Science of the Total Environment 454–455 (2013) 30–39

Contents lists available at SciVerse ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Comparing fuel reduction treatments for reducing wildfire size and intensity in a boreal forest landscape of northeastern China ☆

Zhiwei Wu [a], Hong S. He [a,b,*], Zhihua Liu [a], Yu Liang [a]

[a] State Key Laboratory of Forest and Soil Ecology, Institute of Applied Ecology, Chinese Academy of Sciences, 72 Wenhua Road, Shenyang 110164, China
[b] School of Natural Resources, University of Missouri, 203 ABNR Building, Columbia, MO 65211, USA

HIGHLIGHTS

- Focusing on fuel load may ignore effects of other spatial controls on fire.
- We used burn probability to combine effects of fuel load and other spatial controls.
- We compared fuel-load and burn-probability based fuel treatments' effects in China.
- Burn probability-based treatments were more effective at reducing fire behaviors.
- Burn probability needs further investigation in model development and application.

ARTICLE INFO

Article history:
Received 14 October 2012
Received in revised form 19 February 2013
Accepted 19 February 2013
Available online 26 March 2013

Keywords:
Burn probability
Fuel load
Fuel treatment
Fire size
Fire intensity
FARSITE

ABSTRACT

Fuel load is often used to prioritize stands for fuel reduction treatments. However, wildfire size and intensity are not only related to fuel loads but also to a wide range of other spatially related factors such as topography, weather and human activity. In prioritizing fuel reduction treatments, we propose using burn probability to account for the effects of spatially related factors that can affect wildfire size and intensity. Our burn probability incorporated fuel load, ignition probability, and spread probability (spatial controls to wildfire) at a particular location across a landscape. Our goal was to assess differences in reducing wildfire size and intensity using fuel-load and burn-probability based treatment prioritization approaches. Our study was conducted in a boreal forest in northeastern China. We derived a fuel load map from a stand map and a burn probability map based on historical fire records and potential wildfire spread pattern. The burn probability map was validated using historical records of burned patches. We then simulated 100 ignitions and six fuel reduction treatments to compare fire size and intensity under two approaches of fuel treatment prioritization. We calibrated and validated simulated wildfires against historical wildfire data. Our results showed that fuel reduction treatments based on burn probability were more effective at reducing simulated wildfire size, mean and maximum rate of spread, and mean fire intensity, but less effective at reducing maximum fire intensity across the burned landscape than treatments based on fuel load. Thus, contributions from both fuels and spatially related factors should be considered for each fuel reduction treatment.

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1. Introduction

Aggressive fire suppression can alter fuel load accumulation patterns in forests (Reinhardt et al., 2008; Schmidt et al., 2008; Stephens, 1998). Those forests adapted to infrequent, high severity fires (Noss et al., 2006) or forests with rapid decomposition rates may not have long-term fuel load accumulations (Hely et al., 2000). In some forest, especially dry forests (e.g., ponderosa pine forests), fuel accumulation caused by fire suppression can promote larger and severer fires (Schoennagel et al., 2004). For boreal forests in northeastern China, aggressive fire suppression carried out for over a half century has produced high fuel accumulations (Chang et al., 2008; Xu, 1998). Throughout the region, the resulting increase in horizontal–vertical continuity of fuels has produced more intense and frequent fires than from fires before the 1950s (Chang et al., 2007; Tian et al., 2005; Xu et al., 1997). For example, a wildfire on 6 May 1987 that burned 1.3×10^6 ha occurred in four bureaus (including Xilinji, Tuqiang, Amur and Tahe) of the vast region of Great Xing'an Mountains (covers 8.46×10^4 km^2). This fire affected not

☆ Author contributions: Zhiwei Wu led the fire simulation, data analysis and writing of the manuscript. Hong S. He designed the project, oversaw the data analysis, and contributed to the writing of the manuscript. Zhihua Liu contributed to derive and validate the burn probability map. Yu Liang contributed to the writing of the manuscript.

* Corresponding author at: School of Natural Resources, University of Missouri, 203 ABNR Building, Columbia, MO 65211, USA. Tel.: +1 573 882 7717; fax: +1 573 882 1977.

E-mail addresses: wuzhiwei2001@163.com (Z. Wu), heh@missouri.edu (H.S. He), liuzh@iae.ac.cn (Z. Liu), liangysts@gmail.com (Y. Liang).

0048-9697/$ – see front matter. Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.scitotenv.2013.02.058

only forest composition and structure but human populations and environment as well (Cahoon et al., 1994; Wang et al., 2007; Xiao et al., 1988). Because of increasing forest fuel accumulations coupled with the warmer and drier climate of recent decades, wildfire management has become a major concern in many regions (Ager et al., 2010b; Chang et al., 2008).

Fuel reduction has become an important tool for reducing fire hazard (Ager et al., 2007b, 2010b; Pollet and Omi, 2002; Shang et al., 2004). This hazard is commonly defined as the fuel complex composed of volume, type, condition, arrangement, and location of fuels. In turn, this fire hazard combining with the favorite fuel moisture (affected by weather conditions) determines the degree of ease of ignition, spread and the resistance to fire control (Hardy, 2005). At present, the objectives of fuel treatments for reducing fire hazard are usually aimed at reducing fuel loads (Reinhardt et al., 2008). They can also be designed to reduce unwanted fire effects such as those within wildland urban interface (Ager et al., 2007b, 2010b). Fuel reduction treatments are often implemented using prescribed burning, thinning, or a combination of the two treatments (Ager et al., 2007b; Liu et al., 2010; Pollet and Omi, 2002; Reinhardt et al., 2008). Prescribed burning can reduce wildfire ignition and spread by consuming dead and live surface fuels (Fernandes and Botelho, 2004). Thinning can reduce the likelihood of surface fires spreading into crown fires by removing the “ladder” fuels, including smaller fire-susceptible trees (Stephens, 1998). These fuel treatments are commonly used in many forested ecosystems in North America (Stephens, 1998), Europe (Fernandes and Botelho, 2004), and Australia (Smith et al., 2004). For example, the Healthy Forest Restoration Act (HFRA) of 2003 (HFRA, 2003) called for high priority projects to reduce hazardous fuel loads to reduce the likelihood and severity of catastrophic wildfires in the United States.

In most cases, fuel treatments are often implemented at site or stand level (e.g., 1–10 ha). Fuel load together with fuel characteristics is often used to prioritize stands for fuel reduction treatments (Reinhardt et al., 2008; Schaaf et al., 2004). For example, in order to evaluate the economic tradeoffs between fuel treatments and fire suppression, Schaaf et al. (2004) divided four chaparral types into five fuel load classes and used these classes to establish priorities for prescribed wildfire treatment. Stand density index (SDI), a correlate of fuel characteristics, is widely used to identify stands that are heavily stocked and thereby fire-prone. From this information, stands then can be ranked for fuel reduction treatment (Ager et al., 2010b). For example, Ager et al. (2010b) employed SDI to prioritize stands for fuel treatments to reduce wildfire risk in the urban interface and to preserve old-forest structure.

