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SPATIAL CONTROLS OF OCCURRENCE AND SPREAD OF WILDFIRES IN THE MISSOURI OZARK HIGHLANDS

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Understanding spatial controls on wildfires is important when designing adaptive fire management plans and optimizing fuel treatment locations on a forest landscape. Previous research about this topic focused primarily on spatial controls for fire origin locations alone. Fire spread and behavior were largely overlooked. This paper contrasts the relative importance of biotic, abiotic, and anthropogenic constraints on the spatial pattern of fire occurrence with that on burn probability (i.e., the probability that fire will spread to a particular location). Spatial point pattern analysis and landscape succession fire model (LANDIS) were used to create maps to show the contrast. We quantified spatial controls on both fire occurrence and fire spread in the Midwest Ozark Highlands region, USA. This area exhibits a typical anthropogenic surface fire regime. We found that (1) human accessibility and land ownership were primary limiting factors in shaping clustered fire origin locations; (2) vegetation and topography had a negligible influence on fire occurrence in this anthropogenic regime; (3) burn probability was higher in grassland and open woodland than in closed-canopy forest, even though fire occurrence density was less in these vegetation types; and (4) biotic and abiotic factors were secondary descriptive ingredients for determining the spatial patterns of burn probability. This study demonstrates how fire occurrence and spread interact with landscape patterns to affect the spatial distribution of wildfire risk. The application of spatial point pattern data analysis would also be valuable to researchers working on landscape forest fire models to integrate historical ignition location patterns in fire simulation.

Keywords: burn probability; fire risk; LANDIS; Ozark Highlands; USA; spatial point pattern; wildfire

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INTRODUCTION

Wildfires have burned progressively larger areas of U.S. National Forests recently despite large expenditures for fire suppression (Stephens 2005). The great risk of forest wildfire mandates active fire management plans to reduce excessive fuels that may lead to uncharacteristically intense and damaging wildfires (Stephens and Ruth 2005). Fuel reduction is the primary strategy to mitigate fire risk. Fuel types that are varied in size and shape (e.g., surface fuels, crown fuels) affect wildfire behavior differently (Agee and Skinner 2005). Fuel continuity can also limit the frequency and spread of surface fires on topographically rugged landscapes, such as the Missouri Ozarks (Guyette et al. 2002) and Southern Rocky Mountains (Rollins et al. 2002). However, fuel condition is not the only factor that shapes wildfire risk. Weather and topography are also primary determinants of fire behavior (Agee 1993). Fuels, weather, and topography shape wildfire risk at landscape scales (e.g., Rollins et al. 2002, Mermoz et al. 2005). In addition, human activities influence spatial patterns of wildfire risks in many modern anthropogenic fire regimes (e.g., Cardille et al. 2001, Prestemon et al. 2002, Syphard et al. 2007*b*). Managers must take the effects of abiotic, biotic, and human factors into account when planning to reduce wildfire risk on a forest landscape (Stephens 2005).

Fire planning involves more than just fuel reduction and fire suppression. Federal fire policy has begun to integrate fire use into landscape resource management (NWCG 2001). Fire is an essential ecological process in many forest ecosystems. Some vegetation types, like Rocky Mountain lodgepole pine, are adapted to, and require, periodic high-severity, stand-replacement fires for regeneration (Turner and Romme 1994). Wildland fire use policy can therefore reintroduce, or maintain, fire-favorable communities for forest health and conservation purposes (Stephens and Ruth 2005). Elsewhere, there are grave concerns about the escape of wildfires into wildland urban interface (WUI) areas, inflicting great loss of human life and property (Haight et al. 2004, Radeloff et al. 2005). Such concerns can only be addressed when wildfire use is carefully managed based on solid understanding of spatial controls at a landscape scale.

Wildland fires consist of two basic consecutive processes: fire occurrence and fire spread. Both processes are affected by a wide range of spatial controls. Fire occurrence is a detected fire initiation, which is primarily determined by ignition sources and fuel (Krawchuk et al. 2006). Fire occurrence can be viewed as a stochastic spatial point process at landscape scales (McKenzie et al. 2006). Studies have shown that the spatial pattern of fire origin location is not completely random. Rather, it exhibits a great degree of clustering both on landscapes dominated by lightning-caused wildfires (Diaz-Avalos et al. 2001, Podur et al. 2003) and those dominated by human-caused wildfires (Cardille et al. 2001, Prestemon et al. 2002). Studies of fire occurrence often use empirical methods to quantify spatial controls on fire origin location and fire frequency over large extents at coarse resolutions (e.g., 10000-ha landscape units covering a 9000000-ha extent; Krawchuk et al. 2006). However, they offer little insight into spatial controls on fire growth, size, and perimeter, which are also important to fire risk assessment and planning (Finney 2005).

