Studying the effects of fuel treatment based on burn probability on a boreal forest landscape

Zhihua Liu a, Jian Yang a, Hong S. He a,b, *a

a State Key Laboratory of Forest and Soil Ecology, Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110164, PR China
b School of Natural Resources, University of Missouri, 203 ABNR Building, Columbia, MO 65211, USA

Abstract

Fuel treatment is assumed to be a primary tactic to mitigate intense and damaging wildfires. However, how to place treatment units across a landscape and assess its effectiveness is difficult for landscape-scale fuel management planning. In this study, we used a spatially explicit simulation model (LANDIS) to conduct wildfire risk assessments and optimize the placement of fuel treatments at the landscape scale. We first calculated a baseline burn probability map from empirical data (fuel, topography, weather, and fire ignition and size data) to assess fire risk. We then prioritized landscape-scale fuel treatment based on maps of burn probability and fuel loads (calculated from the interactions among tree composition, stand age, and disturbance history), and compared their effects on reducing fire risk. The burn probability map described the likelihood of burning on a given location; the fuel load map described the probability that a high fuel load will accumulate on a given location. The simulation results indicated that fuel treatment based on burn probability greatly reduced the burned area and perimeter containment and protect high value areas (Finney et al., 2002). However, fire is a landscape process that is not only dependent on the site specific fuel loads, but also the fuel configuration, ignition patterns, and topography (Yang et al., 2008). In this sense, fuel treatment may be more effective if treatment units can fragment fuel continuity and alter fire ignition patterns, rather than reducing fuel loads on individual treatment sites (Schmidt et al., 2008; Wei et al., 2008). Therefore, placement of fuel treatment units across a landscape is usually the centerpiece of landscape-scale fuel treatment planning, if all other treatment elements (e.g., treatment type, treatment intensity, extent) are held constant. Landscape-scale fuel treatment planning should be designed according to spatial interactions between fire and its spatial

Keywords:
Burn probability  
Fire  
Fuel treatment  
LANDIS  
Northeast China

1. Introduction

Fire plays an important role in regulating species composition and age structure in many forest ecosystems (Bowman et al., 2009; Turner et al., 1998; Turner and Romme, 1994; Van Wagner, 1978). However, long-term fire suppression has contributed to the unnatural buildup of flammable fuels that can lead to fires uncharacteristic in extent and intensity in many of these systems (Agee and Skinner, 2005; Stephens et al., 2009), such as boreal forests in Northeast China historically characterized by frequent surface fires (Xu et al., 1997). Fuel treatment is assumed to be a primary tactic to mitigate intense and damaging wildfires (Stephens and Ruth, 2005). Although fuel treatment may not completely stop or eliminate intense wildfires, it can improve perimeter containment and protect high value areas (Finney et al., 2002). Fuel treatment performed at a stand is typically focused on reducing specific aspects of fire behavior, such as fire intensity, rate of spread, and fire severity, as demonstrated by many experimental studies (Miller and Urban, 2000; Pollet and Omi, 2002; Stephens, 1998). However, fire is a landscape process that is not only dependent on the site specific fuel loads, but also the fuel configuration, ignition patterns, and topography (Yang et al., 2008). In this sense, fuel treatment may be more effective if treatment units can fragment fuel continuity and alter fire ignition patterns, rather than reducing fuel loads on individual treatment sites (Schmidt et al., 2008; Wei et al., 2008). Therefore, placement of fuel treatment units across a landscape is usually the centerpiece of landscape-scale fuel treatment planning, if all other treatment elements (e.g., treatment type, treatment intensity, extent) are held constant. Landscape-scale fuel treatment planning should be designed according to spatial interactions between fire and its spatial
controls (e.g., weather, topography, fuel continuity). Because landscape treatment involves large spatial scales, it is impossible to assess the planning with experimental approaches. Simulation modeling presents a useful alternative when designing fuel treatments as a planning tool. Previous studies mainly focused on the effectiveness of alternative spatial arrangements of treatments, such as shaded fuel breaks, defensible fuel profile zones (DFPZs), and strategically placed area treatments (SPLATs), at reducing overall fire risk at the landscape scale (Agee and Skinner, 2005; Finney, 2007; Schmidt et al., 2008). These studies often assumed that fire ignition patterns are spatially random, and therefore the effects of topography and weather on fire ignition were ignored or simplified. Consequently, such studies generally prioritized fuel treatments based on fuel load that can disrupt fire spread or mitigate fire behavior (e.g., slowed the rate of spread and fire intensity). Such methods may be effective at reducing fire risk if topographic effects on fire spread can be negligible (e.g., flat landscapes) and fire ignitions are assumed to be spatially stationary.

