducted for a typical surface fire regime in the Missouri Ozark Highlands.

Methods

Fire modeling methods

We examined eight different fire modeling methods in a two-way factorial design that varied by fire occurrence and fire spread (Table 1). Here, fire occurrence refers to the initiation of a fire event that burns an area of at least one cell on the simulated landscape (Keane et al. 2004). We investigated two fire occurrence simulation methods that applied either a fuel-independent Poisson fire frequency model or a fuel-dependent hierarchical fire frequency model in the simulation. The Poisson fire frequency model (P) assumes that fire hazard is constant and independent of fuel loads. The simulated fire frequency U (i.e., the number of fire occurrences per unit time per unit area) is distributed as a Poisson process with the parameter fire occurrence rate π (Van Wagner 1978):

$$[1] \qquad U \sim \text{Poisson}(\pi)$$

The hierarchical fire frequency model (H) assumes that fire hazard is a function of fuel loading. The model divides a fire occurrence process into two consecutive stages: fire ignition and fire initiation. In a given time step, the number of ignitions X is generated from a user-defined Poisson distribution with the parameter ignition rate λ, which is the expected number of ignitions per unit time and unit area:

$$[2] \qquad X \sim \mathrm{Poisson}(\lambda)$$

Each of the simulated fire ignitions is modeled as a Bernoulli trial with the fire initiation probability parameter P_i, whose value is determined by fuel type and fuel loading on the ignited cell (see LANDIS model section for details about fuel tracking). The result of each Bernoulli trial can be either 1 if it results in a fire initiation or 0 otherwise. The sum of all of these Bernoulli trials is then the fire frequency U:

$$[3] \qquad U|X = \sum_{i=1}^{x} \mathrm{Bernoulli}(P_i)$$

The Poisson fire frequency model is a special case of the hierarchical fire frequency model when fire initiation probability P is a constant (i.e., $P_1 = P_2 = ... = P_x = P$). In this special case, fire occurrence rate π is a product of two components: fire ignition rate and initiation probability (i.e., $\pi = \lambda P$) (Yang et al. 2004).

Fire spread refers to the growth of individual fire events. There are many techniques that require different levels of computation, parameterization effort, and input data preparation to simulate fire spread. We examined four representative methods in this study: (*i*) completely random (CR), (*ii*) dynamic percolation (DP), (*iii*) size-based minimum travel time algorithm (SM), and (*iv*) duration-based minimum travel time algorithm (DM). All of the methods represent the landscape as a grid of square cells but use different techniques to simulate the propagation of fire over the landscape.

The CR method is the simplest and is often used when only the coarse-scale characteristics of a fire regime need to be simulated (Baker et al. 1991; Lenihan et al. 2003). The method first selects a maximum fire size from a user-defined size distribution and then simulates fire spread from the burning cell to its eight directional neighboring forested cells uniformly until the fire reaches the maximum fire size or all available burnable cells have been disturbed. The spread probability is considered to be the same for all of the forested cells. Therefore, forest types do not affect the simulated actual fire size and shape of burned patch. Only landscape configuration of forest/nonforest affects the propagation of fire in this method.

The DP method simulates fire spread similar to the CR method. However, the direction of fire spread in the DP method is adjusted by a spread probability, which is calculated from a set of environmental factors such as wind, topography, and fuel (Hargrove et al. 2000; Wimberly et al. 2000). Here, we employed a self-organized version of dynamic percolation modified from Caldarelli et al. (2001). The method assumes that the spread probability of each cell is dependent on not only fuel loading in the cell but also on the cumulative size of the fire event, which is a surrogate of time-elapsed since fire initiation. It uses an exponential function to calculate spread probability P from fuel loads (F) and size of burned area (S):

$$[4] \qquad P(S,F) = P_0(F)\mathrm{e}^{\frac{S}{S_{\max}}}$$

where $P_0(F)$ is a user-defined step function defining contribution of fuel loads to the spread probability and $S_{\max}$ is the maximum fire size that is randomly selected from a user-defined fire size distribution. $P_0(F)$ is usually set to be larger than P_c (i.e., percolation threshold) so that the burned area is compact at the beginning stage of fire spread. A simulated fire will eventually extinguish because spread probability decreases with the increase in size of burned area. The algorithm can produce burned patches with a compact interior and a fractal boundary, similar to the geometric features of real wildfires as shown by Caldarelli et al. (2001).

The minimum travel time algorithm, proposed by Finney (2002), uses algorithms developed from graph theory (e.g., Dijkstra 1959) to search for minimum cumulative travel times of fires along straight-line paths among cells of a grid. Travel times along the line segments are calculated from rate of fire spread in the underlying cells of the grid using the Rothermel (1972) model in which the shapes of fires are assumed to be elliptical under uniform fuel conditions (Andrews 1986). The paths producing minimum travel time between cells were then interpolated to reveal the fire perimeter positions. The method can produce spatial fire growth and behavior nearly identical to perimeter expansion techniques used in the complex model FARSITE (Finney 1998). The minimum travel time algorithm is easier to implement and is computationally faster than perimeter expansion techniques (Finney 2002). We designed two versions of minimum travel time algorithms: (*i*) the "size-based" version uses a fire size randomly selected from a user-defined distribution to truncate the simulation of fire spread whenever the size of burned area reaches the preselected fire size and (*ii*) the "duration-based" version randomly selects a burning duration from a user-specified distribution and uses it to determine when to stop a fire growth simulation.

LANDIS model

All eight fire simulation methods were implemented in a raster-based spatially explicit model, LANDIS (v. 4.0). The LANDIS model simulates forest landscape change in response to disturbance, succession, and management at large extents (10^3–10^6 ha) over long periods of time (10^1–10^3 years) (Mladenoff and He 1999). We used a 10-year time step and a cell size of 0.09 ha (30 m by 30 m) in this study. Each cell is a spatial object that tracks the presence or absence of age cohorts of individual plant species. LANDIS simulates ecological processes occurring at a cell scale (e.g., competition, succession, seedling establishment, fuel accumulation, and decomposition) and at a landscape scale (e.g., seed dispersal and fire disturbance).