Fire spread is a contagious process with behavior largely determined by weather, fuel, and topographical position at fine spatial scales (Agee 1993). Spatial controls on fire spread are often studied using mechanistic modeling approaches. Simulation models such as FARSITE (Finney 1998) and FlamMap (Stratton 2004) can predict where and how fast a fire will spread across a heterogeneous landscape. The purpose of these fire spread models is not for landscape-scale evaluation of fire pattern. They are designed to assess the effectiveness of fuel treatment on fire growth and behavior. The landscape scale pattern of fire origin location is often ignored in the design of these models.

Effects of spatial controls on fire occurrence are different from those on fire spread. Areas with high density of fire occurrence, for example, do not necessarily have a high probability of being burned by large wildfires (Finney 2005). Therefore, a thorough understanding of wildfire spatial patterns requires consideration of spatial controls on both processes (Mercer and Prestemon 2005). Although the influences of spatial controls on fire occurrence at broad scales have been widely documented, research that integrates both the spatial pattern of fire origin location, as well as mechanistic characteristics of fire growth and behavior, are scarce (Finney 2005).

This study jointly examines fire occurrence and spread in the Central Hardwood Forests of the Missouri Ozark Highlands, USA. We quantified spatial controls on both fire occurrence patterns (i.e., spatial patterns of fire origin locations) and spatial burn patterns (i.e., spatial distribution of burn probability that fire will spread to a location). Fire occurrence patterns are analyzed from reported data on fire origin locations using a spatial point process (SPP) modeling technique (Diggle 2003). Spatial burn patterns are investigated using a landscape fire simulation model (LANDIS), which simulates fire occurrence and spread processes limited by vegetation, topography, and human factors. The resulting high-resolution maps show predicted fire occurrence density and burn probability across the study area. Influences on fire occurrence patterns from vegetation, topography, and human activities are compared with influences on spatial burn patterns. We addressed the following specific questions: (1) Which vegetation types are more susceptible to fire occurrence? (2) Are those vegetation types the same ones associated with high burn probability when fire spread is considered? (3) How do ownership, human accessibility, and topography affect fire origin locations and spatial burn patterns? (4) Does the relative importance of spatial controls on fire occurrence differ drastically from the relative importance on spatial burn patterns?

STUDY AREA

The Ozark Highlands is a plateau that covers much of the southern half of Missouri, as well as portions of northwest and north central Arkansas, USA. The region extends westward into northeastern Oklahoma and southeastern Kansas. The Ozark Highlands area, nearly 75200 km^2 (47000 square miles) in size, is by far the most extensive mountainous region between the Appalachian and Rocky Mountain ranges.

The Ozark Highlands region is characterized by many small surface wildfires (Westin 1992, Guyette et al. 2002). The dominant upland vegetation of the south central Ozarks is an oak and oak–pine forest matrix juxtaposed with patches of open woodlands and grasslands. Vegetation types are characterized by differing amounts and arrangements of herb and shrub fuels, litter, twigs, and branches, as well as ladder fuels and canopy fuels. Hence, those vegetation types have different flammability (Grabner et al. 2001). Most wildfires in this region are caused by humans (primarily arson). Human accessibility (e.g., roadway coverage, municipalities) and ownership strongly affects the likelihood of fire ignition. Topography influences road locations, and hence, affects fire ignition patterns. Topography also affects fire spread behavior by increasing radiant energy transfer from a fire front to upslope fuels. Furthermore, topography limits human accessibility for fire suppression. The influences of landscape heterogeneity are prominent in the surface fire regime of the Midwest Ozark Highlands region (Guyette et al. 2002). In contrast, the crown fire ecosystems, like subalpine and boreal forests in the Pacific Northwest (Agee 1993) and chaparral shrublands in the West (Moritz 2003), have less significant spatial controls on wildfire during extreme fire weather conditions (Turner and Romme 1994).