However, evidence is growing that placing too much emphasis on reducing fuel load may underestimate or ignore the importance of other factors (Graham et al., 2004). For example, in some mixed conifer forests, fuel load is less important than weather and topography in determining wildfire severity (death of canopy trees affected by fires) (Schoennagel et al., 2004). Wildfire is a spatial process, not only related to forest fuel load accumulation but also to a wide range of spatial controls, such as human activity, weather, and topography (Aldersley et al., 2011; Yang et al., 2008). Human activity can influence the potential number, timing, and spatial locations of wildfires (Fry and Stephens, 2006); weather conditions can influence the occurrence, size, and behavior of wildfires (Parisien et al., 2010); and topographical positions associated with fuels can determine wildfire spatial spread direction and rate (Yang et al., 2008). A thorough understanding of wildfire growth and behavior therefore requires a landscape-level consideration of the interacting effects of spatial controls.

Wildfires consist of two basic consecutive spatial processes: occurrence and spatial spread. Wildfire occurrences (lighting- and human-caused), which are also called ignitions, are complicated spatial point processes that are likely to be highly clustered within a given forested landscape that is under the control of factors such as topography, weather, fuel, and human activity (Yang et al., 2008). A wildfire does not necessarily spread to neighborhoods and burn large areas (Finney, 2005). The spatial spread pattern of wildfire is further affected by its surrounding contexts (e.g., fuel type and topography). Therefore, wildfires are stochastic, not random, spatial processes that can be explained and modeled with spatial controls. For example, a single lighting fire may be viewed as a random process. However, at the landscape level, studies have shown that the spatial pattern of lighting fire origin location is not completely random. Rather, it exhibits a great degree of clustering on landscape. This situation was observed in other studies (Diaz-Avalos et al., 2001; Podur et al., 2003). Therefore, we propose using burn probability to address both the combination of occurrence (ignitions) and likely spread patterns of a wildfire across a forest landscape (Finney, 2005; Yang et al., 2008).

In application, burn probability has been used to determine where and when wildfire occurrence and spread potential are greatest (Parisien et al., 2007); it can also be used to quantify the influences of alternative fuel treatments (Ager et al., 2007a). In addition, fuel reduction strategies based on burn probability can be designed to limit or interrupt the occurrence and rate-of-spread potential related to various sources of wildfires. Thus, a given fuel reduction treatment might reduce rate of spread and thus, burn severity, or it might even stop a wildfire after ignition. However, because it is a relatively new wildfire management tool, burn probability needs further testing and verifying because its effectiveness has not been well studied. Currently, for the most cases, fuel load and fuel characteristics (e.g., stand density) are employed as the primary measures in fuel treatment by many management agencies. A possible alternative would be to apply fuel treatment based on burn probability. The objective of this study was to compare two approaches to assess the effectiveness of fuel treatment for reducing wildfire size and intensity. The first approach is based on burn probability; the other on fuel load. Given the high risk and cost of conducting forest fuel treatments across a real landscape, effective allocation of resources is critical.

2. Material and methods

2.1. Study area

The study was conducted in the Huzhong National Nature Reserve (HNNR) at Huzhong Forest Bureau (HFB) on the north side of the Great Xing'an Mountains in northeastern China (122°42′14″–123°18′05″ E, 51°17′42″–51°56′31″ N) (Fig. 1); it covers 166, 886 ha and ranges in elevation from 660 to 1200 m. The study area falls within the cool temperature zone, which is affected by Siberian cold outbreaks and is a typical terrestrial monsoon climate. According to weather data (covered the period from 1972 to 2005) from the Huzhong weather station, the mean annual temperature for the area is −4.0 °C with a January mean minimum of −35.8 °C and a July mean maximum of 24.5 °C. Mean annual precipitation is 458.3 mm, of which more than 60% occurs between June and August.

The primary trees are larch (*Larix gmelini*), pine (*Pinus sylvestris* L. var. *mongolica*), spruce (*Picea koraiensis*), birch (*Betula platyphylla*), and two species of aspen (*Populus davidiana* and *Populus suaveolens*). Birch is a pioneer species whereas larch is a late succession climax species in this region. With the exception of wetlands near rivers, larch is widely distributed over 65% of the study site. Birch and pine are mixed with larch in most areas due to fire and timber harvesting (mostly clear cut). However, pine covers only 1.8% of the area (from the stand map). Aspen, which is shade-intolerant, is limited to moist terraces along rivers. In contrast, the shade-tolerant spruce occurs primarily in valleys. Dwarf Siberian pine (*Pinus pumila*) occurs largely limited to elevations >800 m.

The primary carrier of wildfire for the birch and aspen is broadleaf litter and herbaceous plants, which produce the least severe fires. Nevertheless, under high winds, the broadleaf forest can cause high

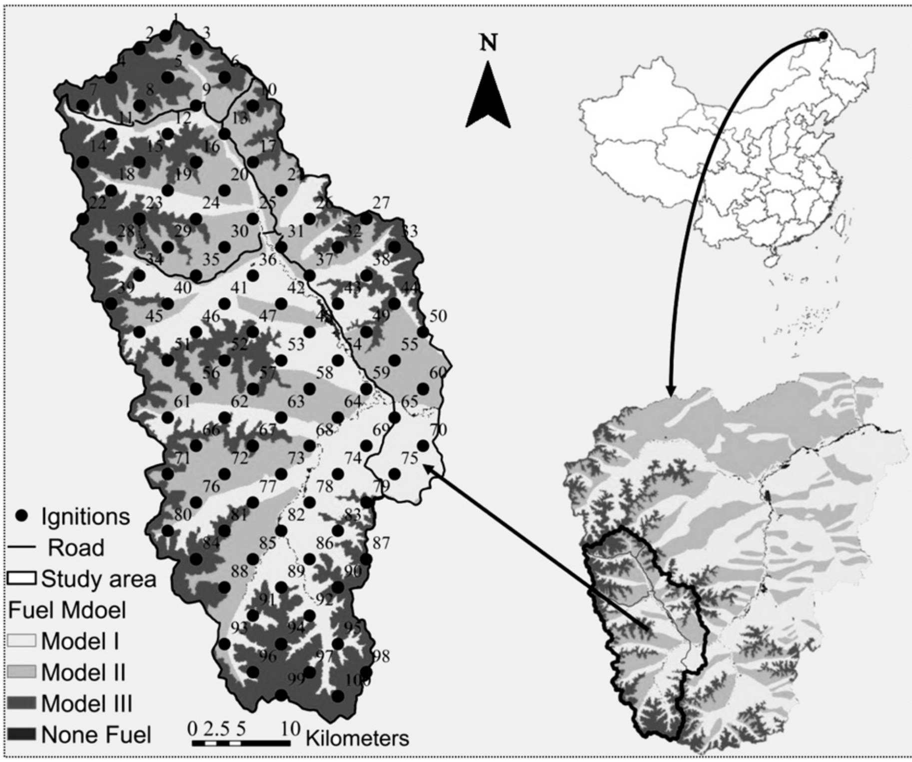

Fig. 1. Map of Huzhong National Nature Reserve (HNNR) in Huzhong Forest Bureau (HFB) showing locations of the 100 simulated fire ignitions, roads, and fuel models.