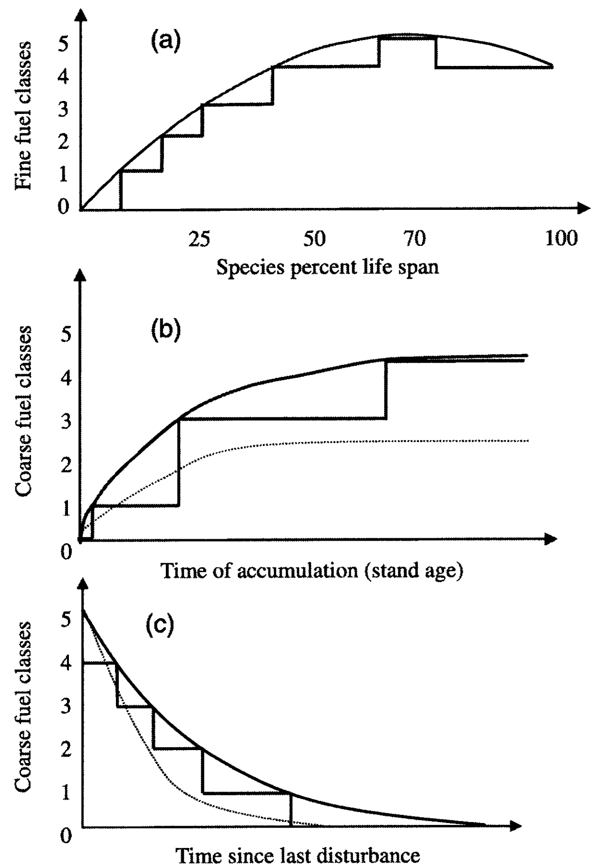
LANDIS stratifies a heterogeneous landscape into land types, which are generated from GIS layers of climate, soil, or terrain attributes. The model requires parameters for species establishment, fire disturbance characteristics, and fuel accumulation regime for each land type. LANDIS is a stochastic model that uses random number generators to simulate the stochastic processes of seed dispersal, seedling establishment, fuel accumulation, and fire disturbance. Seed dispersal is modeled as a function of species' effective and maximum seeding distances. A negative exponential distribution is used to describe seeding probability in relation to distance from available seed source. Estimates of these seed dispersal parameters are based on generalized classification of seed dispersal mechanisms (Wimberly 2004). In this study, effective seed dispersal ranges were 50 m for gravity-dispersed species (e.g., oaks) and 100 m for wind-dispersed winged seeds (e.g., sugar maple). Seedling establishment is determined based on shade tolerance of the seeding species relative to the species already occurring on the cell. Details about LANDIS succession and seed dispersal are available from He and Mladenoff (1999).

The LANDIS fuel module tracks fine fuels and coarse fuels for each cell. Fine fuels correspond to 1- and 10-h time lag fuels, which include leaves, twigs, ground litter, needles, and fine woody debris that fall from trees annually (He et al. 2004). Coarse fuels correspond to 100- and 1000-h time lag fuels, which include snags, logs, branches, stems, and coarse roots. Fine fuel loads are approximated by vegetation types (species composition) and species age. In general, mature or old trees produce more fine fuels than small young trees. In LANDIS, a curve was defined for each species to approximate how fine fuel loads vary with species age (Fig. 1*a*). The relationship between fine fuel and species life span (which may include multiple peaks) for each species is derived from empirical data (He et al. 2004). Decomposition rates of fine fuels also vary by land types. Generally, most of the leaf litter in a hardwood forest decomposes in a few years (Kolaks et al. 2004). Therefore, the LANDIS fuel module assumes that most fine fuels decompose in less than 10 years, which is shorter than the LANDIS 10-year time step. At each time step, fine fuels are recalculated based on the live species/age cohorts (He et al. 2004).

In contrast with the calculation of fine fuel loads, LANDIS does not use species/age cohorts to approximate coarse fuel loads. Instead, the model uses stand age (the oldest age cohorts in the stand) and disturbance history (e.g., time since last disturbance) to determine coarse fuel loads. In the absence of disturbance, the accumulation process dominates until the amount of coarse fuel reaches a level where decomposition and accumulation rate are in balance (Fig. 1*b*). In the LANDIS fuel module, coarse fuel accumulation is modeled as a continuous process in which the accumulations rates vary by land types, which encapsulate environmental variables (e.g., climate, soil, slope, and aspect). The decomposition process is modeled based on the decomposition curve (Hale and Pastor 1998; He et al. 2004), which is also user-defined for each land type (Fig. 1*c*). Some disturbances (e.g., windthrow) add to the coarse fuel pool, while other disturbances (e.g., fire) can consume fuels. Due to the long temporal scales involved in estimating the amount of fine and coarse fuels, uncertainty is high. To reduce the potential false precision and the parameterization burden, LANDIS lumps fuel loads into five categorical classes (very low to very high). This is consistent with the design of disturbance intensity and severity in the LANDIS fire, wind, and insect modules (He et al. 2004). Details about the definition and parameterization of the five fine and coarse fuel loading classes for this study area can be found in Shang et al. (2007).

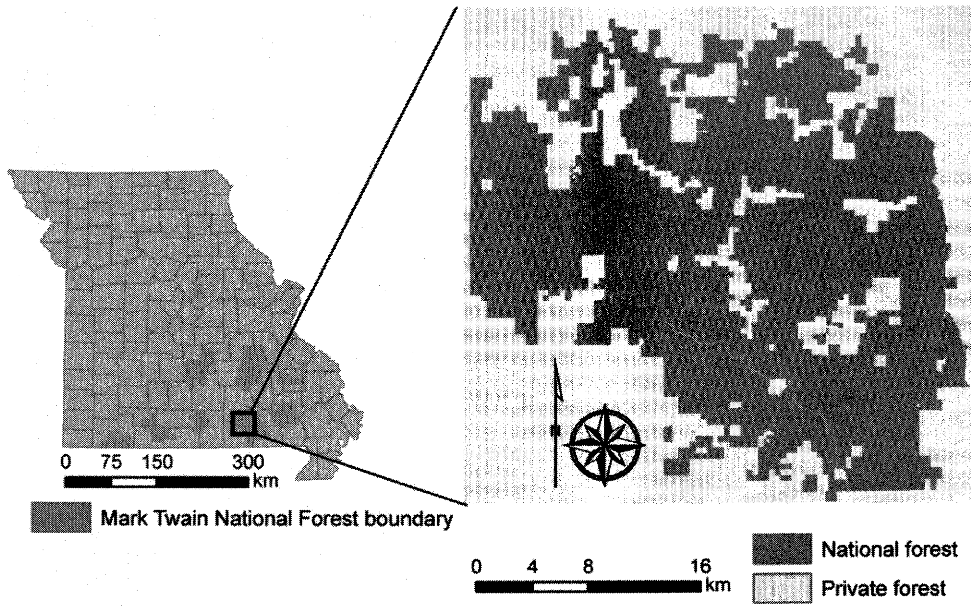
Within a 10-year time step, the LANDIS fire module simulates a random number of fire events, which are randomly ignited on the landscape and burn a random number of cells.