The 1.3×10^5 ha study area in southern Missouri is located in the Eleven Point Ranger District of the Mark Twain National Forest (MTNF). The area is largely covered by oak and oak–pine forests, with white oak (*Quercus alba* L.), post oak (*Quercus stellata* Wangenh.), black oak (*Quercus velutina* Lam.), and shortleaf pine (*Pinus echinata* Mill.) as the dominant tree species. The landscape is dissected by a dense stream network creating ridges and valleys, some with steep (>30°) slopes (see Plate 1). Elevation ranges from 140 m to 350 m above sea level. The area consists of three ownership groups with different vegetation cover characteristics: (1) large contiguous blocks of National Forest land (NF, 61%); (2) small patches of private forests, open woodlands, and cool-season grasslands of fescue inside the district boundary of the MTNF (PV, 25%); and (3) urban lands, grasslands, and forests outside the MTNF boundary (non-MTNF, 14%). Forests were further classified into two categories: deciduous oak forests and mixed oak–pine forests (Fig. 1).

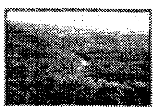

Plate 1. The study area is heavily forested and occurs on an ancient plateau that has eroded to produce a ridge and valley topography. U.S. Forest Service photograph by S. R. Shifley.

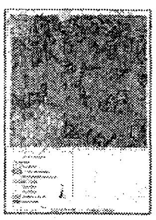

Fig. 1. Map of the study area, the Midwest Ozark Highlands region, USA, showing land ownership and vegetation type (MTNF, Mark Twain National Forest).

The natural fire rotation (number of years necessary for an area equal to the entire area of interest to burn) was <20 years during the period prior to European settlement (Guyette et al. 2002). It now ranges between 300 and 500 years because of effective fire suppression beginning in about 1940 (Westin 1992). Heavy logging between 1890 and 1920 followed by vigorous natural forest regeneration and decades of effective fire suppression dramatically changed forest composition in this area. Historic reconstruction of tree species composition in the early 19th century (Batek et al. 1999) showed that fire-adapted shortleaf pine was the dominant tree species before European settlement. Present shortleaf pine abundance in southeast Missouri is only 25% of the level ca. 1900. As a result of fire suppression, oak decline, and oak mortality, the buildup of surface fuels has significantly increased in recent years. This may lead to large and intense wildfires that were historically rare in this region (Shang et al. 2004). Prescribed burning is now being widely applied in the Mark Twain National Forest for both reducing excessive fuels and restoring the fire-favorable natural communities of the Ozarks by emulating the historic fire regime (Mark Twain National Forest 2005). Humans strongly influence this modern fire regime both by igniting fires and by suppressing the spread of those fires. Arson caused 75% of all wildfires reported between 1970 and 2002. Wildfires are frequent (0.3 fires·km^{-2}·decade^{-1}), but the average size is small (<10 ha).

METHODS

We started from spatial point pattern analysis of reported wildfires origin locations to derive a fire occurrence density map. There were 1299 fires reported to either the Mark Twain National Forest or the Missouri Department of Conservation (MDC) in the study area between 1970 and 2002. The derived fire occurrence density map was then used in LANDIS to simulate both fire occurrence and spread. Simulations were based on (1) where we expect fires to occur, and (2) how we expected fires to spread based on vegetation, topography, and weather. We conducted 200 fire simulation replicates to estimate the burn probability that fire will spread to a particular location. The estimated burn probability map was then compared to the map of burned patches (size >10 acres) recorded between 2003 and 2004 ($n = 31$). A chi-square test was used to evaluate model prediction power. Finally, we used classification and regression tree (CART) analysis to determine the relative importance of spatial controls on fire occurrence density and burn probability maps (Fig. 2). The following sections describe details of the major components of our analysis.

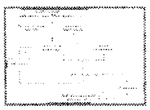

Fig. 2. Flowchart of the overall methods. Each parallelogram stands for underlying data, and each rounded rectangle stands for a statistical analysis or modeling procedure. "CART" stands for classification and regression tree.

LANDIS fire model design

We used a raster-based spatially explicit model, LANDIS, to derive the burn probability map. The 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), with a 10-year time step (He and Mladenoff 1999). LANDIS can operate with cell sizes ranging from 0.01 ha to 100 ha; a cell size of 0.09 ha (30 × 30 m) was used 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 site scale (e.g., competition, succession, seedling establishment, fuel accumulation, and decomposition) and a landscape scale (e.g., seed dispersal and fire disturbance). This paper describes the simulation of fire occurrence and spread. Additional information about LANDIS design and application is available from other sources (He and Mladenoff 1999, Gustafson et al. 2000, He et al. 2005).