rates of spread when fueled by high accumulations of leaf mass. The primary carrier of wildfire for the coniferous forests of larch, pine and spruce is coniferous litter interspersed with grasses and shrubs. Although these coniferous litters typically produce surface fires, under drought conditions they may cause crown fires, spotting fires and torching fires that sometimes torch individual trees. The primary carriers of wildfire for the shrublands of dwarf Siberian pine are live and dead shrub twigs and foliage in combination with dead and down shrub litter. The influence of this fine fuel depends largely on its moisture content. These shrublands usually do not produce crown fires because of the absence of a tree layer sufficient to carry one (Wu et al., 2011b). However, the shrubs can also produce crown fires with sufficient surface fire intensity under favorite weather conditions (e.g., high wind speed).

Historically, wildfires in this region were characterized by frequent, low intensity surface fires mixed with sparse stand-replacing fires on relatively small areas with fire return interval ranged from 30 to 120 years (Xu et al., 1997; Zhou, 1991). Currently, fires have been infrequent with a fire return interval about 500 years (Chang et al., 2007); but often burn intense and larger fires (Chang et al., 2008), especially since 2000. For example, fires burned areas of 71.2×10^4 ha and 11.3×10^4 ha in 2003 and 2005 based on fire data from 1965 to 2005 (Zhang, 2008). There is no specific fuel treatment strategy for reducing wildfire potential in this region. Nevertheless, fuel reduction treatments sometimes inadvertently occur when forest understories are thinned for stand regeneration or other timber harvesting practices. Approximately 2000 ha are harvested (clear cut) per year within HFB, but this may increase to 9300 ha (takes up about 1% of the HFB) depending on fluctuation in timber markets. Earlier studies in the region have indicated the need for fuel treatments to mitigate the severity of wildfires and their effects (Chang et al., 2008; Liu et al., 2010).

2.2. Deriving of fuel load map

We reclassified the stand map into the three models (Fig. 1; Table 1). The fuel models were from previous studies (Shan, 2003), in which 21 fuel models were developed for northern China and four of them (including a non-fuel model) occurred in our study area. These fuel models have distinct fire behaviors. Through running the Behave Plus fire modeling system, rate of spread of these fuel models follows the order Model II > Model I > Model III (Table 2). The conditions of the fuel models are described as follows: (1) Model I: Wet, cool north-facing slopes and valleys dominated by two shrubs, *Ledum palustre* and *Vaccinium uliginosum* (up to 0.4 m tall), with little herbaceous cover. Fuel loads are high and more contiguous but less flammable than in other models due to lower

Table 1
Fuel model parameters for Huzhong Natural National Reserve (HNNR).

Fuel Model	Fuel load (Mg/ha)/SAV[a] (m^2/m^3)				FBD[b] (m)	MEDF[c] (%)	D/LHC[d] (kJ/kg)
	1-h	10-h	100-h	Live			
I	8.46/9000	2.48/358	4.38/98	2.58/3448	0.20	60	23,281/21,866
II	8.82/9962	3.21/358	2.66/98	1.14/3790	0.15	37	20,644/21,112
III	5.12/7030	4.32/358	2.36/98	13.41/3448	1.22	55	21,052/21,541

[a] Surface Area-to-Volume ratio.
[b] Fuel bed depth.
[c] Moisture of Extinction Dead Fuel.
[d] Dead/Live heat content.

Table 2
Estimated rate of spread (ROS, m min^{-1}) for the three fuel models over a range of slope and wind conditions using the Behave Plus fire modeling system. In increasing order of ROS, there are Model II, Model I and Model III.

Fuel Model	Wind speed (km/h)					
	0.0	4.0	8.0	15.0	20.0	30.0
Slope = 2°						
I	1.1	9.3	21.1	45.8	65.8	110.1
II	0.9	3.5	10.5	32.3	54.9	116.8
III	0.9	3.6	9.9	27.8	45.3	90.8
Slope = 7°						
I	1.5	9.7	21.5	46.2	66.2	110.5
II	1.1	3.7	10.7	32.5	55.1	117.0
III	1.1	3.8	10.1	28.0	45.5	91.0
Slope = 12°						
I	2.4	10.6	22.4	47.1	67.1	111.4
II	1.5	4.1	11.1	32.9	55.5	117.4
III	1.5	4.2	10.6	28.5	46.0	91.5
Slope = 17°						
I	4.0	12.1	23.9	48.7	68.7	112.9
II	2.3	4.9	11.9	33.7	56.3	118.2
III	2.3	5.0	11.3	29.2	46.7	92.2
Slope = 24°						
I	7.0	15.2	27.0	51.7	71.7	116.0
II	3.8	6.4	13.4	35.2	57.8	119.7
III	3.8	6.5	12.8	30.8	48.3	93.7

flammability and higher moisture content. (2) Model II: Dry south-facing slopes mainly dominated by the shrub *Rhododendron dauricum* (up to 2.0 m tall) but also with herbaceous ground cover. Fuel loads are lower than on north-facing slopes but more flammable due to the fineness of fuels. (3) Model III: Ridge tops (elevations >800 m) dominated by *P. pumila* (up to 4–5 m tall), with an understory of *L. palustre* and *V. uliginosum* (up to 0.4 m tall) (Wu et al., 2011a). Details for the fuel model map parameters (e.g., fuel load, fuel bed depth and Dead/Live heat content) are presented in Table 1. During both FARSITE and LANDIS simulations roads were considered as nonfuel; these were delineated on the fuel map.

2.3. Deriving of burn probability map

The burn probability distribution map was derived using LANDIS. LANDIS is a raster-based, spatially explicit forest landscape simulation model that can simulate disturbance, succession, and forest management at large spatial (10^3 to 10^6 ha) and temporal scales (10^1 to 10^3 years) (He et al., 2005). We first derived a fire occurrence density map with spatial point pattern analysis of historical fire locations from 1990 to 2005. The derived fire occurrence density map provided input for the LANDIS model to predict burn probability. The model accounts for both future fire occurrence and spread location. The inputs for the model were vegetation, fuel, topography, weather and historical wildfire regime. We parameterized 8 tree species (e.g. fire tolerance classes) and 7 land types in which each species is assumed to respond uniformly with respect to mean fire size and fire return interval. Since the focus of this study was to compare approaches to current fuel treatment scenarios, we ran LANDIS simulations for only a single 10-year interval (2006–2016). Moreover, we assumed that vegetation and fuel remained relatively constant during the 10-year simulation period. Finally, the estimated burn probability map was validated based on historical burned patches from 2006 to 2009 by using the chi-square test.

