Forest Ecology and Management 264 (2012) 134–149

Contents lists available at SciVerse ScienceDirect

Forest Ecology and Management

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

Modeling tree-level fuel connectivity to evaluate the effectiveness of thinning treatments for reducing crown fire potential

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ARTICLE INFO

Article history:
Received 27 April 2011
Received in revised form 1 September 2011
Accepted 3 October 2011

Keywords:
Fire behavior
Fire simulation modeling
WFDS
LiDAR
Thinning treatments

ABSTRACT

Land managers have been using fire behavior and simulation models to assist in several fire management tasks. These widely-used models use average attributes to make stand-level predictions without considering spatial variability of fuels within a stand. Consequently, as the existing models have limitations in adequately modeling crown fire initiation and propagation, the effects of fuel treatments can only be evaluated based on average conditions, where the effects of thinning design (e.g., cut-tree locations) on changing fire behavior are largely ignored. To overcome these limitations, we coupled an advanced physics-based fire behavior model with light detection and ranging (LiDAR) technology to capture the spatial distribution of trees within stands and model crown fire initiation and propagation in more detail. Advanced physics-based fire behavior models are computationally demanding, and it is not currently feasible to run such models for large landscapes (thousands of hectares) at which fuel treatments are often considered. Thus, to extend the capabilities of these fine scale models to larger landscapes, we developed logistic regression models based on tree data and fire behavior model output to predict crown fire initiation and propagation for given tree locations and attributes for two weather scenarios, representing average and severe conditions, for our study area. We applied these regression models and used tree-level fuel connectivity prediction as measures to evaluate the effectiveness of thinning treatments for reducing crown fire potential. We demonstrate this method using LiDAR-derived stem map and tree attributes developed for a 4.6-ha forest stand in western Montana, USA.

1. Introduction

Historically, low intensity fires burned frequently in the western US, with ignitions caused by lighting and humans (Allen et al., 2002; Hessl et al., 2004). These fires functioned to control regeneration of fire sensitive species, promote fire tolerant species, maintain open forest structures, and reduce forest fuel loads (Swetnam et al., 1999; Arno and Allison-Bunnell, 2002). Over the last six decades, successful fire exclusion has contributed to the accumulation of understory vegetation and increased stand densities, creating a greater vertical and horizontal continuity of fuels in stand structures, which has increased the potential for high-intensity wildfires in the western US (Arno and Brown, 1991; Mutch, 1994). Some estimates suggest that more than 27 million ha of forestland in the western US have departed significantly from natural wildland fire conditions and are at medium to high risk of catastrophic wildfires (Schmidt et al., 2002). In response to the continuing threat of severe wildfires, the National Fire Plan (USDA and USDI, 2001) and the Healthy Forest Restoration Act (2003) mandate that land managers restore forest habitats and reduce the risk of wildfires in federal forests.

Land managers and decision makers have been using fire behavior and simulation models as a tool to predict fire potential, identify stands with high risk of wildfires, and allocate resources for fuel treatments (Finney, 2006; Ager et al., 2006; Chung et al., 2009) However, the widely-used existing fire behavior and simulation models, such as FARSITE (Finney, 1998), NEXUS (Scott, 1999), FFE-FVS (Reinhardt and Crookston, 2003), BehavePlus (Andrews et al., 2005), and FlamMap (Finney, 2006) use the average attribute values of a forest stand for stand-level predictions without considering spatial variability in fuels and vegetation within a stand. For example, the existing models for predicting crown fire initiation (e.g., Van Wagner, 1977) and crown fire occurrence (Rothermel, 1991) are based solely on the stand canopy base height that represents the vertical distance from the top of the surface fuels to the lower limit of canopy fuels that can sustain and vertically propagate fire. However, due to variability within a stand, it is difficult to represent an entire stand with a single canopy base height value

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doi:10.1016/j.foreco.2011.10.001