Many landscape-scale studies suggested that wildfire occurs as a function of ignitions, fuels, topography, and weather at large spatial scales (Cardille et al., 2001; Parisien and Moritz, 2009). Wildfires are usually simulated as two consecutive processes: fire ignition and spread (Yang et al., 2008). Fire ignitions are stochastic but not random, in that ignition locations are spatially aggregated in somewhat predictable ways at the landscape scale (Wang and Anderson, 2010). Fire spread is a contagious process whose behavior is largely influenced by many spatial factors at fine scales (Sullivan, 2009); therefore, wildfire risk assessment should take both fire ignition and spread patterns into consideration. The combined output of fire ignition and spread, which integrated stochastic and deterministic characteristics of fire processes, describes the spatial explicit likelihood of burning on a given location, known as burn probability (Parisien et al., 2005).

Landscape-scale simulation models that explicitly simulate fire ignition and spread in response to topography, fuels, and weather conditions can generate a burn probability map (Yang et al., 2008). The estimated burn probability map can be used to indentify high fire risk areas (Parisien et al., 2007, 2005; Yang et al., 2008) and guide the placement of fuel treatments at the landscape scale (Konoshima et al., 2010; Wei et al., 2008). Burn probability maps have been used to find the optimal placement of fuel treatments and, subsequently, evaluate placement effects on fire risk (Parisien et al., 2007), wildlife habitat (Ager et al., 2007), and timber harvest (Konoshima et al., 2010). Although placement of fuel treatment based on burn probability is increasingly applied, its advantages and effectiveness remain largely unexplored, such as whether the approach is more effective at reducing fire risk than fuel treatment based on fuel load at the landscape scale. Our hypothesis in this study is that prioritizing fuel treatment based on burn probability is more effective at reducing fire risk by reducing the probability of fire spread into high fuel load areas.

The Huzhong Forest Bureau (Fig. 1), located in the central part of the Great Xing’an Mountains of Northeastern China (52°25′N 122°39′E to 51°14′N 124°21′E), has an area of 937 244 ha. The climate is cool temperate zone with a long and severe winters (Zhou, 1991). Mean annual precipitation is ~500 mm, with most occurring between June and August. Mean annual temperature is 4.7 °C. February is the coldest month, with an average of −28.9 °C; July is the hottest, with an average of 17.1 °C. The vegetation of this area is cool temperate coniferous forests, the southern extension of eastern Siberian boreal forests (Xu, 1998; Zhou, 1991). The forest area accounts for 87% of the study area, and diversity is relatively low. Dahurian larch (Larix gmelinii), a widely distributed coniferous species, is the most dominant tree species and covers more than 65% of the study area. White birch (Betula platyphylla), a widely distributed broadleaf species, accounts for 15–20% of the study area. Other species, including Scots pine (Pinus sylvestris var. mongolica), Korean spruce (Picea koraiensis), and two aspen species (Korean aspen: Populus davidiana, Mongolian poplar: Populus susheolens) intersperse with larch forest and usually have a small area of distribution (~1.8%). Willow (Chosenia arbutifolia) is confined to terraces along the rivers, and Siberian dwarf pine (Pinus pumila) occurs mostly at >800 m elevation and also comprises a small proportion of distribution (Xu, 1998).

Humans exert a complex influence on modern fire regimes through increased fire ignition density due to logging and firewood collecting, and decreased fire size due to fire suppression. Fire behavior (e.g., fire intensity and rate of spread) in the study area is
largely determined by aspect, topographic position, and associated understory fuel characteristics (Xu, 1998). Generally, soil moisture, irradiation and understory fuel characteristics are closely related.

