CHAPTER 9

Spatial Simulation of Broad-Scale Fire Regimes as a Tool for Emulating Natural Forest Landscape Disturbance

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To emulate natural forest disturbance, forest managers must select appropriate disturbance regimes to emulate, based on the relative significance of such disturbance agents as fire, wind, and insect epidemics in the landscape. This decision also depends on the spatiotemporal scale of the proposed management activities, such as the extent of the unit being managed, the spatial resolution, the planning horizon, and the time interval between planning steps. Next, the forest manager must understand the nature of the disturbance regimes and be able to quantify the regimes to set unambiguous management goals. These steps presume the availability of reliable knowledge about the disturbance regimes of interest. In other words, explicit information about natural disturbance regimes is a prerequisite to moving from the concept of emulating natural disturbance (e.g., Perera and Buse, chapter 1, this volume) to the practice.

Although there are many possible approaches to understanding natural disturbance (Suffling and Perera, chapter 4, this volume; Keane, Parsons, and Rollins, chapter 5, this volume), the approaches can be broadly grouped into historical reconstruction and simulation modeling. The first group includes various methods for obtaining evidence of past disturbances (e.g., Heinselman 1973; Bergeron et al. 2001). The second group includes theoretical predictions based on empirical information (e.g., Johnson and Van Wagner 1985), mechanistic processes (e.g., Finney 1999), or a hybrid of both (e.g., Keane et al. 1996a). Further descriptions of these approaches are available in Egan and Howell (2001) for the historical methods and Gardner et al. (1999) for the modeling methods.

Simulation modeling can be further categorized based on the nature of the variation in the predicted outcome (deterministic versus stochastic) and the explicitness of the outcome (spatial versus nonspatial). Deterministic models use functions based on nonprobabilistic processes. In contrast, stochastic models of disturbance account for inherent variation in processes (e.g., fire ignition, spread, extinction) and inputs (e.g., weather, fuel), and thereby predict a probabilistic outcome. Spatially explicit models use georeferenced data for inputs (e.g., forest cover, climate, terrain), encapsulate spatial interactions within the model's functions, and produce georeferenced outputs (e.g., age, species). They also explicitly scale the model's functions (e.g., fire spread in 100-m steps determined by weather that changes at 1-h intervals) and account for spatial processes (e.g., propagule dispersal).

Our objective in this chapter is to describe a spatially explicit stochastic simulation modeling method and demonstrate its use for quantifying broad-scale natural fire disturbance regimes in the boreal forest. We believe it will provide useful information to support forest management based on emulating natural forest disturbance. Specifically, we simulate a series of spatial and aspatial characteristics of a *null fire regime*—one that starts with the existing forest cover and present-day climate—as if fires were allowed to ignite and spread without human interference. This does not assume a "natural" or pre-European settlement fire regime. We ask readers to keep in mind that this chapter only presents a case study meant to illustrate the approach, not a detailed ecological examination of the fire regime and its causal factors in the study area in the strictest sense.

Simulating the Fire Regime of a Region in North-Central Ontario

Model Description

The Boreal Forest Landscape Dynamics Simulator (BFOLDS), a grid-based, spatially explicit model, was used in this case study. This model contains a simulation module for crown-fire regimes (FSM) and a vegetation transition module (VTM). BFOLDS simulates the fire regime and fire-induced forest cover dynamics at broad spatial and temporal scales (>10 million ha and ≤300 yr), but uses a relatively fine spatial scale for some processes (1-ha spatial resolution). The VTM operates on a fixed time step (1 yr), and the FSM operates on a variable time step (the time for fire fronts to propagate to the centers of adjacent 1-ha cells). If a 1-ha cell burns with sufficiently high intensity in the FSM, the model assumes complete canopy destruction, and the cell is subsequently occupied by an appropriate tree species determined by the VTM. If a pixel does not burn, its forest cover may or may not be replaced, based on the probability of succession in the VTM, with these probabilities based on a combination of age and site type. In both cases, the elapsed times since burning and since a species transition occurred are tracked separately in each year. Figure 9.1 provides a conceptual overview of this model. BFOLDS uses several raster GIS data layers that include forest cover composition and stand age, terrain, fuel type, time since last disturbance, and a suite of geoclimatic variables (table 9.1). Details of the model, including its architecture, simulation functions, input data structure, output information, and operating instructions, are provided in Perera et al. (2004) and Yemshanov and Perera (2002). Here we provide only a brief overview of the model, based on figure 9.1.