(Scott and Reinhardt, 2001). In addition, the existing models predict crown fire propagation through canopy fuels (e.g., Van Wagner, 1977) based on predicted crown fire rate of spread (Rothermel, 1991) and the stand canopy bulk density (CBD). The calculation of CBD assumes that canopy fuels are distributed uniformly throughout the stand, but this is unlikely the case even in stands with simple structures (Scott and Reinhardt, 2001). Consequently, the widely-used existing fire behavior models have limitations in modeling crown fire initiation and propagation, as well as assessing fire–atmosphere interactions that influence the initiation and cessation of rapid and intense fires within a stand (Rothermel, 1991; Potter, 2002). Furthermore, the effects of fuels treatments, such as fuel reduction thinning, can only be evaluated based on average conditions (Van Wagtendonk, 1996), where the effects of thinning design (e.g., cut-tree locations) on changes in fire behavior are largely ignored.

To overcome the limitations of the existing fire behavior models, recent effort has been put into the development of advanced physics-based numerical fire behavior models capable of considering spatial variability of fuels within forest stands as well as fire–fuel and fire–atmosphere interactions (Mell et al., 2009). The wildland-urban interface fire dynamics simulator (WFDS) developed by the National Institute for Standards and Technology is one of the models that simulate crown fire initiation and propagation as a fine-scale, physics-based process that takes into account size, shape, composition and spatial arrangement of fuel particles (Parsons, 2006). WFDS can be coupled with the light detection and ranging (LiDAR) technology, which has been widely used to obtain tree locations and attributes (Maltamo et al., 2004; Packalén and Maltamo, 2006; Suratno et al., 2009), to provide spatial arrangement and characteristics of fuels within stands. The advanced, fine-scale fire behavior modeling approach can be a promising method to model crown fire initiation and spread in more detail, as well as evaluate stand level effects of fuel treatments. However, practical applications of the fine-scale fire behavior models have been limited due to the large amount of data and computation time required to represent detailed variability of fuels within a stand and model the time-dependent fine scale fire–fuel and fire–atmosphere interactions (Mell et al., 2007).

In this study, we developed an alternative method to use a fine-scale fire behavior model (e.g., WFDS) for the purpose of improving evaluation of fuel treatment effects on changes in fire behavior. Instead of running WFDS on an entire forest stand, which is a very computationally intensive process, we run the model on different combinations of tree arrangements to represent various spatial distributions of trees and tree attributes. Logistic regression models were then developed to predict crown fire initiation (the transition of fire from surface fuels to elevated crown fuels) and propagation (spread of fire through adjacent tree crown fuels) for given tree locations (spacing) and attributes. Crown fire initiation was predicted to occur for a given tree location and weather condition if the simulated fire rose from surface fuels to crown fuels burning more than 50% of crown fuels. In such case, the tree's crown fuels were considered vertically connected with surface fuels. Crown fire propagation was predicted when fire spread from a burning tree crown to an adjacent tree crown consuming more than 50% of its crown fuels. When crown fire propagation was predicted between two adjacent trees, then both trees crown fuels were considered horizontally connected. Tree-level fuel connectivity predictions from these regression models were then used as a measure to evaluate the effectiveness of thinning treatments for reducing crown fire potential. We demonstrated this method using LiDAR-derived stem map and tree attributes developed for a 4.6-ha forest stand in the University of Montana's Lubrecht Experimental Forest (LEF) in western Montana, USA.

2. Methods

2.1. LiDAR-Derived Stem Map and Tree Attributes

In the summer of 2005, the National Center for Landscape Fire Analysis (NCLFA) acquired LiDAR data over the LEF located approximately 48 km northeast of Missoula, Montana in the Blackfoot River drainage (N 46°53′30″, W −113°26′3″) (Fig. 1). Table 1 shows the LiDAR data acquisition parameters used for LEF. These parameters provided an average return density of ~1 return per 2.29 m^2 on the ground with a vertical accuracy of 0.15 m and a horizontal accuracy 0.25 m (Suratno et al., 2009).

Researchers at the NCLFA separated the raw three-dimensional LiDAR points into vegetation (aboveground) and bare earth points using a triangulated irregular network densification method available in the TerraScan software suite (Terrasolid, 2004). Ground points were used to create a digital elevation model (DEM) using inverse distance weighted interpolation at 1 m resolution. The DEM and aboveground points were used to calculate the canopy height model (CHM) using the spot elevation method (Daniels, 2001). This approach computed the canopy height (elevation above ground level) at each point by subtracting the DEM height from the CHM (Suratno et al., 2009).