In the LANDIS model, wildfire occurrences consist of two processes: fire ignition (a wildfire occurrence) and fire initiation (becoming a wildfire). The ignition attempts across a landscape were simulated based on the occurrence density map. Whether an ignition continued on into an initiation or not was determined by fuel and vegetation characteristics at the site (Yang et al., 2004, 2008). Once initiated, fire spread was simulated using the minimum travel time algorithm (MTT). This algorithm is an expedient method that solves for arrival time of the fire front from a set of source cells (Finney, 2002). The algorithm involves the calculation of rate of spread for each cell with respect to fuel type (fuel model), wind, and slope conditions (Yang et al., 2008). We calculated equilibrium head-fire spread rates for each fuel model for all possible combinations of fuel moisture, wind, and topography with the Behave Plus fire modeling system (Andrews et al., 2008). LANDIS then reads in equilibrium head-fire rates of spread for all the combinations before fire spread simulations start. Thus, the raster-based MTT used in LANDIS produces results similar to the vector-based fire growth predictions in FARSITE. Additional information on how the LANDIS simulates fire burn probability is available in Yang et al. (2008).

To account for the stochasticity of fire occurrence, LANDIS simulations were replicated 200 times. Burn probability was defined as the proportion of the number of replicates in which the cell was burned to the total number of replicates for 10-year simulation intervals. Our burn probability is a conditional burn probability that is the probability of a fire burning an area of pixel given that a fire burns the area of interest. The derived burn probability thus considers every pixel containing a probability value, and thus reflects the probability of burning at a particular location. From that, fuel treatment locations can be prioritized (Fig. 2).

2.4. Design of fuel treatment scenarios

Both fuel-load-based and burn-probability-based fuel treatments consisted of six treatment intensities (percent of area treated) and two treatment prioritization approaches. The fuel treatment intensities were constrained to 10, 20, 30, 40, and 50% of the areal extent of the study area. In each case, the fuel treatment consisted of removing 50% of surface fuel loads and bed-depths. It was assumed there was no change in canopy cover and bulk density (Stephens, 1998). This fuel treatment was based on the observation of local forest and fuel management practices. In the study area, there is no fuel treatment practices currently implemented for reducing crown fuels. Surface fuels are treated by crews using hand tools such as chainsaw and chopper (no prescribed burns). This fuel treatment with hand tools does not change the crown fuel attributes. There was no recurrent treatment applied over the course of each fuel treatment scenario.

The treatment scenarios based on fuel loads were assigned the highest treatment priorities in areas where fuel loads were highest. Similarly, the treatment scenarios based on burn probability were assigned the highest treatment priorities in areas where burn probabilities were highest. While selecting fuel treatment locations, we employed road accessibility as a secondary criterion when rankings of fuel loads or burn probability were the same. The 0% treatment intensity (Notreat) was a baseline scenario representing the current situation (without fuel treatment). Spatial distributions of fuel treatment units were mapped (Fig. 3).

2.5. Wildfire simulations

We used the FARSITE model to simulate fire spread process. FARSITE requires five raster-based themes (elevation, slope, aspect, fuel models, and canopy cover) and three crown fuel themes (stand height, crown base height, and crown bulk density), as well as meteorological files (Finney, 1998). More information on the FARSITE model can be obtained from Finney (1998).

The variables of elevation, slope, and aspect were extracted from the digital elevation model (DEM). Three fuel models were created and parameterized as fuel load distribution maps (Fig. 1). The

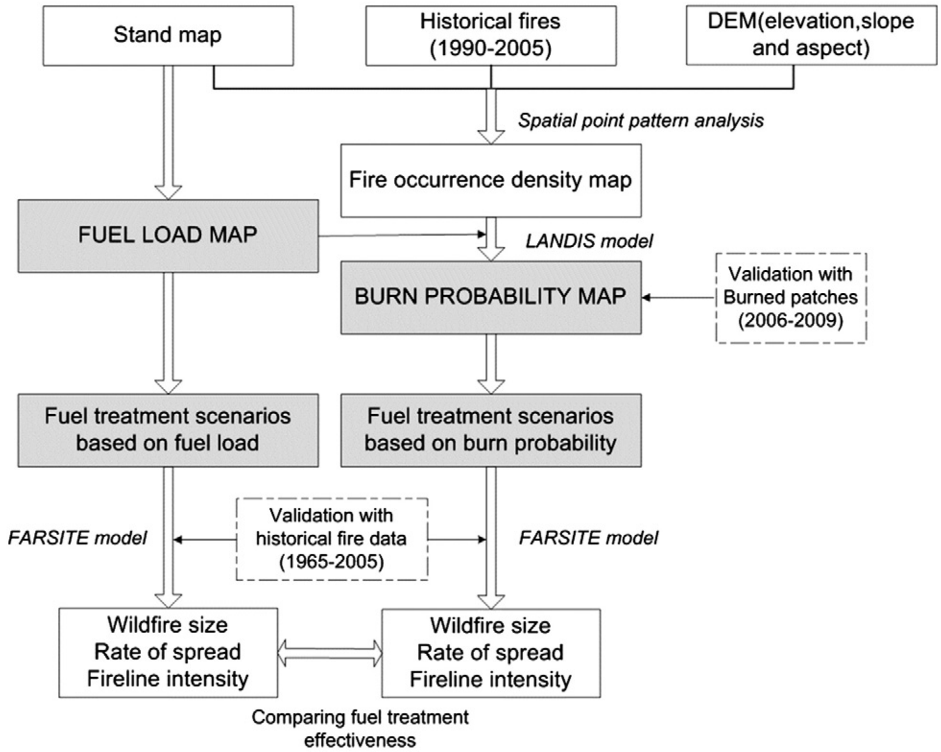

Fig. 2. The steps used to facilitate comparing the effectiveness of fuel reduction treatments based on burn probability vs. fuel load.

crown fuel attributes (canopy cover, stand height, crown base height, and crown bulk density) were derived from local knowledge as well as our own field samples and published literatures. The canopy cover (0–100%) and stand height were derived from the stand map of the China Forest Management and Planning Inventory (FMPI) database (conducted every 10 years). The canopy cover in each stand was estimated with 1–6 plots (10 m × 60 m). The stand map was in the form of a polygon with an average size of 26.2 ha. The crown base height (m), crown extent and length (m) were collected in the field sample plots each with 20 m × 20 m. The crown biomass (kg) was estimated using an algometric equation developed by Yu et al. (2010). The crown volume (m^3) was estimated using a regression equation developed by Chen et al. (2003). Both Yu et al.'s (2010) and Chen et al.'s (2003) works were developed for much larger region. The crown fuel variability was assumed to be small within a fuel model. We therefore set constant values of the crown fuel