The FSM is process-based, and contains submodules for fire ignition, fire spread, and fire extinguishment. It represents the current state of our knowledge of fire processes (e.g., influence of fuel, terrain, and weather on fire spread) rather than empirical data (e.g., mean fire size) or assumptions about the fire regime (e.g., size class distribution of fires, mean annual proportion burned). We used Ontario fire and weather history databases for the past four decades (1963–2001), which contain the locations of lightning-caused fire ignitions, to "seed" fire ignitions in the model. The number of ignitions was selected randomly from a Poisson distribution (after Cunningham and Martell 1973), and the spatial positioning of these potential ignitions in the study area was also random. The actual ignition

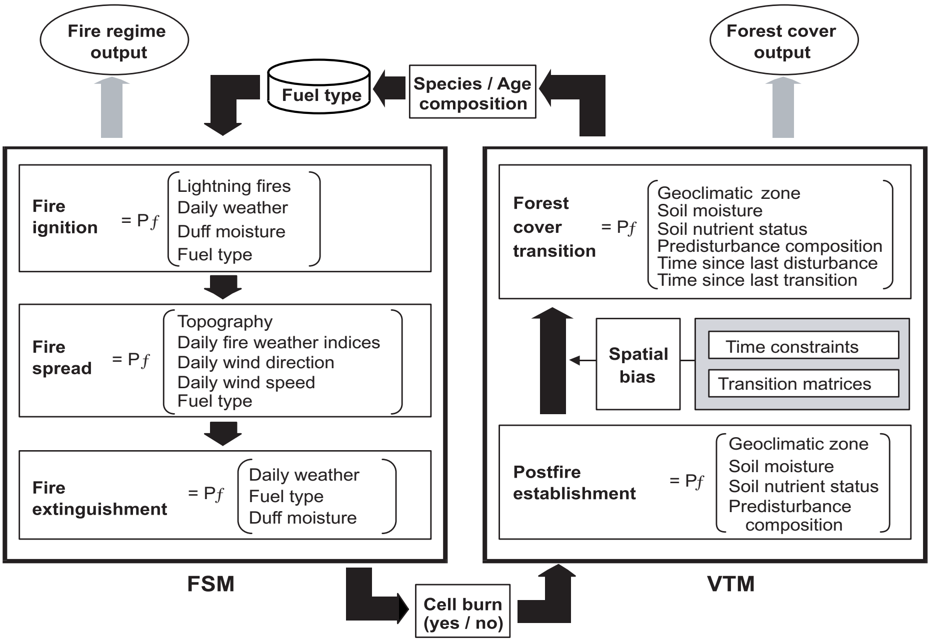


FIGURE 9.1. Conceptual overview of the Boreal Forest Landscape Dynamics Simulator (BFOLDS), including the Fire Simulation Module (FSM) and the Vegetation Transition Module (VTM). P_f denotes that the probability of the outcome is a function of the stated variables.

TABLE 9.1. Spatial Data Layers Used as Input in the Boreal Forest Landscape Dynamics Simulator (BFOLDS) to Simulate a 200-yr Fire Regime

Data Type	Source
Slope and aspect	Digital elevation model (Centre for Topographic Information 2000) corrected for watershed and stream networks
Time since last fire	Ontario forest fire history database (Perera et al. 1998)
Geoclimatic zone	Forest ecoregion map of Ontario (Hills 1959; Rowe 1972)
Soil nutrient status	Soil texture database (Ontario Ministry of Natural Resources 1977), corrected by using a flow accumulation index (ESRI 1998) for lowlands and 30-m LANDSAT-TM land-cover classification (Spectranalysis 1999) for outcrops and treed bogs
Soil moisture	Soil moisture database (Agriculture and Agri-Food Canada 1996, Ontario Ministry of Natural Resources 1977), corrected by using a topographic wetness index (Wolock and McCabe 1995)
Forest stand age	Ontario Forest Resource Inventory database (Ontario Ministry of Natural Resources 1996b)
Forest cover composition	Ontario Forest Resource Inventory database (Ontario Ministry of Natural Resources 1996b)
1962–2002 daily occurrence of fire ignitions[1]	Fire Science and Technology Unit, Aviation Forest Fire Management Branch, Ontario Ministry of Natural Resources
1962–2002 daily fire weather indices (FFMC, DMC, DC)[1]	
1962–2002 daily wind speed and direction data[1]	

[1] Point-source data. All others are raster data, with 100-m resolution.

and subsequent spread of these fires resulted from the local weather patterns (simulated by using daily fire weather data for the 1963–2001 period) and their interactions with the spatial patterns of fuel and terrain. The FSM uses cellular automata to simulate the processes of fire ignition, spread, and extinguishment, based on the indices of the Canadian Forest Fire Weather Index System (Van Wagner 1987); these include the Fine Fuel Moisture Code, Duff Moisture Code, and Buildup Index, as well as wind speed, wind direction, and terrain characteristics. The model predicts fire intensity and rate of spread on an hourly basis when any fires are burning by using the Canadian Forest Fire Behaviour Prediction System (Hirsch 1996).