NCLFA researchers delineated individual trees using a stem identification algorithm based on a combination of variable window local maxima filtering (Popescu and Wynne, 2004) and neighborhood canopy height variance and return density (Rowell et al., 2006). This approach anticipated crown width (CW) as a function of canopy height and stand structure. For a given point in the CHM, the approach searched for higher points within a radius of one half the expected crown width (CW). If no such points were found, the given point in the CHM was assumed to be a tree top. This process was conducted for every point in the CHM to produce a stem map (Suratno et al., 2009). For trees species at LEF, CW was expected to be 33% of the tree height for trees in stands with canopy cover less than 35%, 16% of tree height for trees in stands with moderately closed canopy cover ranging between 35% and 65%, and 11% of tree height for trees in stands with closed canopy cover greater than 65%. After a tree location and expected CW were estimated, crown base height (CBH) was estimated using a square search window of $2 \times$ CW m centered at the tree location. CBH was then estimated as the mean height of all CHM points inside the search window divided by the associated standard deviation of the heights. Individual tree diameter at breast height (DBH) were estimated using the following log-linear model ($n = 1555$, $R^2 = 0.76$, Error = 7.6%) (Rowell et al., 2009).

$$\ln \mathrm{DBH} = 1.732 + (0.041 \times \mathrm{HT}) + (0.798 \times \mathrm{RH}) - (0.007 \times \mathrm{SD}) \quad (1)$$

where, HT is the height of the tree (m), RH is the relative height (m) calculated as the tree height divided by the mean height of dominant and co-dominant trees in a 20×20 m neighborhood, and SD is stem density of dominant and co-dominant stems in the neighborhood.

For the applications of this study, we selected a forest stand in LEF (see Fig. 1). The stand is 4.6 ha in size with elevations ranging from 1270 to 1310 m, on a north-facing aspect, and an average slope of 13.5% (0.0–36.3% slope range). Douglas-fir is the dominant species with a small amount of ponderosa pine. The stand has an established under- and middle-story creating continuous canopy fuels from the ground to the top of the canopy, resulting from logging in the mid-1940s and thinning in the mid-1970s. The LiDAR-derived stem map identified 11,213 stems, most of which are small, suppressed trees (Fig. 2).