The wet, cool north-slope and the valley are dominated by two shrub species, *Ledum palustre* and *Vaccinium uliginosum* (up to 0.4 m in height), with almost no herbaceous species. Fuel loading is high and relatively contiguous, but relatively in flammable due to high moisture content. The dry south-slopes are mainly dominated by one shrub species, *Rhododendron dauricum* (up to 2.0 m in height), and herbaceous ground species. Fuel loading is lower than on the north-slope but more flammable due to more fine fuel. The ridge top (elevation > 800 m) is dominated by Siberian dwarf pine (up to 4.0 m in height), with *L. palustre* and *V. uliginosum* (up to 0.4 m in height) as understory species. Fire is ignited mainly by lightning and is intense due to high flammability of fuels. Site conditions play a central role in fire behavior, making it more similar to those in the Fennoscandian boreal forests (Angelstam, 1998; Angelstam and Kuuluvainen, 2004). Based on the simulated fire behavior, the fuel in the study area can be categorized as three distinct fuel models. A fuel model is defined as “an identifiable association of forest fuel components of distinctive species, form, size, arrangement, and continuity that will exhibit characteristic fire behavior under defined burning conditions” (Anderson, 1982). Fuel models have been widely developed for fire behavior prediction worldwide. Fuel model 1 corresponds to fuels on the ridge top; fuel model 2 corresponds to fuels in the south slope; and fuel model 3 corresponds to fuels in the north-slope and valley. These fuel models differed significantly in rate of spread (ROS), fireline intensity, and flame length (Table 1). Details for fuel model parameters, such as fuel loading and moisture content, and associated fire behavior can be found elsewhere (Shan, 2003; Wu et al., 2011).

### 2.2. LANDIS model and its parameterization

Landscape-scale fuel treatment and its evaluation required a spatially explicit modeling of succession, spatially varied ignition patterns, mechanistic fire spread, and management in response to a complex suite of environmental controls over large spatio-temporal scales. LANDIS model is a succession-centric model in which fire and fuel treatment activities interact with forest dynamics (Fig. 1). Study area with reported fire locations from 1990 to 2005, roadway coverage, and proximity to roads.

<table>
<thead>
<tr>
<th>Fuel modela</th>
<th>Wind speed (km/h)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0</td>
</tr>
<tr>
<td>Slope – 2°</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.1</td>
</tr>
<tr>
<td>2</td>
<td>0.9</td>
</tr>
<tr>
<td>3</td>
<td>0.9</td>
</tr>
<tr>
<td>Slope – 7°</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>1.5</td>
</tr>
<tr>
<td>2</td>
<td>1.1</td>
</tr>
<tr>
<td>3</td>
<td>1.1</td>
</tr>
<tr>
<td>Slope – 12°</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>2.4</td>
</tr>
<tr>
<td>2</td>
<td>1.5</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
</tr>
<tr>
<td>Slope – 17°</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>4.0</td>
</tr>
<tr>
<td>2</td>
<td>2.3</td>
</tr>
<tr>
<td>3</td>
<td>2.3</td>
</tr>
<tr>
<td>Slope – 24°</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>7.0</td>
</tr>
<tr>
<td>2</td>
<td>3.8</td>
</tr>
<tr>
<td>3</td>
<td>3.8</td>
</tr>
</tbody>
</table>

a Fuel model are classified based on Shan (2003), and field investigation. The ranking of ROS is fuel model 3 < 2 < 1 for most wind conditions.
b A moisture scenario is a set of fuel moistures for 1-h, 10-h, and 100-h dead fuel and herbaceous and woody live fuel. D2L2 is a fuel moisture scenario code used in BehavePlus model to represent a set of live and dead fuel moisture values. Under the D2L2 fuel moisture scenario, fuel moisture contents are 6%, 7%, and 8% for 1-h, 10-h, and 100-h fuels, respectively (Andrews et al., 2005).
succession at cell level. LANDIS model is suitable for our purpose because it can simulate the interaction of ignition patterns, fire spread behavior, fuel management, and forest succession over large spatial and time scale $\left(10^3\text{ to } 10^6 \text{ ha}; >100 \text{ years}\right)$ on a raster map in a 10-year time step (Gustafson et al., 2000; He and Mladenoff, 1999a,b; He et al., 1999; Mladenoff and He, 1999). In LANDIS, each cell records presence or absence of species and their 10-year age cohorts and simulates vegetation response to natural processes (e.g., fire) and management practices (e.g., fuel management). LANDIS can output maps for vegetation type, disturbance (e.g., fire), and fuel load in each time step. LANDIS has been successfully parameterized and tested in the boreal forests of Northeast China (Chang et al., 2008; He et al., 2002; Liu et al., 2010; Wang et al., 2006; Xu et al., 2005).