The VTM contains two steps: postdisturbance recruitment of tree species, which is based on knowledge of the regeneration ecology of boreal tree species, and postdisturbance succession of the forest cover. The latter is simulated as a semi-Markovian transition process that predicts succession of the forest cover, based on the probability of the persistence of individual tree species in the canopy, the length of the postdisturbance period, and geoclimatic conditions, with discrete states corresponding to the dominant tree species. The probabilities of discrete state transitions are stratified spatially, based on geoclimate, soil moisture, and edaphic gradients. BFOLDS also contains a submodule that applies a spatial bias to the transition probabilities used to predict the change in forest cover; to do so, the submodule uses local spatial autocorrelation of environmental site conditions (Weaver and Perera, in press) to reduce the artificial spatial randomness introduced by Markov models.

Study Area

The area selected for this simulation exercise occupied 2.15 million ha in north-central Ontario, Canada (figure 9.2). It covers portions of the Northern Clay Belt (in the northern third of the study area) and the Missinabi-Cabonga sections of Rowe's (1972) classification of the boreal forest region of Canada. The major land use in this area since the early twentieth century has been commercial forestry, with widespread timber harvesting (Perera and Baldwin 2000). In addition to forest harvesting, this area has been subjected to

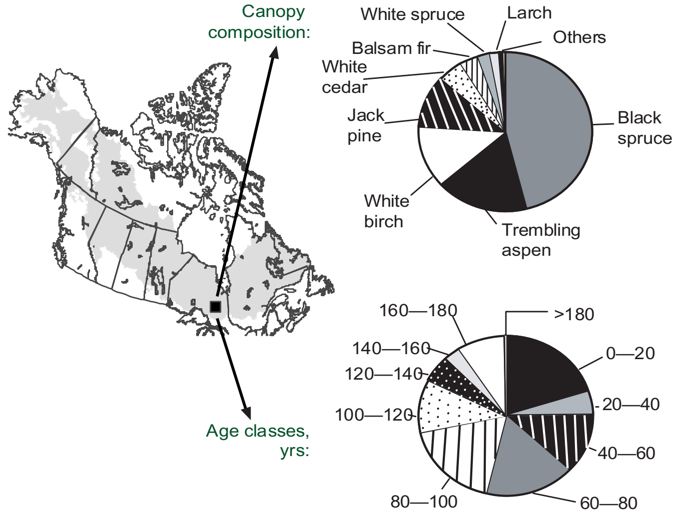


FIGURE 9.2. Location of the boreal forest landscape used in the simulation study, and its forest cover and age composition. (White spruce = *Picea glauca* [Moench] Voss, balsam fir = *Abies balsamea* [L.] Mill., white cedar = *Thuja occidentalis* L., and larch = *Larix* spp.)

periodic forest fires (Perera et al. 1998) and insect epidemics (Candau et al. 1998) during the past century. The present forest cover in the area has therefore resulted from extensive anthropogenic and natural disturbances. Spatial data are readily available for this area from databases on geoclimate (Ontario Ministry of Natural Resources 2000), soils (Ontario Ministry of Natural Resources 1977; Agriculture and Agri-Food Canada 1996), terrain (Centre for Topographic Information 2000), and forest inventory (Ontario Ministry of Natural Resources 1996b). Based on the forest inventory data, roughly 50% of the forested area is composed of stands 40–100 yr old. Around 20% of the forest is younger than 20 yr, and around 13% is older than 120 yr. Forest cover is primarily boreal and is dominated by black spruce (*Picea mariana* [Mill.] B.S.P., 45% by area), followed by trembling aspen (*Populus tremuloides* Michx., 17%), birch (*Betula* spp., 13%), and jack pine (*Pinus banksiana* Lamb., 11%), as shown in figure 9.2.