Fire occurrence in LANDIS is simulated as a two-stage process (i.e., fire ignition and fire initiation) using a hierarchical fire frequency model (Yang et al. 2004). In the first stage, fire ignition X for a given area is modeled as a Poisson process with the parameter ignition rate λ, which is the expected number of ignitions per unit time and unit area:

$$[X|\lambda] \sim \mathrm{Poisson}(\lambda). \qquad (1)$$

The second stage involves determining whether or not an ignition can become a wildfire (i.e., initiation). The process in this stage is modeled as a Bernoulli trial whose parameter initiation probability P is determined by vegetation type. LANDIS model assumes P is constant (i.e., vegetation remains unchanged) within a simulation time step (i.e., 10 years). Therefore, fire occurrence conditional on ignition in a LANDIS modeling time step follows a Binomial distribution:

$$[U|X] \sim \mathrm{Binomial}(X, P). \qquad (2)$$

The marginal distribution of fire occurrence U is then another Poisson process with the parameter λP:

$$[U|\pi] \sim \mathrm{Poisson}(\pi = \lambda P). \qquad (3)$$

In this study, fire spread was simulated based on a minimum travel time algorithm (Finney 2002). The algorithm calculates, for each cell, the least cumulative time required for a fire to travel through from a set of source cells. It involves the calculation of rate of spread (ROS) for each cell in response to wind direction, wind speed, fuel type, and slope based on elliptical fire spread behavior (Rothermel 1972). However, because there are so many fires (~ 400 fires/decade) to simulate on the landscape, calculating ROS in this way for each simulated fire event is computationally expensive. To mitigate the computational cost, LANDIS reads in equilibrium head fire spread rates for all the possible combinations of fuel type, slope, and wind speed before the simulation starts. The model then updates ROS for all other directions along a fire front (e.g., flanks of a fire) with a direction correction factor during the simulation. The model simulates prevailing wind direction and speed from user-specified wind distribution for each fire spread. The simulated wind direction and speed are used when calculating ROS.

To eliminate instantaneous jumps to a faster ROS, acceleration (i.e., elapsed time for a fire to reach the equilibrium ROS) is estimated using a formula from the Canadian Forest Fire Prediction System (Forestry Canada Fire Danger Group 1992):

$$\mathrm{ROS}_t = \mathrm{ROS}_{eq} \times (1 - e^{-at}) \qquad (4)$$

where ROS_t is the rate of spread at elapsed time t (m/min), ROS_{eq} is the predicted equilibrium rate of spread (m/min); t is the elapsed time (minutes) since fire initiation; and a is a coefficient valued 0.115 when assuming 20 minutes to 90% of ROS_{eq}. Fire spread simulation and the calculations of ROS are stopped when t reaches the burning duration. The burning duration is randomly drawn from a user-specified duration distribution which reflects climate conditions and fire suppression efforts for the region. The input burning duration t (minutes) was modeled as a general exponential distribution with the parameters describing average initial-attack response time μ and control time μ + β:

$$f(t) = \frac{1}{\beta} e^{-(t-\mu)/\beta} \qquad t \geq \mu \qquad \beta > 0. \qquad (5)$$

Model parameterization and calibration

The two parameters used to simulate fire occurrence, the spatially varying ignition rate λ for every cell and the initiation probability P for different vegetation types, were estimated using a spatial point process (SPP) modeling approach (Diggle 2003). SPP modeling has been widely used in analyzing point pattern data such as tree locations (e.g., Larsen and Bliss 1998) and fire origin locations (e.g., Podur et al. 2003, Genton et al. 2006). In this study, SPP was used to estimate fire occurrence density across the landscape. Fire occurrence density π for any location u on the landscape was specified through a log-linear Poisson process model:

$$\log \pi(u) + \boldsymbol{\theta}^{\mathrm{T}} \mathbf{Z}(u) \qquad (6)$$

where **Z** is a list of spatial covariates that includes abiotic, biotic, and human factors (Table 1), and **θ** is the vector of coefficients to be estimated. We used the AIC (Akaike Information Criterion) method to select an appropriate inhomogeneous Poisson process model that best fits to the reported fire occurrence location data. The fitted model selected important spatial covariates and quantified their effects. Additional details about this procedure were described in Yang et al. (2007). The estimated coefficients for vegetation type were further separated from contributions of other factors to calculate the fire initiation probability and fire ignition rate (Appendix).

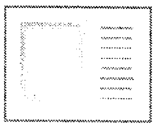

Table 1.

Estimated rate of spread (ROS, m/min) for three fuel models over a range of slope and wind conditions under D2L2 fuel moisture scenario (fuel moisture contents are 6%, 7%, and 8% for 1-h, 10-h, and 100-h fuels, respectively) using the BehavePlus model (Andrews et al. 2005).