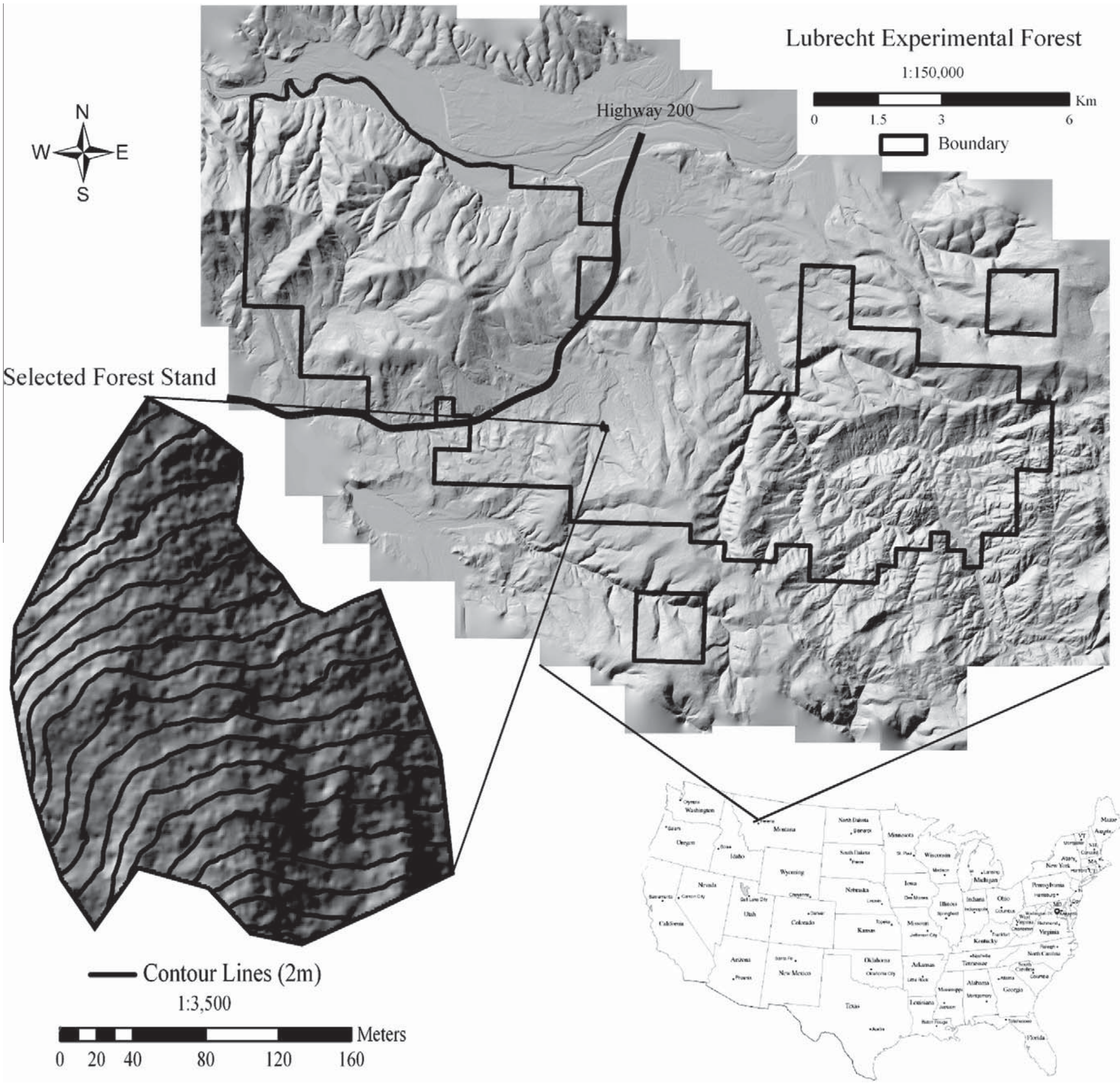

Fig. 1. University of Montana's Lubrecht Experimental Forest boundary and the selected forest stand for the study area.

Table 1
LiDAR data acquisition parameters used for Lubretch Experimental Forest.[a]

Date of acquisition	June 2005
Elevation	1100–1900 m
LiDAR system	Leica geosystems ALS50
Average flight height above surface	1900 m
Average flight speed	70.76 m s^{-1}
Number of strips	54
Scan frequency	25.5
Laser pulse frequency	36200 Hz
Scan angle	±35°
Sidelap	50%
Average swath width	1150 m
Average return density	0.44 m^2
Average footprint	1 m^2

[a] Taken from Suratno et al. (2009).

2.2. Wildland-urban interface Fire Dynamics Simulator (WFDS)

WFDS is an extended version of the fire dynamics simulator developed by the National Institute of Standards and Technology, and designed to include fire spread in vegetative fuels (Mell et al., 2009). WFDS is a fully three-dimensional model that, in recent year, has received considerable research attention because it can provide more detailed predictions of fire behavior and its effect over a wider range of conditions than existing widely-used models (Linn et al., 2002; Mell et al., 2005). WFDS is a physics-based computational fire model able to predict fine-scale time-dependent fire behavior, fire–fuel, and fire–atmosphere interactions in three dimensions (Mell et al., 2005). WFDS attempts to solve in some approximation equations governing fluid dynamics, combustion, and heat transfer, where all modes of the latter one (conduction, convection, and radiation) present in both fire–fuel