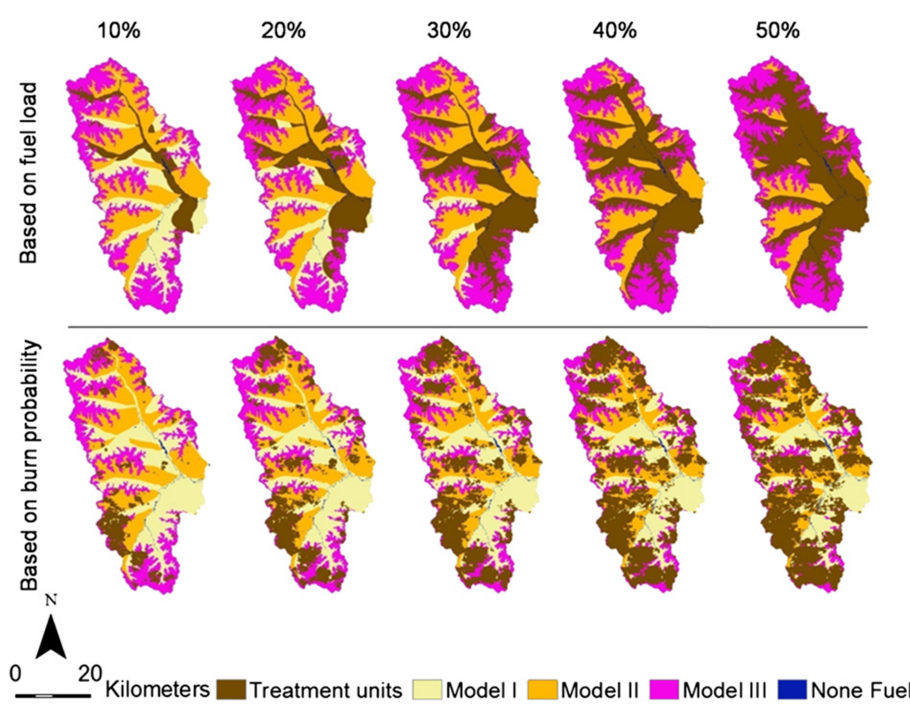

Fig. 3. Maps of treatment units of fuel treatment scenarios for two fuel treatment prioritization approaches. 10, 20, 30, 40, and 50% stand for fuel treatment intensities.

parameter series (stand height, crown base height, and crown bulk density) for each of the three fuel models. The spatial resolution of all the raster inputs of the FARSITE model was 90 m × 90 m.

Meteorological inputs to the FARSITE model are weather, wind, and fuel moisture. Weather inputs include minimum and maximum daily air temperature, relative humidity, and precipitation; and wind input files include wind speed, wind direction, and cloud cover (Finney, 1998). Meteorological inputs were derived from historical wildfire records from 1965–2005 (including ignition location, cause, duration, and size) and suggestions from local forest and wildfire managers. The extreme wildfire weather that would most likely result in "catastrophic wildfire" was used in the simulations for pre- and post-treatment situations (Table 3). Simulations of wildfire spread were run for 24 h because most wildfires were suppressed in that time interval based on historical wildfire records in the Great Xing'an Mountains. During the simulation period, temperature and humidity are assumed to respond inversely over time as approximated by a cosine curve spanning maxima and minima values (Finney, 1998). We used a 24 h conditioning period to adjust fuel moisture prior to the start of simulations (Finney, 1998).

We evenly placed 100 ignitions across the landscape to cover the combinations of fuel models and topography variations, while maintaining computation efficiency of the FARSITE model. Each ignition point was assigned a numerical identification number (1–100) from northwest to southeast (Fig. 1). The 100 points were then separately used in the FARSITE model as the ignitions for wildfire spread simulation. In all treatment scenarios, we used the same wildfire ignition points. Model parameters for the simulations were set to a time step of 30 min, perimeter of 60 m, and distance resolution of 30 m to obtain the expected spatial and temporal resolutions of simulation. We set the 5% ignition probability for the spot fires during all the simulations. During the simulations, we did not consider the effects of fire suppression and roads that were considered as nonfuel.

2.6. Validation of model prediction results

Validating how the burn probability map reflects the actual burned patterns provided insight into the reliability of model predictions. We used the 2006–2009 burned patches (n = 55) to validate the LANDIS-derived burn probability map (where probabilities ranged from 0 to 0.12 with a mean of 0.0175). We then determined whether burned patches were located in areas with high burn probabilities (i.e. > 0.035, which accounted for 10% of the landscape). After this determination was made the 55 burned patches were overlain on the simulated burn probability map. We then identified the areas with probabilities lying above and below the threshold value of 0.035 across all 55 burned patches. Finally, we used chi-square to test for association between areas above and below the threshold probability of 0.035 across the 55 burned patches and across the simulated burn probability map for the entire study area.

We calibrated the FARSITE simulations under the Notreat treatment scenario using the weather, fuel and simulation period parameters. The simulated wildfire fire size, rate of spread and intensity were compared to historical fire data from 1965 to 2005 in the Great Xing'an Mountains in northeastern China. We used only historically burned areas and fire size to calibrate FARSITE because we lacked observed data on wildfire behavior (e.g. rate of spread and fire intensity). We selected the calibration fires that burned approximately 24 h (standard deviation being 5.4). Consequently, we set our average fire simulation time at 24 h for comparing with the actual fires. The significance of difference between wildfire sizes on historical burn simulations was tested by non-parametric Mann–Whitney *U* test with SPSS 13.0 software.

2.7. Comparing effects of fuel load based and burn probability based treatments

Wildfire size (ha), rate of spread (m min^{-1}) and fire intensity (kW m^{-1}) are important in wildfire management decision-making. We compared amount and rate of decline in these three variables among the various fuel reduction scenarios of the two fuel treatment priorities. Significant differences in responses among fuel treatment scenarios were tested by non-parametric Kruskal–Wallis tests with SPSS 13.0 software. Because there was a range of values in rate of spread and fire intensity across burned pixels for each simulation, the mean values of these variables for the 100 ignitions are presented along with their standard errors.

3. Results

3.1. Validation of burn probability map and simulated fires

On average, there were 59.1 simulated wildfires per decade over the entire landscape. The standard deviation for the simulations was ±8.5 fires per decade, or about 14.4% of the mean. The LANDIS-derived burn probability map was validated with the actual 2006–2009 burned patches. The chi-square test result (chi-square = 2549.817; $p < 0.001$) indicated that locations with high burn probability (>0.035) had more fires burned there ("hot spots") (Fig. 4).

We calibrated the FARSITE simulations under the Notreat (no fuel treatment) scenario using historical wildfire data on fire size from 1965 to 2005 in the Great Xing'an Mountains. Average wildfire size of historical fire data was compared to the FARSITE simulations in Table 4. The comparisons reveal that simulated average wildfire size was close to the historical average from 1965 to 2005. Parameters calibrated in FARSITE thus appear to realistically simulate fire patterns within the study area, which suggests they can be extended to simulating wildfire size and intensity under our defined fuel treatment scenarios.