Input equilibrium spread rates were estimated using the BehavePlus fire modeling system (Andrews et al. 2005). The software can calculate potential fire behavior in various fuel types over a range of moisture, slope, and wind conditions (Table 1). There are three distinct BEHAVE (Anderson 1982) fuel types in our study landscape according to local fuel studies (Grabner et al. 2001). In increasing order of ROS, they are hardwood litter (BEHAVE class 9), open woodland (BEHAVE class 2), and short grassland (BEHAVE class 1). Cells that intersect with primary rivers and roads were treated as firebreaks in the simulation. Parameters for adjusting ROS at directions other than prevailing wind direction were calibrated with the computer program utility VFS (Visualized Fire Spread). The utility can simulate fire spread patterns comparable to that predicted by fire behavior model FARSITE (Finney 1998; B. R. Miranda, B. S. Sturtevant, J. Yang, and E. J. Gustafson, *unpublished manuscript*).

Fire season wind statistics were used to define probabilities of different wind directions and corresponding wind speed classes, which are parameters for simulating wind events in LANDIS. Currently, average response and control times for wildfires in this region are within the ranges of 20–30 min and 50–70 min, respectively, according to reported Missouri wildfire statistics (Westin 1992).

Analysis of landscape influence

We conducted 200 replicates of LANDIS fire simulation for one time step (i.e., 10 years) to estimate burn probability across the landscape. Burn probability for each cell was calculated as the ratio of the number of replicates in which the cell is burned to the total number of replicates. The resulting map of burn probability was characterized further with regard to a wide range of spatial covariates (Table 2) including elevation, slope, aspect class, vegetation type, ownership, road proximity, and proximity to municipalities. We compared group mean burn probabilities using a univariate ANOVA test (Neter et al. 1985) for discrete covariates (e.g., ownership). The ANOVA test enabled us to show whether burn probabilities differed significantly among discrete categories of each tested covariate. For a continuous covariate Z (i.e., a gradient) such as elevation, a characteristic gradient function was calculated using the following formula:

$$C(h) = 100 \times \frac{\frac{1}{n_h}\sum_{u \in B(h)} P(u) - \frac{1}{n}\sum_{u \in D} P(u)}{\frac{1}{n}\sum_{u \in D} P(u)}$$

$$B(h) = \{u \in D, Z(u) \leq h\} \quad (7)$$

where $C(h)$ denotes the departure (in percentage) of mean burn probability (MBP), for a sub-region $B(h)$, from the total-landscape MBP. The total landscape is denoted by D. $B(h)$ denotes the subregion of D in which the covariate $Z \leq h$. Using elevation as an example, if $h = 200$ m, then $B(200$ m) is the subregion with elevation ≤ 200 m. $P(u)$ denotes burn probability for grid cell u. The total number of grid cells within the entire region is denoted by n, and n_h is the number of grid cells within the subregion $B(h)$. The range of $C(h)$ is [−100%, +100%]. $C(h) < 0$ when the MBP for the subregion $B(h)$ is less than the total-landscape mean, and vise versa. The same analysis was also conducted for fire occurrence density to capture landscape characteristics of fire occurrence.

Table 2.

Description of the covariates used in modeling fire occurrence and characterizing burn patterns.

Classification and regression tree (CART) analysis were used as an exploratory tool to discover relative importance of factors contributing to spatial patterns of fire occurrence and spread. CART is a nonparametric, recursive partitioning technique used for classification and prediction (Breiman et al. 1984). CART analysis iteratively partitions a larger data set (i.e., 100000 cells randomly sampled from the fire occurrence density and burn probability grid maps) into two relatively homogeneous subsets (nodes) such that the split reduced the most impurity (i.e., the degree of heterogeneity within a node) measured by the deviance (i.e., residual sum of squares). Trees were pruned using the 10-fold cross-validation procedures of Atkinson and Therneau (2000), in which the partitioning was stopped when the control argument cp (complexity parameter) reached the threshold value 0.01. The CART diagram hierarchically illustrates the relative importance of variables and their thresholds in partitioning a response variable of interest. All the statistical analyses were done with the statistical software R.