Fig. 1. Modeling fine fuel and coarse fuel accumulation and decomposition in LANDIS. (a) Fine fuel accumulation changes throughout the life span of a given species. In this example, the amount of fine fuel created by each species (thin line) is positively correlated with age until approximately 70% of the species' life span is reached and is negatively correlated with age as the species' age approaches maximum species longevity. In the LANDIS fuel module, fine fuel accumulation is converted into five categorical classes represented by the thick line. The relationship between fine fuel and species life span (which may include multiple peaks) for each species is derived from empirical data. (*b*) Coarse fuel accumulation on two land types (e.g., mesic and xeric) in the absence of disturbances. (*c*) Coarse fuels decomposition after disturbance on two different land types.



Cells are not allowed to burn more than once during the 10-year time step in LANDIS to circumvent the inconsistency between the temporal scale used in fuel tracking (10 years) and the one used in fire spread simulation (<10 years). This model assumption is acceptable for our study landscape, which has a relatively long fire cycle (300–500 years). Hence, cells are seldom burned more than once within 10 years on this landscape. The combination of the fine and coarse fuel loads in each cell is used to determine fire intensity (five categorical classes: very low to very high) if the cell is burned (He et al. 2004). Fire intensity is low to very low for surface fires and high to very high for crown fires. Fire is a bottom-up disturbance, and fires of increasing intensity affect younger age classes first. Also, fire tolerance varies among species. LANDIS uses species-specific fire-tolerance class combined with age-specific fire-susceptibility class to determine whether a species cohort of a certain age can survive a given fire intensity class (He and Mladenoff 1999).

Fig. 2. Study area, a portion of Mark Twain National Forest located within the sourthern Missouri Ozark Highlands.



A large heterogeneous landscape in LANDIS may be stratified with a few fire regimes characterized by ignition rate (expected number of fire ignition per unit time per unit area) and fire cycle (Li 2002). The fire regime map may be either the same as or different from the land type map. For each individual fire spread, LANDIS simulates a prevailing wind direction from a user-specified wind distribution. Variations in other weather factors such as temperature and rainfall are not explicitly simulated in this version of LANDIS. The model uses fire size distribution or burn duration distribution to simulate when to stop a fire. LANDIS can simulate expected number of fires and fire size that agree with the historical fire statistics (Yang et al. 2004). However, the simulated temporal and spatial fire patterns can vary with the different fire simulation methods.

Study area

Our study area, 71 142 ha in size, is located within the southeastern Missouri Ozark Highlands (Fig. 2). The study area includes large, contiguous blocks of the Mark Twain National Forest that are surrounded by (and in some areas intermixed with) privately owned forests. The dominant tree species in this area include white oak (*Quercus alba* L.), post oak (*Quercus stellata* Wangenh.), black oak (*Quercus velutina* Lam.), and shortleaf pine (*Pinus echinata* P. Mill.). Heavy logging between 1890 and 1920 and continuing fire suppression since 1940 in this region have decreased the abundance of fire-favorable shortleaf pine to 25% of that ca. 1900 (Batek et al. 1999). The fire cycle (number of years necessary for an area equal to the entire area of interest to burn) was less than 20 years during the early 1900s (Guyette et al. 2002), but it is now approximately 300–500 years (Westin 1992). Fires are very frequent but most of them are small non-stand-replacing surface fires; the range of average fire size is about 8–10 ha (Guyette and Larsen 2000).

Comparing effects of different fire simulation methods

We conducted 10 replicates of 1000-year simulations using each of the eight fire simulation scenarios (Table 1). The parameters of the simulations (Table 2) were estimated from fire statistics reported in this region (Westin 1992) and the BEHAVE fire modeling system (Andrews 1986) and further calibrated interactively to produce acceptable simulated fire cycle and mean fire size. The simulated results were mainly analyzed using a two-way ANOVA to examine how fire occurrence simulation method and fire spread simulation method affected simulated fire and succession patterns, respectively. The response variables were fire frequency, fire size, burned area, shape index, and dynamic time warping (DTW) similarity index.

Fire frequency, fire size, and burned area

Fire frequency and fire size are two primary characteristics of a fire regime. In our analysis, fire frequency was defined as the number of fire occurrences per 1000 km^2 per decade. Fire size was defined as the average simulated fire size (hectares) per decade. Although different fire modeling methods can all produce a similar mean fire frequency and mean fire size, we deemed that their simulated variability and temporal dynamics could still be different. In addition to fire frequency and fire size, we also used burned area, defined as the area (hectares) burned per 1000 km^2 per decade, as a major response variable in the analysis of fire modeling comparison. Burned area equals the product of fire frequency and fire size in each 10-year time step. It is a synthesis of both fire frequency and fire size.

Shape index

The shape of simulated burned patch is an important aspect for describing the effects of fire simulation method. We hypothesized that fire spread simulation method greatly affects the shape complexity of simulated burned patches, while fire occurrence simulation exerts very little influence. We imported simulated burned patch maps into FRAGSTATS (McGarigal et al. 2002) to quantify the shape complexity of burned patches using the shape index. The shape index equals patch perimeter divided by the minimum pe-

Table 2. Parameters used in each individual fire modeling method.