A LANDIS fire module was used to simulate fire ignition and spread. Fire ignition was simulated as a two stage process. First, a number of fire ignition attempts were simulated based on fire ignition density map. In this study, we used a spatial point pattern analysis (Baddeley and Turner, 2005) to generate a fire ignition density map based on 1990–2005 reports of wildfire origination locations (Fig. 1). This process incorporated the spatial variability of fire ignitions with respect to abiotic, biotic, and human factors (Yang et al., 2007) (Table 2). Second, the possibility that an attempt can be initiated or not was simulated based on fuel load in the site (Yang et al., 2004). Once initiated, fire spread was simulated based on fuel, topography, and weather (wind) using the duration-based minimum travel time algorithm, similar to fire behavior and spread model FARSITE (Finney, 2002; Yang et al., 2008). The algorithm calculates, for each cell, the least cumulative time required for a fire to travel through from a set of ignition cells. It involves the calculation of ROS for each cell in response to wind direction, wind speed, fuel model, and slope based on elliptical fire spread behavior (Rothermel, 1972). To mitigate the computational cost, LANDIS reads in equilibrium head fire ROS, which has been estimated from the BehavePlus model (Table 1), for all the possible combinations of fuel model, slope, and wind speed before the simulation starts. Fuel model for each cell was converted from vegetation type, which is produced by LANDIS output. Slope was calculated from a digital elevation model. Frequency of different wind speed (e.g., 0, 4, 8, 15, 20, 30 km/h) and direction was calculated based on 1990–2009 records from local weather station. Wind conditions were held constant within one replicate, but may vary between replicates. The final fire size was determined by a lognormal distribution of mean fire size and its standard deviation (Yang et al., 2004). Based on the amount of fuel, LANDIS simulates five levels of fire intensity from surface fires (class 1) to crown fires (class 5).

Fires in LANDIS are the emergent properties of the interactions among forest succession (vegetation type), fuel management, and other abiotic factors (e.g., topography, wind). Thus, LANDIS, a succession-centric model, can assess landscape fire risk and fuel treatment effects more realistically than fire-fuel only model, which may be suitable for one time fire behavior prediction but may not suited for fire effect study on large spatio-temporal scales.

The LANDIS fire module tracks fine fuels and coarse fuels for each cell and evaluates the effects of various fuel treatment alternatives (e.g., prescribed burning or mechanical removal) on fuel loads, fire intensity, and fire frequency at the stand level (He et al., 2004; Shang et al., 2004). Fine fuels are primarily foliage litter fall and small dead twigs, which correspond to 1 and 10-h lag fuels. Fine fuel load for each cell is approximated by vegetation types (species composition) and stand age. Fine fuel load was calculated based on the empirical relationship of fuel quantity and species age, which can be varied with environmental conditions. Coarse fuels, also called coarse woody debris, which correspond to 100 and 1000-h lag fuels. Coarse fuel load for each cell is determined by the combination of stand age (used to determine fuel accumulation) and time since last disturbance (used to determine fuel decomposition). Therefore, coarse fuel amount is the interplay between accumulation and decomposition. Such interplays may vary by land types, which encapsulate environmental variables (e.g., climate, soil, slope, and aspect). The accumulation and decomposition together form the “U-shaped” temporal pattern observed in our study area (Xu, 1998). To reduce false precision and the parameterization burden, fuel loads are modeled as five categorical classes from very low (class 1) to extremely high (class 5). The actual loading for five categories in this region has been quantitatively defined (Liu et al., 2009). Fuel loads can be modified by land type, fire, fire management activities, and forest dynamics.

### 2.3. Generating baseline burn probability map and fuel load map

We conducted 200 Monte Carlo LANDIS simulations for one time step (i.e., 10 years) to produce the baseline burn probability map and fuel load map. Baseline 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 ($n = 200$). The baseline burn probability map describes the likelihood of burning at a particular location across the landscape. The aim of a baseline burn probability map is threefold: (1) to assess current fire risk at the landscape scale in a spatially explicit manner; (2) to identify high fire risk areas to guide the placement of fuel treatment across the landscape; and (3) to use baseline burn probability to compare the effects of different fuel treatments on the spatial configuration of high burn probability areas that result from different fuel treatment scenarios.

Fuel load for each cell was calculated as the combination of both fine and coarse fuels. A cell with both fine and coarse fuel loads higher than class 3 was considered high fuel loading. High fuel load probability for each cell was calculated as the ratio of the number of replicates in which the cell accumulated a high fuel load to the total number of replicates ($n = 200$). Therefore, a high fuel load probability map describes spatial distribution of high fuel loading across the landscape. The estimated fuel load map was also used to guide the fuel treatment at landscape scale.