RESULTS

Simulated fire regime and burn probability

There were 390 fires on average simulated within one decade over the entire landscape. This was very close to the observed mean fire frequency (394 fires/decade). Seventy three percent of simulated fires were ignited in the public lands, a value close to the corresponding statistic (75%) in the fire database. The standard deviation for simulated fire frequency was 19 fires/decade, about 5% of the mean. In contrast, the simulated fire size distribution exhibited a much larger variability. Its standard deviation was 18.2 ha, which is 275% of the simulated mean fire size (6.6 ha). The majority (80%) of simulated fire sizes were less than the mean. Only 3% of simulated fires were larger than 40 ha (100 acres). Such a strongly skewed fire size distributions is consistent with the observed data for this fire regime, which consists of many small fires and few large fires that escape initial fire suppression efforts (Westin 1992).

The mean burn probability on a 0.09-ha cell in the landscape over a decade estimated from 200-replicates LANDIS fire simulation was 0.02. Across the entire landscape, 35% of the cells ("hot spots") had estimated burn probabilities higher than the average (Fig. 3). We used a map of burned patches reported between 2003 and 2004 (beyond the temporal range of the fire ignition data we used to model burn probability) to validate our estimated burn probability map. We found that the areas actually burned in 2003 and 2004 were twice as likely to be on the hot spots as on the sites with low (≤ 0.02) burn probabilities (Fig. 3). The association of burned sites in 2003 and 2004 with predicted high (>0.02) probability was statistically significant ($P < 0.001$) based on a chi-square test.

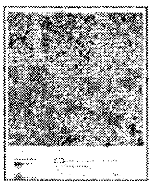

Fig. 3. Map of estimated burn probability, defined as the probability to be burned at least once on a 0.09-ha size cell over a decade, overlaid with roadway coverage, relief, and map of burned patches reported in 2003 and 2004 in the study area.

Landscape characteristics of wildfires

Simulated fire occurrence density averaged 0.3 fires·km^{-2}·decade^{-1} for the entire landscape. The densities for the three ownerships were distinctively different (Fig. 4a). The mean fire occurrence density was 0.02 fires·km^{-2}·decade^{-1} for the non-MTNF land, 0.3 fires·km^{-2}·decade^{-1} for private inholdings within the MTNF district boundary, and 0.38 fires·km^{-2}·decade^{-1} for the public land. Vegetation type influenced fire occurrence with a general ranking as grassland < open woodland < deciduous forest < oak–pine mixed forest (Fig. 4b). Univariate ANOVA found significantly ($P = 0.03$) fewer fires on mesic aspects than xeric aspects.

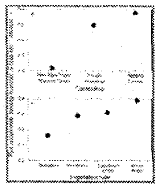

Fig. 4. Simulated mean fire occurrence density for different (a) ownerships and (b) vegetation types.

The effects of the discrete ownership and vegetation type categories on burn probability differed from those for fire occurrence. Mean burn probability on public land was 130% higher than that on non-MTNF land, but 30% lower than that on private land within the MTNF district boundary (Fig. 5a). The ranking for influences of various vegetation types on burn probability was deciduous forest < mixed forest < grassland < open woodland (Fig. 5b). Since fire occurrence density was low in grassland and open woodland, the high burn probability suggests that fire sizes are generally large in these two vegetation types. There was no significant ($P = 0.61$) difference in burn probability between mesic and xeric aspects.

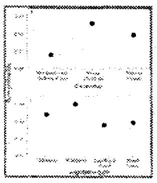

Fig. 5. Simulated mean burn probability for different (a) ownerships and (b) vegetation types.

Among all the continuous covariates, road access and municipalities exhibited the most conspicuous effects on fire occurrences. Increasing distance to the nearest road monotonically decreased fire occurrence density (Fig. 6a). Areas closer than five kilometers to municipalities had relatively low fire occurrence density, but fire occurrence density within a distance of 7–10 km from municipalities was greatly elevated, resulting in a curvilinear effect (Fig. 6b). Topographical effects were also obvious, but to a lesser degree than those of roads and municipalities. The absolute departure from mean fire occurrence density against slope and elevation was <40%. Fire occurrence density was lower at the intermediate elevations and higher in valley bottoms and on ridge tops (Fig. 6c). The highest (10% more than average) fire occurrence density along the gradient of slope steepness was found at the scale of <20 degrees (Fig. 6d).

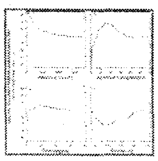

Fig. 6. Gradient analysis of fire occurrence density in response to (a) distance to road, (b) distance to municipalities, (c) slope, and (d) elevation. The percentage departures were calculated based on Eq. 7.