Simulation Runs and Study Assumptions

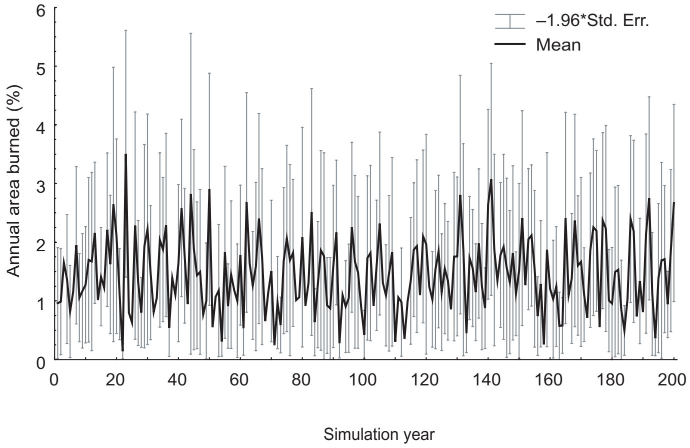
The fire regime in the study area (2.15 million ha) was simulated at 1-ha resolution for 200 yr, with annual reporting of the number of fires, area burned by each fire, spatial geometry of the burns, succession of the forest cover, composition of the forest cover, and age composition of the forest. Forest age was tracked with respect to the times elapsed since the last disturbance ("site age") and since the last change in forest cover ("canopy age"). We replicated the entire 200-yr simulation 20 times, always starting the simulation runs with the currently existing forest cover and age composition. Therefore, the simulation results provide insight into the uncontrolled natural fire regime of the study area starting with the present forest cover (representing the legacy of more than a century of human intervention) rather than with "pristine" forest conditions.

This approach was chosen because no methods were available to generate the potential natural forest cover to use as input in a reliable, spatially explicit manner. Similarly, we assumed that climatic conditions would remain stable during the 200-yr simulation period, because spatially explicit models of climate change are not yet available for Ontario. Because spatially detailed fire weather data have only been available since the 1960s, we could not simulate fire weather scenarios that lie beyond the extremes that have occurred during the past 40 yr. We address the significance of these assumptions in the discussion on applying the study results. The simulation parameters used here (a 200-yr period, 2.15 million ha extent, and 20 replications) were arbitrary, and have been selected solely to illustrate the use of the method. In consequence, they lack real ecological significance.

Results of the Simulation

Once a simulation was complete, we imposed an internal 5-km-wide buffer (0.250 million ha) to eliminate edge effects caused by fires originating outside the area being simulated and spreading into the study area. This decision reduced the extent of the study area to 1.902 million ha. A further 238,000 ha (including water

FIGURE 9.3. The mean percentage of the total area burned annually (annual burn rate) during the 200-yr simulation period, and standard error bars ($n = 20$).



and unvegetated areas, such as settlements and bedrock) was deemed unburnable under the Canadian system of fuel classification (Forestry Canada Fire Danger Group 1992). Consequently, the simulations applied to only 1.664 million ha of the study area, and this value was used in reporting the results of the simulations.

Annual Burn Rate

For the 200-yr simulation period, 1730 ± 38 (mean ± standard error) fires occurred within the burnable extent of the study area. For the 4000 yr of simulations (200 yr × 20 replicates), at least one fire occurred in 73.3% of the years. The overall mean annual burn rate for the 200-yr period (i.e., the proportion of the total area burned) was 1.45 ± 0.03%, with values during the simulation period that ranged from less than 0.2% to more than 3.5% (figure 9.3). The corresponding mean fire cycle, commonly estimated as the reciprocal of the annual burn rate (Johnson and Gutsell 1994), was 69 yr.

Size Class Distribution of the Fires

The mean fire size in the simulated fire regime was 2814.7 ± 42.6 ha, with the largest individual fire exceeding 145,000 ha (8.7% of the burnable area). The number of fires per year and the total annual area burned were significantly correlated, as would be expected. The size class distribution for fires during the simulation period showed a negative-exponential trend, with numerous small fires (figure 9.4). Based on the total number of fires and the total area burned during the simulation period, we constructed probability distributions for the number of fires and for the area burned for each size class (figure 9.5). The probability of a fire being larger than 1000 ha was 41.0 ± 1.0%, versus 16.6 ± 0.4% for fires larger than 5000 ha, 8.2 ± 0.3% for fires larger than 10,000 ha, and 3.2 ± 0.2% for fires over 20,000 ha. In other words, most fires (nearly 60%) were smaller than 1000 ha. Only a very small proportion (1.6%) of the burned area was caused by these

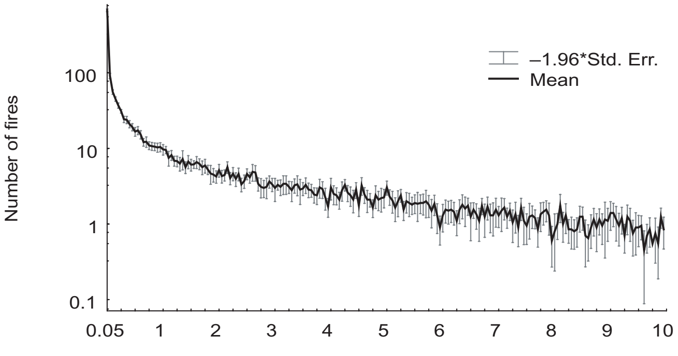


FIGURE 9.4. The mean size class distribution for fires during the 200-yr simulation period, and standard errors of the values ($n = 20$).