Finally, we conducted 200 fire simulation replicates with prescribed fuel treatments to estimate the resultant fire risk from these two fuel treatments for the next time step (one fuel treatment is designed based on baseline burn probability map, and the other is based on the fuel load map). The burned area, number of fires by different fire intensities, and spatial pattern of high burn probability area following the two fuel treatments were analyzed and contrasted to show their effectiveness (Fig. 2).

### Table 2

Estimated coefficients of the spatial covariates included in the optimal inhomogeneous Poisson model, and the corresponding fire initiation probabilities for the vegetation type (the procedure for model selection and separating the contribution of vegetation type to fire ignition from factors are similar to Yang et al., 2008).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient</th>
<th>Fire initiation probability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Biotic factor (vegetation type)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Valley or marsh</td>
<td>-5.38521e-01</td>
<td>0.583331</td>
</tr>
<tr>
<td>Coniferous</td>
<td>-3.63649e-01</td>
<td>0.694891</td>
</tr>
<tr>
<td>Broadleaf</td>
<td>6.582450e-01</td>
<td>1.930927</td>
</tr>
<tr>
<td>Harvest or burned area</td>
<td>1.129167e+00</td>
<td>3.095657</td>
</tr>
<tr>
<td>Non-forest</td>
<td>N/A</td>
<td></td>
</tr>
<tr>
<td><strong>Abiotic factor</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DEM</td>
<td>1.236125e-03</td>
<td></td>
</tr>
<tr>
<td>(Distance to nearest road)$^2$</td>
<td>3.391772e-09</td>
<td></td>
</tr>
<tr>
<td>(Slope)$^2$</td>
<td>-1.735930e-03</td>
<td></td>
</tr>
<tr>
<td>Distance to nearest settlement</td>
<td>-2.273847e-05</td>
<td></td>
</tr>
<tr>
<td>Intersect</td>
<td>-1.857046e-01</td>
<td></td>
</tr>
</tbody>
</table>
2.4. Design of simulation experiments

We designed two fuel treatment scenarios: fuel treatment based on the burn probability map (BP_Treat) and fuel treatment based on the fuel load map (FL_Treat). Currently, only 1% of the landscape can have fuel treatment each year in Huzhong Forest Bureau due to limited resources, and therefore, total treatment area for each model iteration was 10% of the landscape (10-year time step).

For the BP_Treat scenario, cells with a burn probability higher than 0.035 were treated according to the baseline burn probability map because this resulted in approximately 10% of the landscape; therefore, areas with a burn probability higher than 0.035 are defined as high burn probability patches.

For the FL_Treat scenario, we also identified 10% of the landscape with highest fuel load to be treated, to be consistent with the treatment area as in the BP_Treat scenario. For comparison, we also designed a base scenario without fuel treatment (No_Treat) to represent the current situation and show the effectiveness of the two fuel treatments scenarios on reducing fire risk.

The primary fuel treatment method included prescribed fire and mechanical removal of coarse fuel (e.g., coarse woody debris and small diameter understory trees). Mechanical treatment removed mostly coarse fuel, while prescribed fires burned mostly fine fuel.

Many studies have demonstrated that mechanical treatment plus prescribed fire was the most effective in reducing both fire ignition and intensity (Agee and Skinner, 2005; Stephens and Moghaddas, 2005; Stephens et al., 2009). Therefore, on each eligible site, if the fuel load in the stand was high (class 4) or extremely high (class 5), coarse fuel was reduced to low class (class 1). For the fine fuel, we assumed that prescribed fires removed all the fine fuels and reduced coarse fuel by one class.

The simulation began with the realistically parameterized forest composition and species and age classes that represented the initial status of 2000. We conducted 200 fuel treatment simulation replicates to estimate the effects of different fuel treatments on reducing fire risk across the landscape for one time step.

2.5. Analysis

To contrast the effectiveness of alternative fuel treatment scenarios, we compared the burned area and numbers of fires for different fire intensities: low intensity fire (class 1 and 2); medium intensity fire (class 3); high intensity fire (class 4 and 5); and total fires (class 1–5). LANDIS generated a fire distribution map with different intensities (class 1–5). Burned area and number of fires for different fire intensities were summarized separately based on different intensities within each time step for each replicate.
Separating fires into different fire intensities allowed us to better address how fires with different intensities respond to different fuel treatments at landscape scales. An independent-sample T test was conducted to test the difference between the different fuel treatment scenarios (including No_Treat scenario) at the 0.05 significance level using the response variables (burned area and numbers of fires for different fire intensity) as the dependent variables.