The characteristics of burn probability in response to road proximity were quite different from those of occurrence density (Fig. 7a vs. Fig. 6a). Areas near roads had very low burn probability because primary roads served as firebreaks in the simulation. However, burn probability increased rapidly and reached a peak within a few hundred meters of roads, then decreased gradually afterwards (Fig. 7a). The effect of municipalities on burn probability was similar in form to that for fire occurrence density, but of a smaller magnitude (Fig. 7b vs. Fig. 6b). Burn probability was lower in valley bottoms and intermediate elevations (Fig. 7c), and higher on moderate slopes (Fig. 7d).

Fig. 7. Gradient analysis of burn probability in response to (a) distance to road, (b)

distance to municipalities, (c) slope, and (d) elevation. The percentage departures were calculated based on Eq. 7.

Relative importance of contributing factors

The final CART models for fire occurrence density and burn probability (Fig. 8) illustrated the hierarchical relationships among spatial covariates (i.e., explanatory or predictor variables) in order of importance from top to bottom. The primary covariate affecting fire occurrence was proximity to road, which separated 44% of the total landscape that is far (>520 m) from roads into a relatively homogeneous group with a low (0.17 fires$\cdot$km$^{-2}\cdot$decade^{-1}) mean fire occurrence density (Fig. 8a, node 1). Ownership and municipalities were also important covariates in characterizing landscape patterns of fire occurrence. High fire occurrence density was found on public land close to municipalities (<10 km) and roads (<520 m) (Fig. 8a, node 5). Environmental variables (i.e., vegetation type and topography) were not identified as key descriptive covariates in the classification tree.

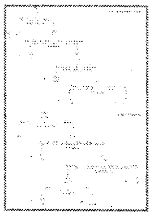

Fig. 8. Classification and regression tree (CART) partition of (a) fire occurrence density and (b) burn probability across the landscape (MTNF, Mark Twain National Forest). End nodes are boxed and numbered in boldface. Each node shows the percentage of area (top and underlined) and the mean (a) fire occurrence density (number of fires per km^2 per decade) and (b) burn probability (bottom).

The CART model identified four key covariates for burn probability. The primary variables remained road proximity and ownership; the two top covariates on the CART analysis for fire occurrence density. However, vegetation type and topography were also identified as important secondary factors influencing patterns of burn probability at a local level (Fig. 8b). High burn probabilities were found in grassland and open woodland in the MTNF district (Fig. 8b, node 3) and forested land in the MTNF district that was on high (>290 m) elevations (Fig. 8b, node 5).

DISCUSSION

Landscape controls of wildfires

Many modern fire regimes in the United States are anthropogenic. Human-caused wildfires comprise 31%, 55%, 22%, 64%, 94%, and 97% of the total amount of area burned from 1940 to 2000 in United Stated Forest Service Northern, Rocky Mountain, Pacific Northwest, Pacific Southwest, Southern, and Eastern regions, respectively (Stephens 2005). Recent studies for various fire regimes have shown that human-related factors are replacing fuel and topography as the primary drivers for the modern period (e.g., Cardille et al. 2001, Prestemon et al. 2002). This was also true in our Missouri study area. CART analysis picked three of the four potential explanatory human-related covariates as key variables in describing fire occurrence patterns (Fig. 8a). Population density was not a significant factor in the analysis, partially because our study area is one of the most rural landscapes in Missouri. There is relatively little variation in the spatial distribution of population density in the area. Most fires were ignited in public forests within 10 km of the municipalities. Our CART analysis found that arsonists appeared to set fires close to roads (Fig. 8a), presumably because of easy access and easy escape. This finding was also supported by our fire database, in which 75% of reported arson fires were ignited <520 m from roadways. There were obvious fire occurrence patterns in response to vegetation type, slope, elevation, and aspect. Univariate ANOVA (F test) showed that individually all these variables were significant ($P < 0.05$). However, such statistical associations were not strong enough to be included in the final CART model, suggesting that environmental factors had comparatively little influence on where fires occurred.

When burn patterns following ignition were considered, biotic (i.e., vegetation type) and abiotic (i.e., elevation) factors appeared as important secondary factors influencing patterns of burn probability at a local level (Fig. 8b). Grassland and open woodland, which have high fractions of one-hour time lag fuels, can carry surface fires much faster than closed-canopy forests (Anderson 1992). Therefore, those vegetation types are associated with higher burn probabilities (Fig. 5b), despite their association with low fire occurrence densities (Fig. 4b). Topography plays a bigger role in determining burn patterns than it does in shaping fire occurrence patterns. At the landscape scale, burn probability is higher in gentle slopes than in steep slopes (Fig. 7c). Individual fires generally burn faster upslope, but steep slopes imply that there is a greater topographical roughness in the highly dissected Ozarks Highlands, which can impede the propagation of fire across the landscape due to natural fire breaks, creeks, and cool or mesic aspects (Guyette el al. 2002). Elsewhere, topographically complex areas (e.g., in northern Arizona [Dickson et al. 2006]) can actually facilitate fire occurrence and spread, suggesting that the effect of topography on wildfires is landscape specific.