3.2. Comparing effects of fuel load based and burn probability based treatments

Treatment scenarios based on both fuel loads and burn probability reduced wildfire size and intensity compared to Notreat as treatment intensity increased (Table 5). However, the effectiveness of the two fuel treatment prioritizations on reducing wildfire size and intensity differed greatly (Fig. 5). Treatment scenarios based on burn probability were considerably lower in wildfire size, and mean and maximum rate of spread than those based on fuel load for a given treatment area. For example, mean and maximum rate of spread under treatment scenarios for burn probability were, respectively, 0.55 and 6.35 m min^{-1} lower than those based on fuel load.

Moreover, rates of reduction in wildfire size and mean and maximum rate of spread were more acute for treatment scenarios based

Table 3
Weather and fuel moisture parameters used in wildfire simulations. These weather data were collected from the Huzhong weather station from 1972 to 2005.

Variables	Value
Precipitation (mm)	0
Low temperature (°C)	15
High temperature (°C)	28
High relative humidity (%)	25
Low relative humidity (%)	15
Wind speed (km/h)	30
Wind direction (degree)	245
1-h fuel moisture (%)	3
10-h fuel moisture (%)	4
100-h fuel moisture (%)	5
Herbaceous moisture (%)	70
Live woody moisture (%)	70

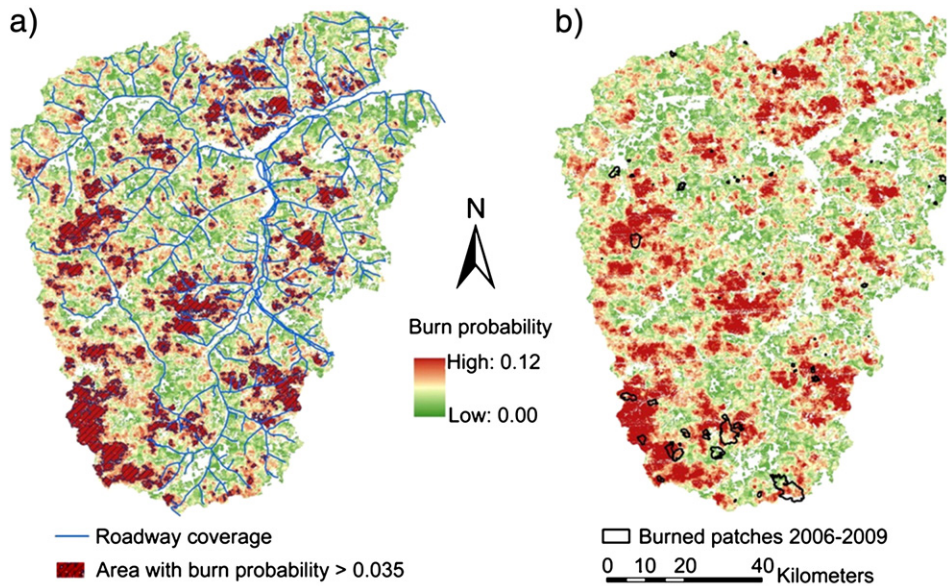

Fig. 4. Map of estimated burn probabilities. We defined burn probability as the probability of burning at least once per decade per 0.81-ha sample cell. (a) Overlay showing roads and areas of high burn probability (burn probabilities > 0.035). Areas with high burn probabilities accounted for about 10% of the total study area. (b) Overlay showing observed patches that actually burned between 2006 and 2009.

on burn probability than those based on fuel load (Fig. 5). For example, as treatment intensity increased, the decline in average wildfire size increased from 7 to 31% under treatment scenarios based on fuel load; based on burn probability, fire size declined from 10 to 42% with increasing treatment area. The decline in average rate of spread with increasing treatment area ranged from 1 to 7% under fuel-load scenarios and from 5 to 25% based on burn probability. The simulations also revealed that fuel treatments based on burn probability were more effective at reducing large wildfire size and high spread rate (Table 5). Note that as treatment area increased, the effectiveness of treatments based on burn probability was more obvious when treated areas exceeded 40% of the area compared to treatments based on fuel load (Table 5; Fig. 5). Our results further confirmed those that Finney found that when fuel treatments were randomly assigned to a landscape, we need to treat a very large area before achieving the reduction in potential fire behavior (Finney, 2007).

Fuel treatments based on burn probability also were more effective at reducing mean fire intensity, but less effective at reducing maximum fire intensity than treatments based on fuel load when the treated area was <50% of the forested landscape. For example, the decline in maximum fire intensity with increasing treatment area ranged from 9 to 17% under treatment scenarios based on fuel load and from 2 to 13% for those based on burn probability (Table 5; Fig. 5).

4. Discussion

4.1. Treatment schemes of two fuel treatment prioritization approaches

The differences in the two analytical approaches to predicting fire size and intensity could be attributed to differences in fuel treatment schemes. Generally, fuel load is the primary factor that determines wildfire intensity and area; as fuels increase, fire intensity increases (Sah et al., 2006). For example, Sah et al. (2006), in studying the relationship between fuel loads and fire regimes in pine forests of the Florida Keys, found that fire intensity increased with surface fuel loads. These conclusions were similarly confirmed by our study, which showed that maximum fire intensity increased with increasing fuel load (Table 5; Fig. 5). However, fuel treatments based on fuel load were less effective at reducing mean fire intensity, fire size, and mean and maximum rate of spread than treatments based on burn probability. This outcome resulted because the emphasis is placed on fuel hazard in defining fuel treatments based on fuel load, and ignoring fire spread.

Areas with heavy fuel loads did not necessarily burn at high spread rates or cover large areas (Finney, 2001, 2005; Yang et al., 2008). This is because wildfire is a spatial process that is not only related to fuel load, but is also affected by spatial controls such as human activity, topography and weather conditions (particularly wind direction and speed) (Mermoz et al., 2005). For example, Yang et al. (2008) analyzed spatial controls of wildfires in the Missouri Ozark Highlands and concluded that human accessibility and landownership were the primary limiting factors in shaping wildfire location whereas vegetation had negligible influence. Wildfire ignition and spread probabilities usually occur in places where fuel loads are directly related to fire intensity (Finney, 2005; Miller et al., 2008; Parisien et al., 2007). Fuel treatments based on burn probability in this study have incorporated fuel load, ignition probability, and spread probability (all of which are spatially controlling) (Ager et al., 2010b; Miller et al., 2008; Pollet and Omi, 2002). Since ignition and spread probabilities account for the places where fires are most likely to occur and fuel load is directly related to fire intensity (and thus burn severity), burn probability as used in this study has already accounted for fire intensity and fire effects. Thus, our fuel treatments based on burn probability were probably more effective at reducing wildfire size and intensity than those based on fuel load (Ager et al., 2010b).