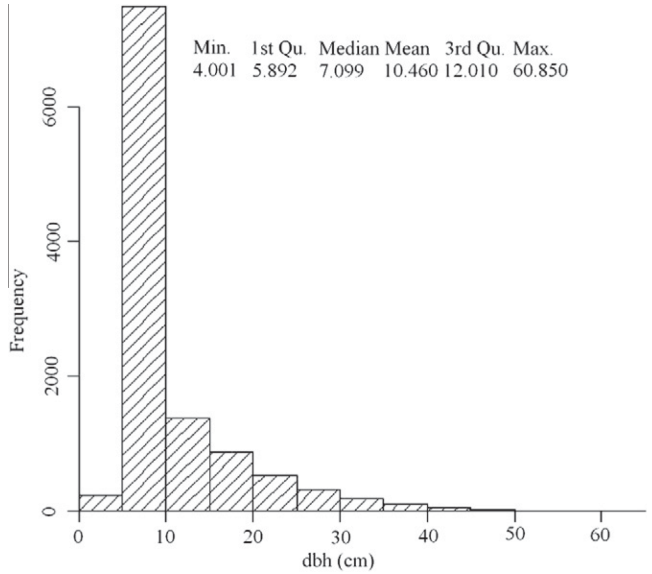

Fig. 2. Histogram and summary statistics of DBH distribution of LiDAR-derived trees in the study area.

and fire–atmosphere interactions are modeled (Mell et al., 2005). WFDS uses voxels to represent the spatial distribution of fuels. Voxel dimensions might vary from centimeters to meter based on the scale of the fire simulation and level of detail. Fluid dynamics, combustion, and heat transfer equations are solved for each voxel to simulate fire behavior over the entire simulation domain.

2.2.1. Tree-level fuel representation

We used LiDAR-derived stem map and tree attribute inputs to represent the spatial distribution of canopy fuels in WFDS fire simulations. Each tree is defined by its base *x*-, *y*-, and *z*-coordinates as well as DBH (cm), HT (m), CBH (m), crown length (m), and CW (m). Tree crowns are represented as frusta of right circular cones where the bottom (larger) diameter equals the crown width at CBH and the top (smaller) diameter equals a single voxel size. WFDS can then determine the three-dimensional location and volume of each tree crown, identify all voxels inside tree crowns, and assign them canopy fuels characteristics such as bulk density and moisture content. Although fuel density varies within a tree crown, we assumed a homogeneous fuel density of 2.2 kg m^{-3}. This bulk density refers to thermally thin material only (<6 mm in diameter) and was determined by bioassays on Douglas-fir trees in tree burning experiments (Mell et al., 2009). Note that this within-tree crown bulk density is considerably higher than the stand level bulk densities used in operational models such as NEXUS (Scott, 1999), which include substantial void space within the canopy and thus rarely exceed 0.5 kg m^{-3}. Additionally, moisture content is also likely to vary according to the fuels position inside the crown as well as during the course of the year. For simplicity, we assumed a constant foliar moisture content (FMC) throughout the tree crown volume.

Amount and arrangement of surface fuels can have a significant effect on fire behavior. Different sampling methods can be used to estimate the amount and type of surface fuels, but surface fuels are highly variable and detailed spatial distributions are rarely available (Sikkink and Keane, 2008). In operational fire models, surface fuels are classified according to fuels models (Anderson, 1982), assumed to be homogeneously distributed over the study area (Scott and Burgan, 2005; Scott, 2006), and the surface fire is then modeled with the Rothermel model (Rothermel, 1972). In this study, we also assumed a homogeneous surface fire bed.

2.2.2. Weather conditions and input data

Weather conditions can have a significant effect on fire behavior (Rothermel, 1972; Scott and Reinhardt, 2001). For the purpose of evaluating the effects of fuel removal on fire behavior, either a range of values for weather parameters such as wind speed and FMC or values representing some condition of interest are usually considered (Scott and Reinhardt, 2001; Scott, 2006). In this study, we considered two cases representing the average and severe weather conditions of a typical fire season in western Montana (June–September), defined by the 50th and 90th percentiles of each weather parameter, respectively. More extreme weather conditions were not considered in this study because most fuel treatments are not likely effective in changing fire behavior under such conditions (Finney and Cohen, 2003). In WFDS, weather conditions are defined by wind speed (m/s), ambient temperature (°C), ambient relative humidity (%), and FMC (%). We used historical observation data from the Seeley Lake (N 47°10′58″, W −113°26′50″) weather station, located approximately 30 km north of LEF, obtained from the National Fire and Aviation Management web application (http://famtest.nwcg.gov/fam-web/). Weather records consist of daily observations recorded at 13:00 h from July 1st 1954–January 4th 2010. From these observations, we selected independent percentiles of wind speed, temperature, and relative humidity values associated with both weather conditions. Due to the lack of historical FMC data in our study area, we used a default FMC of 100% and 75% for the average and severe weather conditions, respectively.