To quantify the spatially explicit information of fuel treatment effects on reducing fire risk, spatial patterns for high burn probability areas (burn probability > 0.035) were analyzed using FRAGSTATS (Ver 3.3) (McGarigal and Marks, 1995). Response variables for spatial patterns include Mean Patch Size (MPS), Percent of LANDscape (PLAND), Mean Euclidean Nearest Neighbor Distance (MENND), and Mean Distance to Nearest Road (MDNR) of high burn probability areas. MPS describes the average size of high burn probability patches present on the landscape (used as an indicator of aggregation of high burn probability patches in the landscape). PLAND indicates the overall high burn probability area present on the landscape. MENND measures the mean distance of high burn probability patches present on the landscape (used as an indicator of conglomeration of high burn probability patches in the landscape). MDNR shows the mean distance between high burn probability patches and nearest road on the landscape (used as an indicator of accessibility of fire suppression resources in case of fire). Analyzing the spatial pattern of high burn probability patches enabled us to understand the spatial arrangement and configuration of high burn probability patches following different fuel treatment scenarios.

2.6. Validation of model prediction

Validating how the baseline burn probability map reflected the actual burned behavior provided insight into model prediction ability and the resultant fuel treatment effectiveness. We used the 2006–2009 burns (n = 55) to validate the model-derived baseline burn probability map. A Pearson’s chi-square was used to assess the model prediction power.

3. Results

3.1. Validation of simulated fire regimes and baseline burn probability map

There were about 59.1 fires on average simulated within one decade over the entire landscape. The standard deviation for simulated fire frequency was 8.5 fires per decade, about 14.4% of the mean. This was very close to the observed mean fire frequency (63 fires/decade). The simulated mean fire size was 260.9 ha, with the standard deviation for simulated mean fire size 73.14 ha, about 28% of the mean. The simulated mean fire size was also close to the observed mean fire size (240 ha); therefore, after a careful calibration process, the model seems to realistically simulate the fire regimes of the studied landscape.

The burn probability on a 0.81-ha cell in the landscape over a decade estimated from 200 replicates in the LANDIS fire simulation was between 0 and 0.12, with mean burn probability 0.0175 (Fig. 3a). Burn probability maps indicated a highly heterogeneous fire risk across the landscape due to the combined effects of topography, human accessibility (e.g., distance to nearest road), and the distribution of vegetation types. Across the entire landscape, 10% of the cells with burn probability higher than 0.035 were considered as high fire risk area and selected to be treated based on the burn probability. High fire risk areas were primarily located near the road and within P. pumila dominated areas on the ridge tops. The simulated high fire risk areas are consistent with observed data for this area, which indicated that fires mainly occurred near the road due to human accessibility and ridge top due to high lightning density and flammability of vegetation type (Shan, 2003). We used a map of burned patches reported between 2006 and 2009 to validate our estimated burn probability map and found that the burned areas were likely to be located in areas with high (>0.035) burn probabilities (Fig. 3b). The association of burned

![Fig. 3. Estimated baseline burn probability, defined as the probability to be burned at least once on an 0.81-ha size cell over a decade overlaid with (a) roadway coverage and high burn probability area (burn probability > 0.035), and (b) recorded burned patches between 2006 and 2009.](image-url)
patches between 2006 and 2009 with predicted high (>0.035) probability was statistically significant based on a chi-square test (chi-square value = 2549.817; \( P < 0.001 \)).

3.2. Comparison of two fuel treatment effects

Simulated effects of fuel treatment on reducing fire risk differed significantly between the two fuel treatment scenarios. Both fuel treatments scenarios significantly reduced the burned area and numbers of fire per decade for different fire intensities, but they varied considerably in magnitude (Fig. 4). Generally, the BP_Treat scenario was more effective at reducing overall fire risk than the FL_Treat scenario. For example, total burned area was reduced by 13% under the FL_Treat scenario and by 30% under the BP_Treat scenario. Total numbers of fires that occurred per decade were reduced from 59 under the No_Treat scenario to 52 under the FL_Treat scenario and to 47 under the BP_Treat scenario. Compared to FL_Treat scenario, The BP_Treat scenario produced more high intensity fire; therefore, mean high intensity fire size was smaller under BP_Treat scenario due to comparable burned area by high intensity fires with FL_Treat scenario (Fig. 5).