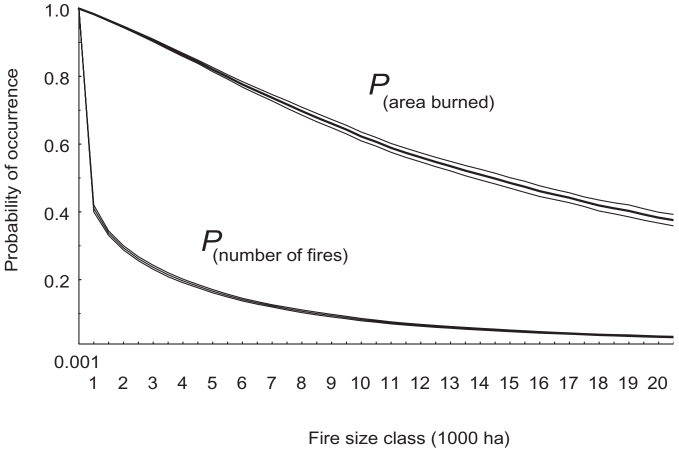


FIGURE 9.5. The cumulative probability of occurrence of fires of different sizes ($P_{\text{number of fires}}$) and the cumulative probability of the study area being burned by fires of different sizes ($P_{\text{area burned}}$) during the 200-yr simulation period, plus the 95% confidence interval for these probabilities ($n = 20$).

small fires, whereas 98.4 ± 0.08% of the burned area was caused by fires larger than 1000 ha; of the latter percentage, 82.0 ± 0.6% was caused by fires larger than 5000 ha, 62.2 ± 1.3% by fires larger than 10,000 ha, and 38.3 ± 1.6% by fires larger than 20,000 ha.

Mean Interval between Fires

The overall mean interval between fires for the study area, which is equivalent to the "point fire frequency" (Lertzman et al. 1998), was 85.06 ± 1.56 yr. This was estimated as the average period between two consecutive fires for each 1-ha pixel in the burnable portion of the study area during the 200-yr simulation, averaged over 20 replicates. The mean interval between fires for most of the area (52%) was 40–80 yr, with another 29% of the area having a mean interval of 80–120 yr. Only 15% of the area had an interval of 120–180 yr. The spatial distribution of these intervals was clustered, which suggests the existence of spatial biases in repeatedly burned areas (color plate 7).

Fire Probability

We defined the probability of a given 1-ha pixel burning as the number of times that pixel burned during the 200-yr period, expressed as a proportion of the maximum possible number of opportunities the model allowed for it to burn. A very large proportion of the burnable area (nearly 77%) has an 8–20% probability of burning during a given 200-yr period. The spatial distribution of these probabilities was also clustered (color plate 8), because of the spatial biases in repeated burns, as discussed in the previous section.

In addition, we examined the spatial probability of occurrence of fires in different size classes. These values were estimated as the number of times a given pixel was burned by a fire of a given size class, expressed as a proportion of the maximum possible number of opportunities for it to burn allowed by the model. The spatial probability of occurrence of very small fires (<250 ha) was low: more than 60% of the area had a probability of less than 0.2% of being burned by a very small fire. This is because most of the very small fires (although highly frequent) are spatially random, without any apparent biases (color plate 9a). With the next-largest size class, small fires (250–1000 ha), the probability of occurrence increased (>60% of the area had a probability >0.3%), and the spatial patterning was still dispersed (color plate 9b). As size class increased from medium (1000–5000 ha; color plate 9c) to large (5000–10,000 ha; color plate 9d), the spatial probability of occurrence also increased (>60% of the area with a probability >1.2% for medium fires, and >2.0% for large fires), and the spatial patterns became more clustered. With very large fires (>10,000 ha; color plate 9e), the spatial probability of occurrence was even higher (>60% of the area with a probability >8.0%), and the spatial patterns were even more strongly clustered. This is because larger fires are more likely to overlap (hence repeat) in space.

Age Composition

The age composition of the forest cover changed considerably during the simulation period (figure 9.6). The age composition shifted from an initial multimodal distribution (with peaks at <20, 50–100, and 140–160 yr) toward a negative-