Topography and fuel influences on spatial burn patterns were not as prominent as human factors in this landscape (Fig. 8b). This can be explained by the characterization of the fire regime in our study area. The Midwest Ozark Highlands region is characterized by many human-caused, small-size, low-intensity surface fires (Guyette et al. 2002) that are attended with rapid, effective fire suppression measures. The drivers of human-caused fire ignitions (e.g., road proximity) end up also being the dominant drivers of burn probability. The relative impact of topography and fuels will be limited if most fires do not spread far from their ignition points. However, one might end up with different results in a western landscape where larger fires account for a greater proportion of the area burned (Agee 1993, Moritz 2003).

Management implications

Human accessibility affects both fire ignition and suppression, while topography and fuel primarily influence fire spread and behavior. Our analysis suggests that even in a landscape dominated by human-caused fires, burn patterns are still interactively determined by abiotic, biotic, and human factors. Therefore, a careful landscape-scale fire risk reduction plan should consider all three types of influences. Anthropogenic fire regimes are characterized by fire occurrences clustered near roads (Yang et al. 2007). It is easier for fire managers to identify areas of higher ignition potential and design specific mitigation strategies within such areas. Mitigation strategy alternatives may include: (1) reducing ignition rate by limiting human accessibility and by improving both public education and law enforcement, (2) decreasing initiation probability through vegetation management, (3) increasing fuel discontinuity by prescribed burning, and (4) adding permanent firebreaks in high fire risk areas. Our resultant map of burn probability identified hotspots in this region which exhibited a great level of agreement with the actual burned patches reported between 2003 and 2004 (Fig. 3). It can be directly used to prioritize specific areas for ecosystem restoration and fuel treatment. Our fire simulation modeling can be used to evaluate effectiveness of various management alternatives (Sturtevant et al. 2005).

Our results showed that, although there were more fires occurring in National Forest owned lands, fire sizes in the private inholdings of the MTNF district tended to be larger. This is because private lands consist of more moderate slopes (mean slope steepness is 6 degrees less) and more fire-spread-prone fuel type of grassland and open woodland. A fire set in the public lands may spread into private lands and become an uncharacteristically large fire. Building defensible fuel profile zones (DFPZs, Agee et al. 2000) within public–private intermix areas may effectively reduce burn probability in private inholdings.

Simulation modeling

Simulation modeling is one of the most effective tools for studying the causes and consequences of fire disturbance over large areas and long time spans. The success of simulation models for characterizing both spatial and temporal patterns of ignition, spread, and effects of wildfires is evident by the large number of models that have been developed (see Keane et al. 2004 for a general review). However, many landscape succession and fire simulation models only simulate the statistical properties (e.g., natural fire rotation, mean fire size) of a fire regime and fail to incorporate spatial patterns of fire ignitions in their simulations (e.g., He and Mladenoff 1999). In this study, we linked spatial point process modeling of historical fire occurrences (Yang et al. 2007), minimum travel time algorithm for simulating fire spread (Finney 2002), calculation of ROS using BehavePlus (Andrews et al. 2005), and object-oriented design of LANDIS (He et al. 1999) into a single fire simulation model. The resulting model integrated both stochastic and deterministic characteristics of fire process. Without sacrificing the prediction power of fire spread behavior at landscape scales, our model was able to realistically simulate occurrence and spread of frequent (400) fires across the landscape in about five minutes using a modern personal computer. Such a rapid computation enables users to conduct scenario analyses with a reasonable investment of time. Furthermore, our fire simulation modeling can be linked with other model components (e.g., succession, fuel, and harvest) in LANDIS to address many important ecological questions such as long term interactive effects of fire disturbance with (1) fuel management (Shang et al. 2004), (2) harvest (Shifley et al. 2006), (3) vegetation dynamics (Syphard et al. 2006), and (4) land use change (Syphard et al. 2007*a*) on a forest landscape.

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APPENDIX

Separate the contribution of vegetation type to fire occurrence from other factors in calculating fire initiation probability and fire ignition rate (*Ecological Archives* A018-044-A1).