Nevertheless at present, most fuel treatments focus on reducing fuel load at the site or stand level (Reinhardt et al., 2008). Those studies often assumed that spatial patterns of wildfire spread are completely random, and therefore the effects of spatial controls (e.g. topography) on fire occurrence and spread are ignored or simplified (Agee and Skinner, 2005; Finney, 2007). Studies showed that

Table 4
Comparison of FARSITE simulations with historical wildfire data from 1965 to 2005. The significance of difference between wildfire size based on historical records and simulations was tested by non-parametric Mann–Whitney *U* test with SPSS 13.0 software.

Items	Mean wildfire size (ha ± S.E.)	Number of fires
Historical fire-data	7341.10 ± 878.47	85
FARSITE simulation fire	7677.38 ± 573.75	100
Significance (2-tailed)	$p > 0.01$	–

Table 5
Simulation results of average value (mean and maximum) (±S.E.) of wildfire size, rate of spread and fire intensity for each treatment scenarios of the 100 ignitions. BPtreat: based on burn probability; FLtreat: based on fuel load. 10, 20, 30, 40, and 50% stand for fuel treatment intensities.

Scenarios	Wildfire size (ha)	Rate of spread (m min^{-1})		Fire intensity (kW m^{-1})	
		Mean	Maximum	Mean	Maximum
Notreat	7677.34 ± 573.75	4.83 ± 0.26	64.86 ± 4.70	942.78 ± 47.52	21932.56 ± 2109.46
FLtreat-10	7116.85 ± 553.94	4.80 ± 0.28	63.17 ± 4.67	895.33 ± 45.68	19410.34 ± 1658.48
FLtreat-20	6718.30 ± 534.88	4.75 ± 0.28	61.80 ± 4.69	880.27 ± 51.74	20017.65 ± 1894.01
FLtreat-30	6230.04 ± 538.48	4.68 ± 0.29	59.83 ± 4.73	838.97 ± 53.09	19637.41 ± 2061.28
FLtreat-40	5619.62 ± 514.47	4.57 ± 0.31	58.40 ± 4.86	802.61 ± 54.52	18108.38 ± 1950.28
FLtreat-50	5298.43 ± 505.78	4.50 ± 0.31	57.02 ± 4.81	783.56 ± 56.80	17257.53 ± 1794.80
BPtreat-10	6946.30 ± 541.45	4.59 ± 0.24	62.76 ± 4.86	869.68 ± 42.31	21525.13 ± 2160.32
BPtreat-20	6369.34 ± 512.07	4.32 ± 0.23	58.06 ± 4.69	779.98 ± 37.03	20243.05 ± 2081.18
BPtreat-30	5837.13 ± 472.49	4.07 ± 0.21	55.21 ± 4.39	686.57 ± 28.99	20022.71 ± 2020.56
BPtreat-40	5150.02 ± 439.32	3.83 ± 0.19	49.39 ± 4.11	610.17 ± 25.72	19052.59 ± 2078.14
BPtreat-50	4445.16 ± 505.78	3.60 ± 0.19	42.97 ± 3.72	535.57 ± 23.33	16182.77 ± 1766.80

stand-level fuel treatments can create artificial forest and fuel constructs that are more resilient to wildfires. But a key knowledge gap in fuel treatment design is related to problems associated with the question of how isolated stand-level fuel treatments can be scaled up to landscape level, and also how the spatial arrangement of fuel treatments affects wildfire spread at the landscape level (Schmidt et al., 2008). To achieve this objective, fuel treatments need to consider the effects of spatial controls on patterns of wildfire spread.

Fuel treatment location can be optimized using various methods (schools of thoughts) such as mathematical programming algorithm and fire model simulation. For example, Finney (2007) used a minimum travel time (MTT) algorithm to identify major fire travel routes (areas needing treatment) and their intersections with areas where fuel treatment occurred and reduced the spread rate (opportunity for treatment). Wei et al. (2008) used a mixed integer programming (MIP) formulation to locate fuel treatments with the aim to break fire risk accumulation following major wind directions. Fuel treatments that are based on mathematical programming algorithm often focus on maximum interruption or reducing of fire's rate of spread by placing the fuel treatment units in the predominant fire spread direction over a range of topography, fuel and weather conditions (Finney, 2002, 2007; Konoshima et al., 2010; Wei et al., 2008) Therefore, the mathematical algorithm is particularly designed and useful to identify fuel treatment locations for the purpose of interrupting or slowing fire spread to some important areas such as natural reserves and wildland urban interfaces (WUI). Compared to mathematical programming algorithm, our optimization procedure based on fire model (FARSITE and LANDIS) simulation has incorporated both the potential fire occurrence and spread ability into the identification of critical fuel treatment locations across the landscape. Our

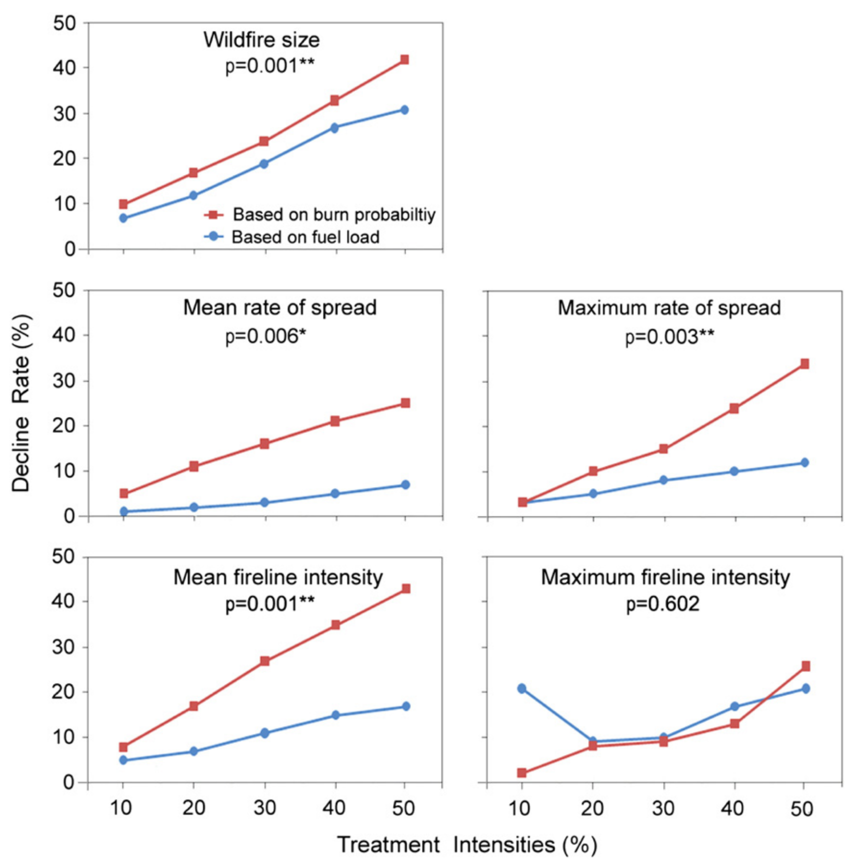

Fig. 5. Reduction in fire size, rate of spread, and fireline intensity in relation to fuel reductions for burn probability and fuel load models. Differences in reductions of the specified fire characteristics were tested by paired-samples *t*-test with SPSS 13.0 software. The *p* values refer to significance of differences between fuel load and burn probability models.

optimization procedure is much more a strategic fuel treatment allocation across the entire forest landscape and is not specific for a given area such as the WUI.