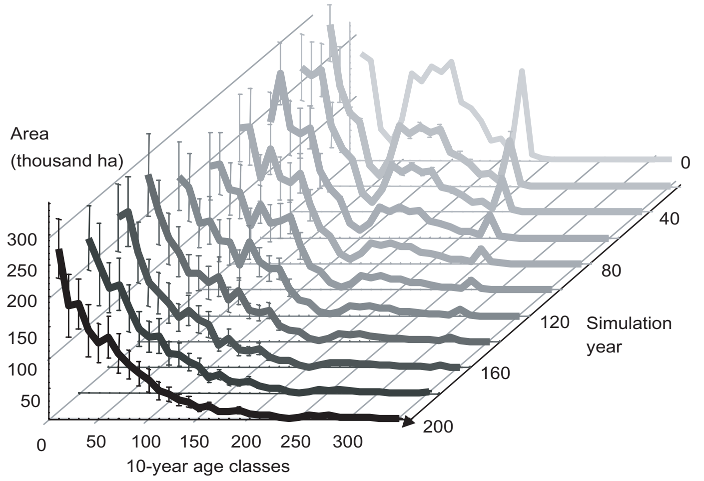


FIGURE 9.6. The initial age class distribution of the study area (year 0) and changes in the mean age class distribution over the course of the 200-yr simulation period (at 20-yr intervals), plus the standard error of the values ($n = 20$).

exponential curve by year 200. The maximum-age cohort also increased from 250 yr to more than 350 yr, because some parts of the study area did not burn during the simulation period. In addition, we tracked the maximum age that every 1-ha pixel in the study area attained during the simulation period. The spatial pattern for the mean maximum site age that was attained (over 20 replicates) is illustrated in color plate 10.

Variability in the Simulated Fire Regime

The inherent variability in a regional fire regime can be manifested in three dimensions: temporal, spatial, and stochastic (Lertzman et al. 1998). For example, in any given year of the simulation, the number of fires that occurred varied from 0 to 75, resulting in annual burn rates as low as 0% and as high as nearly 20%; these values correspond to fire cycles of more than 1000 yr to as little as 5 yr. Every aspect of the fire regime (e.g., size class distribution, location of fires) varied between years. This *temporal* variability results from annual variations in weather and long-term variation in forest cover, whether these changes occur randomly or as a result of autocorrelation. *Spatial* variability in the fire regime results from the spatial heterogeneity of the geoclimate, terrain, and forest cover in the study area. For example, the overall 85-yr mean interval between fires for the study area can be expressed in a spatially explicit manner so as to describe the spatial variability and biases in the study area, as shown in color plate 7. Another example is the burn probability with very large fires. The mean spatial probability of occurrence (9.2%) can be more effectively expressed using a choropleth map (such as color plate 9e) that captures the spatial variability.

The *stochastic* variability approximates the nondeterministic nature of the many processes that may be involved in any natural fire regime, random fluctuations in these processes, and the ensuing changes in forest landscapes. This variability arises in simulations as the result of the product of many stochastic model functions (e.g., fire ignition, spread, extinction), succession in the forest cover, and intrinsic variability in such input data as weather and forest cover. The stochastic variability is captured as the among-replicate variation of the simulations, and can be illustrated as error bars and confidence intervals (e.g., figures 9.3–9.6), or as spatially explicit "surface roughness" (the differences in elevation in color plate 11).

Applying Information on Simulated Fire Regimes to the Management of the Forest Landscape

In approaches to forest management that emulate natural disturbance, knowledge generated by the simulation of fire regimes can be useful for defining the emulation *criteria* (see Perera and Buse, chapter 1, this volume); these criteria represent the characteristics of a disturbance that can be used to quantitatively describe the disturbance regime. Thus, they can be used as a guide in developing strategies and practices for emulating natural forest disturbance, on the assumption that fire is the most prevalent broad-scale disturbance in the management area.

The *degree* to which a fire regime can be emulated based on these criteria may vary, depending on various socioeconomic and ecological

TABLE 9.2. Criteria for Emulating Natural Disturbance and Examples of Their Use in Forest Landscape Management

Emulation Criteria	Fire Regime Characteristic (Null Values)	Forest Management Characteristic
Overall rate of disturbance for a planning region	Mean annual burn rate Regional fire cycle Temporal and stochastic variability in annual burn rate	Mean annual area harvested Regional harvest rotation Bounds of variation for variability in annual area harvested
Spatial and temporal frequency of disturbance	Spatial probability of burning Spatial variability of mean interval between fires Stochastic variability in probability of burning and mean interval between fires	Selection of harvest regions Local harvest rotation Bounds of variation for harvest regions and local rotations
Sizes and patterns of disturbance	Fire size class distribution Temporal and stochastic variability in fire sizes Spatial probability of fire size classes	Harvest patch size class distribution Bounds of variation for harvest patch sizes Spatial distribution of harvest patches
Potential for landscape aging	Distribution of site age and canopy age class Stochastic variability of age class distribution Spatial probability of mean and maximum of site age and canopy age Stochastic variability in probability of site age and canopy age	Age cohort composition, including old-growth extent (by species) Bounds of variation for age-cohort composition Spatial demarcation of old-growth sites Bounds of variation for spatial demarcation of old-growth sites
Forest landscape composition and patterns	Forest cover composition and spatial probabilities Spatial geometry of forest cover Spatial, temporal, and stochastic variability in forest cover and spatial geometry	Future composition and spatial patterns of forest cover "Desired" landscape patch characteristics Bounds of variation for forest cover and patch characteristics