Simulated spatial patterns of the burn probability also differed significantly between the two scenarios (Fig. 6). The burn probabilities for each cell varied between 0 and 0.09 for both fuel treatment scenarios. The BP_Treat scenario produced a much lower mean burn probability (0.0119) than FL_Treat scenario (0.0141) (Fig. 7), however, suggesting that the BP_Treat scenario is more effective at reducing overall fire risk.

3.3. Spatial pattern of high burn probability area following two fuel treatments

Spatial patterns of high burn probability areas (higher than 0.035) also differed significantly between two landscape scale fuel treatments (Fig. 8). Compared to the FL_Treat scenario, high fire risk area decreased more under the BP_Treat scenario (reductions of 2% vs. 6.5% of landscape, respectively) (Fig. 8b). The FL_Treat scenario reduced the MPS of high burn probability areas and slightly increased the MENND between high burn probability areas. In contrast, the BP_Treat scenario reduced the MPS of high burn probability areas and increased the MENND between high burn probability areas (Fig. 8a and c). Both fuel treatment scenarios reduced the MDNR between high burn probability area and nearest road, but BP_Treat scenario further restricted the distance within 2.5 km. Generally, high burn probability areas were smaller and more dispersed under the BP_Treat scenario.

In summary, the BP_Treat scenario was more effective at mitigating overall fire risk and fragmenting high burn probability areas. Moreover, smaller and more dispersed high fire risk areas can also facilitate the subsequent fire suppression.

4. Discussion

4.1. Effectiveness of two fuel treatment scenarios on fire risk reduction

Our results demonstrated that fuel treatment based on burn probability can be more effective at reducing fire risk than that based...
Fig. 5. Number of fires that occurred per decade by different fire intensities under different simulation scenarios: (a) low intensity fires (class 1 and 2); (b) medium intensity fires (class 3); (c) high intensity fires (class 4 and 5); and (d) total fires (class 1–5). Mean and standard deviation were calculated from the 200 model simulations. Values with different letters above the error bars are significantly different in response variables between the results from the alternative simulation scenarios. Statistics were performed in the SPSS (version 13.0) to test the difference. No_treat stands for no fuel treatments and was applied in the simulation as a comparison to the effectiveness of the other two fuel treatments on reducing burned area. FL_treat stands for prioritized fuel treatment area based on fuel load. BP_treat stands for prioritized fuel treatment area based on burn probability.

Fig. 6. Estimated burn probability under (a) BP_treat and (b) FL_treat scenarios, overlaid with roadway coverage and high burn probability area (burn probability > 0.035).
Fire is a spatial process, and its spatio-temporal distribution is affected by biophysical and anthropogenic factors. Fire risk is estimated not only by the level of fuel accumulation, but also by the effects of various landscape features on fire (e.g., ignition and spread). Therefore, fire risk at the landscape-level may be unrelated to individual stands (Loehle, 2004). Managers cannot change weather or topography, but fuel and ignition can be modified to mitigate the burning and loss characteristics at specific locations as well as across large landscapes. As demonstrated in this study, the reduction of burned area was accompanied by the reduction of numbers of fires (Figs. 4 and 5). Therefore, reducing fire ignition may be more effective at mitigating fire risk, and efficient and cost-effective landscape-scale fuel treatment should emphasize on reducing ignitions as well as disrupting fire spread.

Assessing fuel treatment effects in a spatially explicit manner can potentially greatly enhance our ability to mitigate fire risk at landscape scales. Many landscape-scale fuel treatment studies have focused on developing optimal models to efficiently allocate fuel treatment across a landscape (Finney, 2001, 2006; Konoshima et al., 2010). The results provided valuable insight on scheduling fuel treatments at the landscape scale, but most of the previous studies evaluated the fuel treatment effects non-spatially, such as comparing overall reduction of burned area or enhancement of ecological benefits between alternative management scenarios. They offered limited insights on how spatial patterns of high fire risk area may be affected by various mitigation strategies.

Examining the spatial pattern of high-risk areas not only contrasts the effectiveness of different fuel treatments schemes, but...
also provides useful information how to design optimal fuel treatment plans. Ager et al. (2007) compared spatially explicit probabilities of habitat loss for northern spotted owl (Strix occidentalis caurina) and the efficacy of different fuel treatment scenarios. Parisien et al. (2007) assessed the effects of different fuel treatments on reducing burn probability in the boreal mixed-wood forest of western Canada and concluded that spatial data was particularly useful in decision-making for placement of fuel treatments. These assessments, however, did not address critical landscape-level fuel treatments effects such as the spatial pattern of high-risk areas following alternative fuel treatments. Because fuel treatment should be implemented periodically to maintain a low level of fire risk in the landscape, spatial patterns of high-risk areas following previous treatments provide insights on how to design subsequent fuel treatments. Our spatial analysis of high-risk areas following previous treatments indicated that the BP_Treat scenario is more effective at fragmenting high-risk areas than the FL_Treat scenario, and thus can promote effectiveness of subsequent fire suppression. Moreover, the subsequent spatial burn probability map can be directly used to identify high fire risk areas and guide subsequent fuel treatments.