Parameter	Units	Simulation method	Value(s)
Parameters used in fire occurrence simulation			
Ignition rate	No.·ha^{-1}·decade^{-1}	P	0.02832
		H	0.02840
Initiation probability	na	P	0.1 for all five fuel loads classes
		H	0.025, 0.05, 0.1, 0.2, and 0.4 for the five fuel load classes
Parameters used in fire spread simulation			
Initialized mean fire size	ha	CR	8.12
		DP	7.27
		SM	8.00
Initialized mean burn duration	min	DM	55
Fire spread probability	na	DP	0.26, 0.45, 0.59, 0.69, and 0.78 for the five fuel loads classes
Rate of spread	m·min^{-1}	SM, DM	1.2, 5.9, 18.3, 35.4, 56.5, and 81.2 for the five loads classes in a typical fire season

rimeter possible for a maximally compact patch (i.e., a square) of the corresponding patch area. The shape index is the most straightforward measure of overall shape complexity. It equals 1 when the patch is maximally compact and increases as patch shape becomes more irregular (McGarigal et al. 2002).

DTW similarity index

We used the DTW technique to measure the similarity distance of the simulated time series. A time series $T = t_1, ..., t_m$ is an ordered sequence of m real numbers representing measurements of a real variable at equal time intervals. LANDIS modeling results included many time series data such as chronologies of simulated fire frequency, fire size, burned area size, and species abundance. These time series simulated using difference modeling methods may have similar means or variances, but they can have very different temporal fluctuation patterns. In this study, we chose to use the DTW index (Berndt and Clifford 1994) to measure the amount of similarity among the simulated temporal patterns. Given two time series X of length m and Y of length n, the DTW constructs an m by n cost matrix $\mathbf{C}$ where the (ith, jth) element of the matrix $\mathbf{C}[i, j]$ corresponds to the squared distance of data points X_i and Y_j . The algorithm then retrieves a warp path through the matrix starting from $\mathbf{C}[1, 1]$ and ending at $\mathbf{C}[m, n]$ that minimizes the total cumulative distance between them. The warp path W of length K is denoted by $W = w_1, ..., w_K$, where K is between max(m, n) and $m + n$, and the element of the warp path w_k is also an element of the cost matrix $\mathbf{C}[i, j]$. There is also a "monotonic condition" constraint on the warp path that forces i and j to be monotonically increasing in the warp path. The DTW distance is the squared root of the sum of the warp path:

$$[5] \qquad \mathrm{DTW}(X, Y) = \sqrt{\sum_{k=1}^{K} w_k}$$

Before calculating the DTW distance, we normalized the time series data to account for the shifting in the average and scaling in the deviation. Let $\mu(T)$ and $\sigma(T)$ be the average and standard deviation of a time series T. The normalized time series T' is the one with the average 0 and standard deviation 1 by transforming $t_i' = (t_i - \mu(T))/\sigma(T)$. By employing normalization, we were able to filter out the difference in offsets and amplitudes due to calibration process and to focus on comparing the pattern of time series dynamics, which was determined by the simulation method itself (Goldin and Kanellakis 1995). We chose the average of 10 replicates of simulated time series using the method PCR, which is the simplest fire modeling method in our comparison, as a reference condition. The DTW distance ranges from 0 to $2\sqrt{n}$ for two normalized time series both of length n. A larger DTW indicates a lower degree of similarity between the simulated time series and the reference condition.

Results

All fire modeling methods could produce the observed fire cycle (300–500 years) and mean fire size (8–10 ha), which are primary descriptors of a fire regime, after a careful calibration process (Fig. 3). There was a greater variability in simulated fire cycle when using the hierarchical fire frequency model (H) than with the Poisson fire frequency model (P) to simulate fire occurrence process (Fig. 3*a*). Simulated variability in fire frequency and fire size was sensitive to fire occurrence simulation method and fire spread simulation method, respectively. Fire occurrence simulation method explained over 50% of total variance of simulated fire frequency, while fire spread simulation method explained about 30% of total variance of simulated average fire size per decade (Table 3). The interaction of fire occurrence simulation method and fire spread method was also an important factor for simulated fire size, explaining >2.5% of the variability of simulated fire size (Table 3). When the fire spread simulation method was fixed, the pairwise one-way ANOVA tests further showed that the fire occurrence simulation method using the hierarchical fire frequency model (H) significantly ($p < 0.001$) decreased the mean and variance of simulated fire size compared with the fire occurrence simulation method using the Poisson fire frequency model (P) (Fig. 3*b*). The significance of fire occurrence simulation method on simulated fire size, in terms of the relative sums

Fig. 3. Box plots of simulated (*a*) fire cycle and (*b*) average fire size per decade with respect to various fire modeling methods.

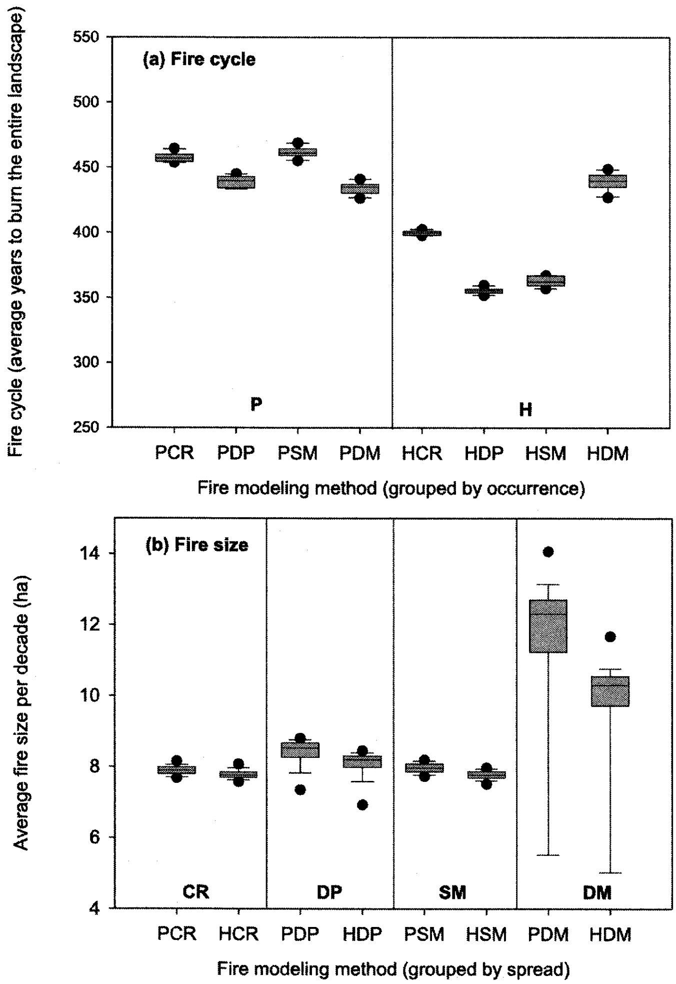


Table 3. Relative sum of squares (%) attributed to different sources of variation in the comparison of fire frequency, average fire size per decade, and burned area with respect to fire occurrence simulation method, fire spread simulation method, and their interaction.