considerations. Several characteristics of a fire regime can be used as the emulation criteria, and the simulated values used as the basis for harvesting regimes (table 9.2). For example, in the broadest (aspatial) sense, annual rates of fire disturbance (annual burn rate) in the region (as illustrated in figure 9.3) provide insight into potential forest harvest rates (Hunter 1993; Armstrong 1999). The concept of a regional fire cycle is heavily debated (e.g., Lertzman et al. 1998; Armstrong 1999; Li 2002), but can nonetheless serve as the basis for "regional woodshed planning" that determines the long-term timber supply and hence the harvest cycles. The spatial variation in rates of disturbance (e.g., spatial patterns for the mean interval between fires in color plate 7 and the probability of burning in color plate 8) provides a spatially explicit template for the region's heterogeneity.

These values can guide the spatiotemporal allocation of rotation length and the size of harvest blocks. The simulated probability distribution of fire size classes (see figure 9.4) presents one possible template for planning the size class distribution of harvest patches, which is required by some forest policies (e.g., Ontario Ministry of Natural Resources 2002a; McNicol and Baker, chapter 21, this volume). Moreover, the spatial probabilities of occurrence for different fire size classes may be used to guide the placement of harvest patches in a landscape. For example, smaller harvest patches may be placed anywhere in the landscape (as per color plate 9a), whereas very large patches may be placed only in certain parts of the landscape (as per color plate 9e). Similarly, the age class distribution resulting from the simulated regime may provide a logical basis on which to plan future forest-age cohorts, something that has been advocated, based on empirically derived fire regimes (e.g., Y. Bergeron et al. 1999). Information on the age patterns that result from simulated fire regimes can also help answer planning questions for old-growth forest (Johnson et al. 1995). Specifically, the temporal and spatial patterns of a simulated age class distribution (see figure 9.6) and of simulated maximum age (color plate 10) can guide strategic decisions about the extent and locations of future old growth (Perera et al. 2003). Although we did not present the forest cover patterns resulting from the simulations described in this chapter, these postfire patterns provide an indication of potential patterns of forest cover in terms of stand composition, spatial tendencies, and the spatial geometry of patches.

In their attempts to emulate natural disturbance, managers recognize that natural disturbance regimes vary by using terms such as *bounds of natural variation* (e.g., Ontario Ministry of Natural Resources 2002a); when resorting to natural history techniques, they may use *historical range of variability* instead (e.g., Morgan et al. 1994). As discussed earlier, simulation can separate variability into three distinct sources (spatial, temporal, and stochastic), each of which has different significance in understanding disturbance regimes. Thus, forest managers can distinguish the spatial variation of a fire regime criterion within their planning area (e.g., the mean interval between fires in color plate 7); the temporal variation during the planning period (e.g., the age class distribution in figure 9.6); and most importantly, the stochastic variation of a spatial or temporal variable (e.g., the spatial probability of fire in color plate 11 and the annual area burned in figure 9.3).

Estimation of the magnitude of these sources of variability, especially the spatial and stochastic sources, is almost impossible in empirical methods of predicting fire regimes. In fact, as Lertzman et al. (1998, p. 4) wrote, the "historical dynamics of any real landscape are [only] one realization of a stochastic process." Furthermore, the historical dynamics are analogous to a single run of a simulation model, with no estimation of the potential for random fluctuations. This is a principal issue in validating these types of long-term models of landscape dynamics. A comparison of what can be reconstructed from the historical record with the results produced by simulation models provides unsatisfactory support for the validity of the model. The inherent spatial and temporal variability of fires is quite high, and the temporal extent of the historical data is limited, because records of past fires have been obliterated by more recent fires. Further complicating this situation is the large spatial extent of most simulations, which consequently encompass high spatial heterogeneity.

The picture that can be reconstructed from the historical record is, as indicated above, only one instantiation of a highly stochastic process, so it can readily fit within the simulated range of variability from landscape models, some of which might not resemble known landscape processes. Comparison with historical data is only one method for validation (e.g., Sargent 2000). In this chapter, our approach was to construct a model using available, accepted components. Validation of the model is also consistent with the approach recommended by Kleindorfer et al. (1998), in which validation is provided by dialog with the model's stakeholders to take advantage of their judgment about what is understood and accepted. The most significant aspect of this approach is that forest managers are not required to predict the fire regime's characteristics in advance. Empirical knowledge of either individual values (e.g., mean fire interval, frequency, or cycle) or their probability distributions (e.g., a negative-exponential fire size distribution) is not decided a priori. Instead, forest managers discover the regional fire regime to be a function of patterns in geoclimate and forest cover in their region, and thereby avoid the circular reasoning inherent in many empirical methods of predicting fire regimes.