Given the costs of implementing fuel treatment over a large area, methods presented here in developing the burn probability map can provide valuable information for fire managers. The burn probability map can be useful in selecting the most critical area to treat according to the resources available. For example, if 0.5% of landscape is evaluated for treatment (half of the current treatment capacity), cells with a burn probability higher than 0.083 would be eligible to treat. Scenario analyses can also be conducted to evaluate the wildfire risk dynamic under different management plans. Our current burn probability map, coupled with our fire ignition pattern analysis, jointly supported the hypothesis that fire is strongly related to human accessibility. Such a pattern reveals that fires are prone to occur near cultural development (e.g., road net and human settlement). The primary strategy to reduce fire ignition rate can be achieved by limiting human accessibility and by improving both public education and law enforcement. In addition, our results also suggest that fire suppression resources should be allocated within a distance of 2.5 km to the road, where high burn probability areas are aggregated.

4.2. Some limitations and future directions

We used fire records from 1990 to 2005 to characterize fire ignition patterns and parameterize the LANDIS fire module. The relatively short time period (15 years) may not fully capture the variation of fire characteristics, which may introduce uncertainty into the model results interpretation. Nevertheless, we think the method may be justified because our primary objective was to compare the effectiveness of alternative fuel treatments. The main value of study is in the method developed to assess fire risk and compare the effectiveness of alternative fuel treatments in a spatially quantitative manner.

A limitation of our approach is that fire effects were not considered in the simulation. The classic definition of wildfire risk considers two components, fire behavior probabilities and fire effects (Finney, 2005). Our simulation approach seems to realistically simulate the fire regimes and thus can represent fire behavior probabilities, such as burn probability on the landscape; however, no attempt was made to quantitatively estimate fire effects, such as fire effects on ecological processes and habitat. Ideally, fuel treatments effects should be assessed not only on fire behaviors, but on a wide range of ecological values, such as timber harvesting, and wildlife habitat.

Fire characteristics can be dynamic due to forest management, vegetation dynamics, climate changes and human development (Shifley et al., 2006; Syphard et al., 2006; Yang et al., 2008). Future fire and fuel management research should therefore focus on (1) the links between fire—vegetation—climate and their consequences on fuel management, and (2) development of simulation models that can incorporate variable fire regimes over large spatio-temporal scales. Testing the hypothesized outcomes provides efficiency and confidence of the model prediction, and therefore is a necessary component of modeling studies. The potential testing alternatives includes (1) comparing long-term observation with model prediction, and (2) cross-validation with other simulation results.

5. Conclusions

Spatially explicit information on wildfire susceptibility is particular useful in assessing fire risk, identifying hotspots of burn probability, and guiding fire and fuel management planning. In this study, we linked the historical fire ignition pattern and fire spreading behavior in response to weather, topography, and fuel into a spatial explicit forest landscape model, LANDIS, to assess landscape-scale fire risk. LANDIS incorporates succession, competition, multiple disturbance and fuel management processes. Within each replicates, LANDIS can simulate multiple fire disturbances (>50 fires in our case). In our study, we have run 200 Monte Carlo simulations, which can result into more than 10,000 fires for each scenario. Thus, a stable burned probability can be generated by such treatment. We then prioritized landscape-scale fuel treatment based on maps of burn probability and fuel loads, and compared their effects on reducing fire risk. Our results indicated that fuel treatment based on burn probability greatly reduced the burned area and number of fires of different intensities. Fuel treatment based on burn probability also produced more dispersed and smaller high-risk fire patches and therefore can improve efficiency of subsequent fire suppression. In the future, more model components (e.g., harvest) can be linked into LANDIS to map the spatially explicit wildfire risk and its dynamics to fire and fuel management, vegetation dynamics, and harvesting.

Acknowledgments

This research is funded by 973 project of Ministry of Science and Technology of China (Grant No. 2011CB403200), Chinese Academy of Sciences (09YBR211SS) and National Science Foundation of China (41071120, 41071121 and 31100345).

References