		Response variable		
Source	df	Fire frequency	Fire size	Burned area
Fire occurrence	1	50.2*	2.6	11.7*
Fire spread	3	1.2	27.8*	19.4*
Occurrence × spread	3	2.0	3.3*	1.3
Error	7992	46.6	66.3	67.6
Total	7999	100.0	100.0	100.0

Note: Factors and their interaction are considered important if they explain more than 5% and 2.5% of the total variance, respectively (Cary et al. 2006). The important factors are indicated by an asterisk.

of squares calculated from the one-way ANOVA tests, is 2.0%, 6.1%, 5.6%, and 8.3% for using fire spread simulation method CR, DP, SM, and DM, respectively. Fire spread simulation method explained more variance in burned area than fire occurrence simulation method (19.4% versus 11.7%), but both were significantly important factors (Table 3).

Fig. 4. Box plots of shape index of burned patches simulated using various fire modeling methods.

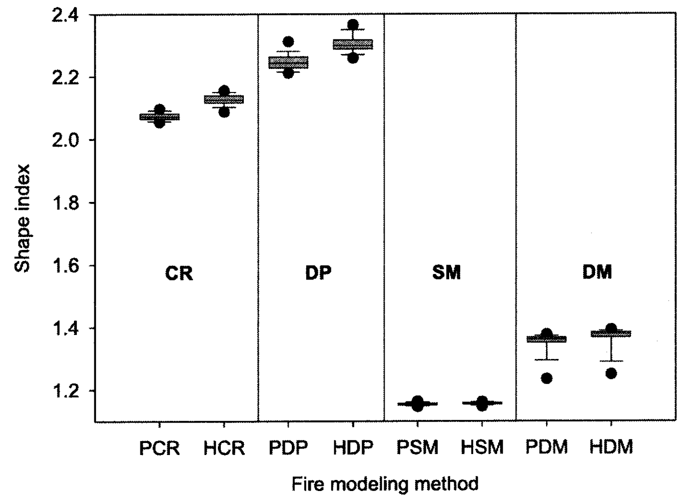


Table 4. Relative sum of squares (%) attributed to different sources of variation in the shape index of simulated burned patches with respect to fire occurrence simulation method, fire spread simulation method, and their interaction.

Source	df	Relative sum of squares (%)
Fire occurrence	1	0.1
Fire spread	3	99.0*
Occurrence × spread	3	0.1
Error	7992	0.8
Total	7999	100.0

Note: The important factors are indicated by an asterisk.

The shapes of burned patches simulated using the minimum travel time algorithm (fire spread simulation methods SM and DM) exhibited much less complexity and were more compact than those simulated using the CR and DP methods (Fig. 4). This reflects the fact that the minimum travel time algorithm derives from the physical-based Rothermel (1972) model in which simulated fire shapes are assumed to be elliptical under uniform fuel conditions, while CR and DP are probabilistic-based percolation methods in which simulated fire shapes are irregular and fractal even under uniform fuel conditions due to the intrinsic randomness of percolation. The DP method produced the most irregular burned patch shapes, and the SM method produced the most compact shapes (Fig. 4). Fire spread simulation method is the only important factor in determining the complexity of simulated fire shapes and it explained 99% of total variance of the shape index (Table 4).

The temporal pattern of fire frequency series simulated using the same fire occurrence simulation method exhibited a great amount of similarity no matter which fire spread simulation method was used (Fig. 5). Fire occurrence simulation methods had a much greater effect on the simulated fire frequency series than fire spread simulation method in the short term (≤500 years i.e., one fire cycle), but the ranking of the importance of these two factors was reversed in the long term (>500 years) (Table 5). Fire occurrence simulation

Fig. 5. Fire frequency series simulated by the eight fire modeling methods varied by the four fire spread simulation methods (*a*) CR, (*b*) DP, (*c*) SM, and (*d*) DM and the two fire occurrence simulation methods, the Poisson fire frequency model (P) and the hierarchical fire frequency model (H).