4.2. Utility of burn probability

Despite its recent development and application, the utility of burn probability to assist wildfire and fuel management as a tool for mitigating the harmful effects of wildfires has been widely reported (Ager et al., 2007a; Parisien et al., 2007). Burn probability can be used to guide implementation of strategic wildfire and fuel management activities. In practice, once potential burn probability distributions are identified, managers can use this information as input into a fire simulation program such as FARSITE to evaluate where and what kind of wildfire management actions may be most effective at achieving defined protection objectives. For example, Ager et al. (2010a, 2010b) used burn probability to calculate wildfire risk profiles for each of the 170 residential structures within the urban interface, and to estimate the expected wildfire mortality for large tress.

Moreover, burn probability can be used as a criterion for quantifying the effectiveness of fuel and fire management activities. For example, Ager et al. (2007b) employed burn probability as one of the fire risk variables used to evaluate landscape-level fuel treatment strategies in the urban interface of the Mt. Emily wildlands in Oregon. Their study showed that burn probability decreased linearly with increasing treatment intensity. The highest burn probabilities occurred where no fuel reduction treatments were applied. Burn probability also has been used to identify relations between the occurrence of spatial controls and the spread of wildfires. For example, Parks et al. (2011) examined the scale-dependent relation between spatial burn probability and some key environmental controls in the southern Sierra Nevada Mountains of California. They concluded that the statistical relation between burn probability and explanatory variables fluctuates across spatial scales, as does the influence of explanatory variables.

Although some burn probability models have been developed (e.g., Burn-P3 and Fire Spread Probability model), there is no generally accepted burn probability model. The burn probability model developments (algorithm), application and validation are problems that need further research. For example, when wildfire occurrence and spread vary greatly with forest fuel composition and succession, burn probabilities should be developed to reflect these dynamic (time-dependent) changes in fuels across fire seasons. Generally, clarifying which modeling approaches are most appropriate for a given management objectives is critical (Miller et al., 2008).

4.3. Some limitations and future directions

Although the results from this study could be used for a range of forest and fire management activities, they have limitations. Ideally, the effects of fuel treatments should be measured not only by the resulting reductions in wildfire size and intensity but also by their direct effects on ecological and social values (e.g. ecological processes and habitat lost) (Ager et al., 2010a, 2010b; Calkin et al., 2010; Finney, 2005). Our assessment of the effects of fuel treatments based on wildfire size and intensity may be weak or strong depending on their direct ecological effects. For example, Ager et al. (2010a, 2010b) modeled effects of fuel treatments on northern spotted owl (*Strix occidentalis caurina*) habitat in Central Oregon, USA and observed a non-linear decrease in the probability of habitat loss with increasing treatment area. Thus, in future studies, ecological and social values associated with fuel treatments should be considered. These include habitat loss, tree mortality, and damage to human infrastructure (Finney, 2005).

We overlaid the 100 ignitions on the fuel model map to analyze the effects of ignition location on wildfire simulations. Most of the larger wildfires and intensities resulting from ignitions occurred on the northeastern and southern edges of the study area where fuels were most hazardous (Fuel Model III). Ignitions in the central portion of the study area were associated with less hazardous fuels (Fuel Model I) and spread at lower rates than other fuel models. These results show that fire size and intensity vary greatly by ignition location. Ignition locations with high fuel loads (once ignited under favorable weather conditions such as high wind speed and temperature) usually produced large, high intensity fires. However, we have not specifically investigated the relationship between ignition location and topography. Previous research in the study area suggests that ignitions on south-facing slopes and upper mountain ridges tend to produce larger fires (Wu et al., 2011a). Fire management efforts accordingly should be allocated to those areas most prone to fire.

Factors not accounted for in our study also may have influenced study results, especially those related to treatment costs. Costs related to financial and human resources are important considerations in designing and prioritizing fuel treatments. For example, Liu et al. (2010) designed a cost-efficiency measure to compare fuel treatment efficiency in different settings. They concluded that cost effectiveness of fuel treatments varied by treatment area and forest type. Reinhardt et al. (2008) pointed out the challenge of estimating the costs and benefits of fuel treatments. Yet despite this difficulty, the influence of investment needs to be considered when making fuel and fire management decisions. Therefore, further researches are needed on how to best allocate fuel treatments under current limited resources for fire control.

Large variability and uncertainty in weather conditions influence fire ignition and spread. Fire simulation results based on extreme weather conditions therefore should be interpreted cautiously when applied to other weather conditions (not the weather conditions used in our study). Moreover, we set the burn period of 24 h to fire simulation. In the future, we need to compare the effectiveness of fuel treatment optimization strategies (based on burn probability vs. fuel load) under longer burning period.

5. Conclusions

Assessing the effectiveness of landscape fuel treatments is essential in making fuel and fire management decisions. Our study indicated that fuel treatments based on burn probability may be more effective at reducing wildfire size, mean and maximum rate of spread, and mean fire intensity, but less effective at reducing maximum fire intensity than those based on fuel accumulation. Burn probability therefore may be more effective at achieving specific forest resource protection objectives.

There are many optimization procedures that can help with the assignment of fuel treatment locations such as the minimum travel time algorithm (MTT) incorporated in the FlamMap fire behavior model (Finney, 2002). Those fuel treatment location optimization procedures based on reducing fire spread in the fastest corridors belong to the “school of thought” of using the mathematical programming (Finney, 2007; Konoshima et al., 2010; Wei et al., 2008). Our study based on burn probability provided an alternative to the fuel treatment optimizing strategy through running fire simulation models (LANDIS and FARSITE). However, because this strategy based on burn probability is relatively new in fire management, burn probability models and their application require further testing and assessment to their reliability. Moreover, it is important to clarify for users that models and approaches need to be evaluated with respect to local fire occurrence and fuel conditions.

Conflict of interest statement

This paper has no financial conflict of interest for any of the four authors, including employment, stock ownership, honoraria, paid expert testimony, patent applications/ registrations, and grants or other funding.

Acknowledgments

This research is funded by the 973 project of Ministry of Science and Technology of China (grant no. 2011CB403200) and the Natural Science Foundation of China (grant no. 41071120). We are grateful to Jian Yang for his constructive suggestions that greatly improved this manuscript. We thank Changhe Hu, Jinglun Huang, and Weidong Sun for their help with the design of weather scenarios. We thank Paul Johnson for his English language editing. We thank four anonymous reviewers for their comments which greatly improved earlier versions of this manuscript.

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