Nonetheless, our approach also requires some assumptions (albeit not about the outcome) that may influence the use of the predicted fire regimes and their emulation by forest managers. First, for reasons explained above, we assumed that regional climate remains stable during the 200-yr simulation period and that extremes in the weather patterns will remain within the limits experienced during the past 40 yr. Although this is more a limitation of the input data than a true assumption, it may nonetheless limit the incidence of large and infrequent disturbances, such as those described by Turner and Dale (1998). In addition, the temporal and spatial variability of the simulated fire regimes, and therefore the variability in the values of the emulation criteria, may be underestimated. As spatial databases expand with time and spatially explicit models of climate change become available, this assumption is likely to become unnecessary.

The second assumption is more of a premise: we simulated the fire regime starting from the existing forest cover rather than beginning with a pre-European settlement or pristine forest cover unaffected by humans. The values of the emulation criteria generated using this approach may not represent any historical fire regime (patterns in cover, climate, and fire weather in the absence of humans) or, more importantly, may fail to represent the natural fire regime. These simulations may more realistically portray disturbance regimes, because we must manage the existing forests. However, the length of our simulation period (200 yr) captures only a short period of temporal variability in the fire regime and in the dynamics of the forest cover, and thus, may not adequately reflect longer-term trends that extend beyond the life spans of the tree species in the region.

Conclusions

Scientists, forest managers, and other stakeholders regularly engage in debate about what constitutes a natural fire regime. The debate may be futile, because the high degree of temporal, spatial, and stochastic variability evident in disturbance regimes suggests that *natural* spans a large range of possibilities. Simulation modeling offers a sound alternative, because the modeled scenarios represent potential outcomes rather than an attempt to define a singular natural outcome.

In this chapter, our goal was to demonstrate the utility of a spatially explicit stochastic simulation model in generating a null fire disturbance regime that could be helpful in planning and management of the forest landscape. The results of our simulations illustrated the usefulness of this approach for emulating natural disturbance. Because this method provides insight into several aspects of disturbance regimes that cannot otherwise be estimated, it complements such empirical methods as natural history surveys and nonspatial empirical models. It also offers several advantages.

First, all characteristics of the simulated disturbance regime are a direct product of scientific knowledge and the mechanistic logic encapsulated in the model's functions. Users discover the potential fire regime based on the knowledge embedded in the model, as well as on geoclimatic and forest cover data. Therefore, the approach avoids the circular reasoning intrinsic in approaches that are based on a priori empirical assumptions about characteristics of the fire regime, such as the annual burn rate, fire cycle, and statistical distribution of the fire size classes. Moreover, because the simulated fire regime is an emergent property of the model's functions and input data, simulations may discover probable but infrequent and spatially rare fire events that are missing from historical empirical information.

Second, the simulation's results are spatially explicit, and go beyond traditional descriptions of fire regimes that represent large regions aspatially by single values, such as the length of the fire cycle or the fire frequency. Patterns in these and other descriptors of the fire regime can be explicitly portrayed as spatial probabilities, thereby allowing forest managers to understand the spatial patterns in the fire disturbance regime of an area and factors that bias these patterns. These patterns may guide the positioning of forest management activities in a planning area.

Third, this simulation approach provides the opportunity to estimate the variability of predictions of the fire regime from three points of view. Year-to-year temporal variation during the simulation period and the spatial variation of the fire regime's characteristics in the study area can be directly estimated to elucidate the spatiotemporal dynamics of the disturbances. In addition, the stochastic nature of the model's several functions lets modelers predict the magnitude of the variation by replicating the simulation. Together, these estimates of variability add robustness to the predictions and give forest managers confidence that they are truly emulating natural disturbance.

In general, there are few obstacles to broadening the use of spatially oriented models of fire regimes. The potential for error propagation due to inaccuracies in spatial databases and the validity of the model's assumptions are the most prominent technical issues, although ongoing advances in the development of spatial databases and in fire science may quickly remedy these shortcomings. In practice, the relative lack of trust in simulation models in comparison with field observations may interfere with adoption of these models. This problem is compounded by the constant calls for testing and validation of models, which itself leads to a complex philosophical debate. The general paucity of adequate (i.e., long-term, accurate, replicated) empirical observations, which are required to validate the simulation models, makes this task difficult. However, modeling methods based on spatial simulation improve incrementally as science provides better logic, data, and assumptions. These methods also provide opportunities to explore "what if?" scenarios by explicitly manipulating input data (e.g., climate change) and linking the simulations with models that simulate other types of disturbance (e.g., insect epidemics).

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