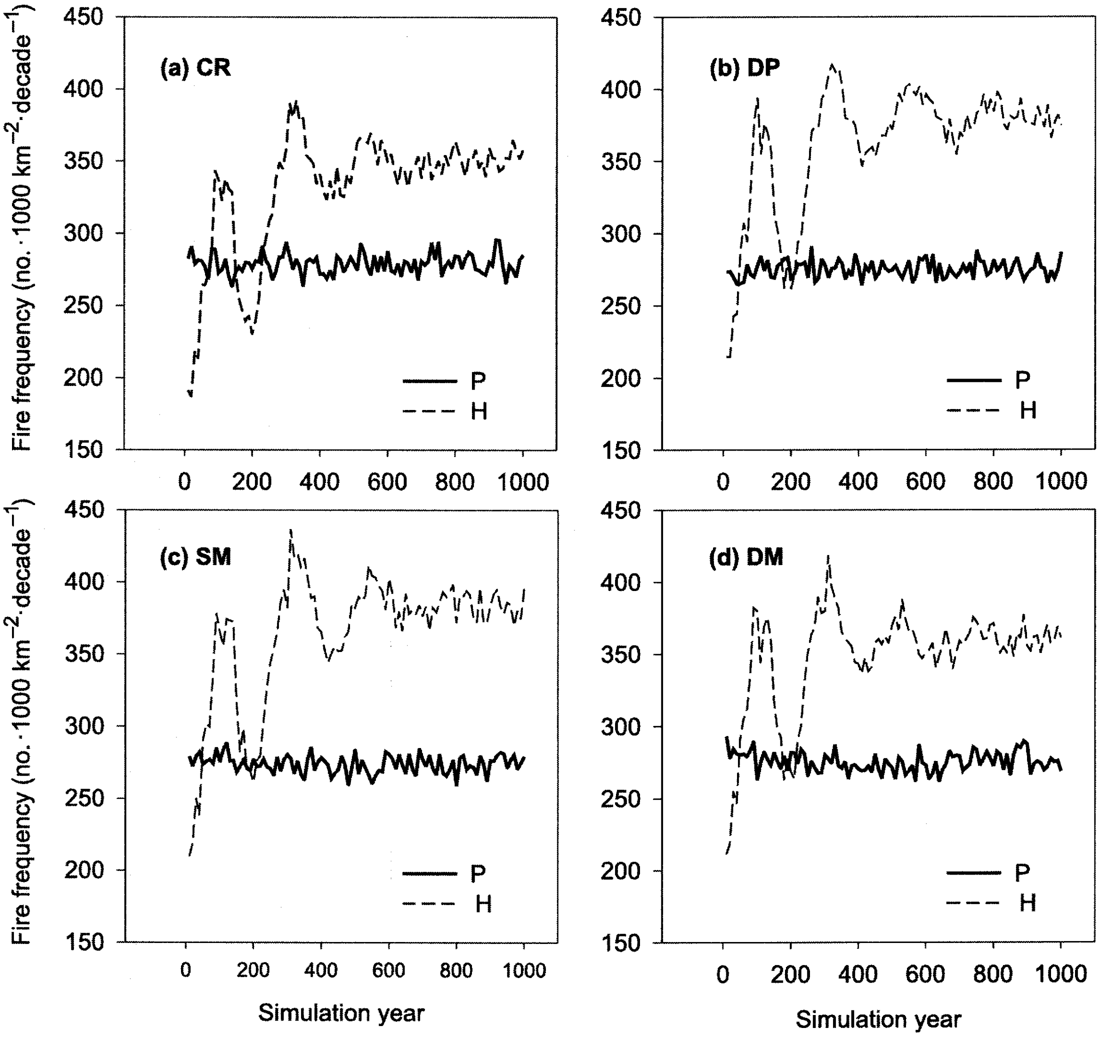


Table 5. Relative sum of squares (%) attributed to different sources of variation in the DTW similarity index of short-term (years ≤ 500) time series and long-term (500 < years ≤ 1000) normalized time series of simulated fire frequency, fire size, and burned area.

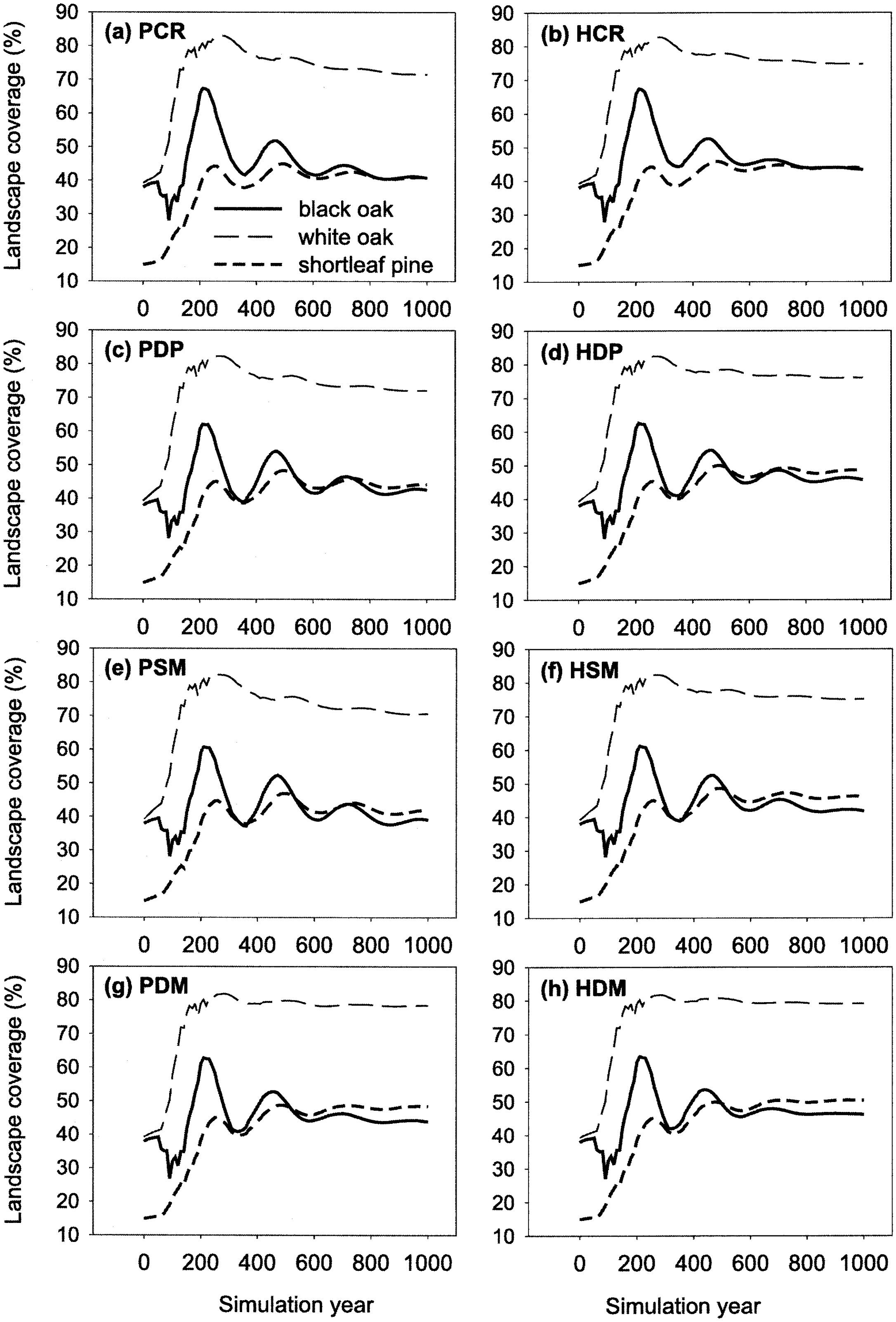
		Fire frequency		Fire size		Burned area	
Source	df	Years ≤ 500	500 < years ≤ 1000	Years ≤ 500	500 < years ≤ 1000	Years ≤ 500	500 < years ≤ 1000
Fire occurrence	1	94.2*	1.5	0.0	0.4	25.0*	11.0*
Fire spread	3	0.1	13.2*	92.4*	15.2*	50.0*	5.9*
Occurrence × spread	3	0.5	1.1	0.3	5.5*	19.4*	1.1
Error	72	5.2	84.2	7.3	78.9	5.6	82.0
Total	79	100.0	100.0	100.0	100.0	100.0	100.0

Note: The important factors are indicated by an asterisk.

method was never an important factor for either short-term or long-term time series of simulated fire size (Table 5). The significance of fire spread simulation method in determining the temporal pattern of burned area size was greater than that for fire occurrence simulation method in the short term, but it was less than that of fire occurrence simulation method in the long term (Table 5). The sum of squares for errors was less for the short-term time series of simulated fire frequency, fire size, and burned area than that for the long-term time series (Table 5). This indicated that simulated fire temporal patterns were greatly affected by fire modeling methods in the short term, but such effects were less prominent in the long term.

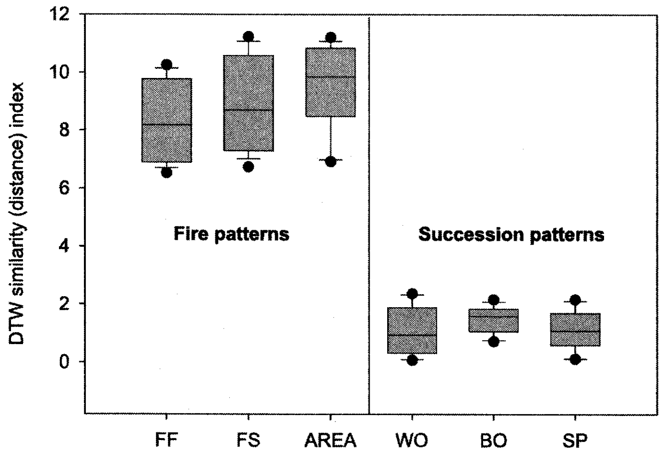
Simulated succession dynamics showed that the abundance of shortleaf pine generally increased over simulation time and gradually reached an equilibrium stage whose values were larger than the equilibrium abundance of black oak when using fire spread simulation methods other than the CR method (Figs. 6*c*–6*g*). Moreover, the shortleaf pine increased more rapidly when using fire occurrence simulation

Fig. 6. Simulated species abundance (i.e., landscape coverage area of each dominant species) time series using the eight fire modeling methods. Each 0.09 ha pixel could contain up to all three of the dominant species groups.



method H than when using method P (e.g., Fig. 6*e* versus Fig. 6*f*). There was a great degree of similarity in the simulated succession patterns across all eight fire modeling methods (Fig. 6). The average DTW similarity distance index of the simulated succession patterns was much less than that of the simulated fire patterns (Fig. 7). This indicated that simulated succession patterns over time across all fire modeling methods were more similar to each other than the simulated

Fig. 7. Box plots of the DTW similarity (distance) index of simulated time series of fire frequency (FF), fire size (FS), burned area (AREA), and landscape coverage of white oak (WO), black oak (BO), and shortleaf pine (SP) using the eight fire modeling methods.



fire patterns over time. Fire spread simulation method had a greater effect on the simulated succession dynamics than fire occurrence simulation method at both short-term and long-term scales (Table 6).

Discussion

The variability of simulated fire frequency and its temporal structure were most sensitive to the factor of fire occurrence simulation method, while the variability of simulated fire size and its temporal structure were most sensitive to the factor of fire spread simulation method (Tables 3 and 5). This is somewhat expected, as fire frequency and fire size are highly related to fire occurrence and fire spread process, respectively. The fire occurrence simulation method H, in which fire hazard accumulation was modeled as a fuel-dependent process, greatly increased simulated variability in fire frequency distribution and imposed a conspicuous temporal structure in fire frequency time series (Fig. 5).

We found very little interactive effects of fire occurrence and fire spread simulation methods on simulated fire frequency and fire size (Table 5). Our explanation lies in the characteristics of the fire regime of our study area and the simulation time step that we chose for this study. The case study area (Missouri Central Hardwood region) has a predominantly anthropogenic fire regime where ignitions are abundant and mostly caused by humans (Guyette et al. 2002). Hence, the relative influence of fuel on fire occurrence process has been mitigated by anthropogenic factors (Brosofske et al. 2007). In this region, fuel types are fairly simple (largely oak–pine forests) and low-intensity small-size fires are much more common than the catastrophic crown fires. Moreover, fine fuels in the most of the disturbed cells need only less than 10 years, which is the LANDIS (v. 4.0) simulation time step, to accumulate to the cells' undisturbed levels (Kolaks et al. 2004). All of these factors contributed to make the presumed interactive effects of fire occurrence and fire spread imperceptible in this study. We intend to apply our comparison to other forest ecosystems with different fire regimes (e.g., crown fire regime) in the future to determine what fire regimes may make such interactive effects discernible.

Statistical and probabilistic fire spread simulation methods (i.e., CR and DP), by their stochastic nature, produced a more irregular and fractal shape of burned patches than the physical methods such as the minimum travel time algorithm (Fig. 4). The duration based method produced the highest variability of simulated fire sizes among all four examined fire spread simulation methods (Fig. 3). Both fire size distribution and burn duration distribution can be used as a surrogate to model climate effects on fire spread (Keane et al. 2004). But the duration based method can also be used to model the effects of different fuel types on the rate of fire spread and on the variability of simulated fire sizes. In contrast, size-based methods cannot capture such effects. This is because such methods allow simulated fires to spread to a preselected fire size as long as the cells surrounding fire fronts are covered by fuels. In this regard, duration-based methods are more appealing. However, duration-based methods also impose a great challenge for users to calibrate the emergent fire regime characteristics due to the higher variability in simulated fire size. In addition, duration-based methods are also computationally expensive in that calculating the rate of spread for every cell on the landscape is very time-consuming (Finney 1998).

Both fire occurrence simulation method and fire spread simulation method were important factors contributing to the variance in simulated burned area, but fire spread simulation method was more important (Table 3). This finding is contrary to the results of Cary et al. (2006) that little or no relationship was observed between fire spread module and variance in area burned. There are at least two reasons for explaining such a contradiction: (*i*) we examined a long-term (1000 years) simulation in which the effects of fire spread became accumulatively prominent, while Cary et al. (2006) examined a 1-year-long simulation and (*ii*) the variability in simulated fire frequency was higher in the Cary et al. (2006) study, as they explicitly modeled the effects of daily weather variation in fire ignition simulation.

We concurred with Li et al. (2008) that although all fire modeling methods could produce the expected fire regime descriptors (e.g., mean fire size and fire cycle) after a careful calibration process, the dynamics of fire patterns simulated using different modeling methods varied. Fire modeling methods greatly affected temporal fire patterns in the short term. There was a larger degree of similarity of simulated temporal fire patterns in the long term than in the short term (Table 5). This was also found to be true for the temporal changes of simulated species abundance at landscape scales (Table 6). Furthermore, we found that succession patterns simulated with various fire modeling methods were much more similar than the simulated fire patterns (Fig. 7). These findings imply that when examining landscape-scale, long-term species changes for a fire-adapted forest ecosystem using a landscape fire succession model, choosing a complex and computationally expensive fire modeling method may not be necessary. A fire modeling method that is easy to calibrate and rapid in computation such as the CR method may be adequate for use with coarse-scale dynamic global vegetation models. Cary et al. (2006) have suggested that because of the lack of sensitivity of burned area size to fine-scale fuel

Table 6. Relative sum of squares (%) attributed to different sources of variation in the DTW similarity index of short-term (years ≤ 500) time series and long-term (500 < years ≤ 1000) normalized time series of simulated abundance of the white oak group, black oak group, and short-leaf pine group.

		White oak		Black oak		Short-leaf pine	
Source	df	Years ≤ 500	500 < years ≤ 1000	Years ≤ 500	500 < years ≤ 1000	Years ≤ 500	500 < years ≤ 1000
Fire occurrence	1	7.2*	0.6	0.2	31.6*	9.9*	21.9*
Fire spread	3	90.6*	79.3*	92.4*	44.8*	89.0*	75.9*
Occurrence × spread	3	1.8	4.4*	6.5*	12.7*	0.5	0.5
Error	72	0.4	15.7	0.9	10.9	0.6	1.7
Total	79	100.0	100.0	100.0	100.0	100.0	100.0

Note: The important factors are indicated by an asterisk.

pattern within a 1-year simulation, the dynamic global vegetation models may not need to incorporate pattern of vegetation within simulation cells. They recognized that this speculation should be tested over a long time simulation. Our 1000-year simulations that used different fire modeling methods with varying levels of ecological details for modeling the interaction of vegetation, fuel, and fire effectively demonstrate this supposition.

Spatially explicit forest landscape models such as LANDIS are useful tools for exploring large-scale, long-term consequences of management practices and disturbances (natural or anthropogenic) on future landscape conditions. Such models can describe the patterns that fire disturbances and succession are likely to create on a forest landscape and provide important information that may aid land managers in the development of forest and fire management plans. However, as our study has clearly demonstrated, different models can produce different simulated landscape patterns, which may even lead to conflicting conclusions. This suggests that researchers and users must understand the effect of alternative fire modeling methods on simulated fire and succession patterns and take such modeling artifacts into account when evaluating resource management plans from simulation results. Our model comparison sheds light on the premise and behavior of various fire modeling methods and provides guidance for users to select a suitable one to meet their specific objective. For example, as our results suggest, if the modeling objective is to study the effects of fire suppression policy or fuel-treatment plans in reducing fire risk (e.g., Shang et al. 2007), then the hierarchical fire frequency model is superior to the Poisson fire frequency model because the prior is able to explicitly simulate the effect of fuel dynamics on fire occurrence (Fig. 5) and area burned (Table 5). If the modeling objective is to evaluate the effects of forest management alternatives (including fire disturbance) on future forest structure and habitat suitability (e.g., Shifley et al. 2006), then the Poisson fire frequency model, along with a simple-to-use fire spread simulation method (e.g., CR), is sufficient to simulate coarse-scale succession patterns (Fig. 6).

Comparing fire modeling methods is an important issue, yet remains challenging. Previous multimodel comparison studies had difficulty filtering out the effect of fire modeling methods from the models' other components such as different succession simulation methods and various input data representation schemes (Cary et al. 2006). This study represents a novel comparison in which all fire simulation methods were implemented in one model (LANDIS) so that all other aspects of the fire succession simulation were constant. However, this design also has its limitations. For example, because we used a coarse temporal resolution (10-year time step) model, effects of weather on simulated fire patterns were not incorporated into these fire modeling methods. Also, LANDIS v. 4.0 only tracks the presence and absence of species/age cohorts. Without any quantity information for each present species/age cohort, the effects of fire on vegetation dynamics could only be quantified at a very coarse level.

Landscape structure is also an important factor that was not considered in our analysis. Our study area is a national forest landscape embedded in a matrix of private land. Because we did not have detailed species composition and age structure information for the private land, we could not simulate the succession dynamics on the private land as accurately as on the public land. Although we excluded private land in our results analysis, there might still remain some edge effects due to species dispersal and fire spread from the private land. Nevertheless, we deemed that such edge effects were not significant because fire sizes in this region and the effective dispersal distances for the dominant oak–pine species were very small.

Conclusions

Fire shapes simulated using the probabilistic fire spread simulation methods are more irregular and fractal than those simulated using the physical methods. The method using a duration distribution to stop fire spreading produces larger variability in simulated fire size than that using a fire size distribution. Incorporating fuel into the fire occurrence simulation can significantly affect simulated variability in fire frequency, burned area, and their temporal structures. Various fire modeling methods greatly affect temporal fire patterns in the short term, but such effects are less prominent in the long term. Simulated landscape-level succession patterns are quite similar among different fire modeling methods, suggesting that a simple fire modeling method may be adequate to use with coarse-scale dynamic global vegetation models.

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