In the WFDS model, the complex dynamics of a fire burning in crown fuels can produce significant fluctuations in the rate of spread and energy released in the surface fire, particularly at fine scales. As this highly dynamic (although realistic) behavior made it difficult to produce consistent surface fire conditions at the individual tree scales of our simulations, we chose to use a less dynamic, but more predictable, approach for characterizing the surface fire behavior. This can be accomplished in WFDS with a user-assigned surface fire, in which, the rate of spread (ROS) in m/s, heat release rate per unit area (HRRPUA) in kW/m^2, and residence time in seconds are all set as model inputs. We arbitrarily selected ROS values of 0.05 and 0.10 m/s, and HRRPUA values of 650 and 700 kW/m^2 for the average and severe weather conditions, respectively. Based on numerous initial test run, we believe these two surface fire characteristics values provide WFDS surface fire behaviors that effectively capture the differences between both weather conditions. Residence time is the time required for the flame to pass a stationary point at the top of the surface fuel (Anderson, 1969). The same residence time was used for both weather scenarios because it is a function only of the characteristic surface-area-to-volume ratio of the fine fuel particles that carry fire spread (Anderson, 1969). Residence time has been reported to range from 7 to 20 s (Rothermel, 1983) based on fuel model (Anderson, 1982), but more recent studies developed to predict ignition of crown fuels (Cruz et al., 2006) have used values between 20 and 80 s. We arbitrarily used a residence time of 20 s set to be within the range of values used in previous studies. Table 2 shows the weather, fixed ROS surface fire, and crown fuel input parameters for the two weather conditions used in WFDS fire simulations. Table 2 shows the weather, fixed ROS surface fire, and crown fuel parameter inputs for the two weather conditions used in WFDS fire simulations. The intent of the user-assigned surface fire with homogeneous burning conditions was to provide consistent surface fire burning conditions for our fine scale crown fire initiation and tree-to-tree propagation simulations. This consistency facilitated our statistical modeling approach for prediction of crown fire initiation and propagation because the surface fire conditions could be described as a single set of conditions, rather than a

Table 2
Weather, fixed rate of spread (ROS) surface fire, and crown fuel inputs used in WFDS fire simulations.

	Average conditions (50th percentile)	Severe conditions (90th percentile)
Weather		
20-ft Wind speed	2.22 (m/s)	3.56 (m/s)
Max. ambient temperature	26.1 °C	32.1 °C
Ambient relative humidity	26%	14%
Fixed ROS surface fire		
ROS	0.05 (m/s)	0.1 (m/s)
HRRPUA	650 (kW/m^2)	700 (kW/m^2)
Residence time	20 (s)	20 (s)
Crown fuels[a]		
Foliar moisture content	100%	75%
Material density	520 Kg m^{-3}	520 Kg m^{-3}
Bulk density	2.2 Kg m^{-3}	2.2 Kg m^{-3}
Surface Area: Volume	4000	4000
Drag coefficient	0.375	0.375
Char fraction	0.25	0.25
Initial temperature	26.1 °C	32.1 °C
Max. Burning Rate	0.4	0.4
Max. Dehydration Rate	0.4	0.4

[a] For more detailed discussion of crown fuel parameter inputs, see Mell et al. (2009).

complex and variable, time and space dependent evolution of surface fire conditions.

2.3. Tree-level Fuel Connectivity

We designed WFDS simulations to model crown fire ignition and propagation independently because the transition of fire from surface to crown fuels and the propagation of fire through adjacent tree crowns are separate processes influenced by different tree and fuel characteristics (i.e., CBH and tree spacing, respectively).

2.3.1. Vertical fuel connectivity – crown fire initiation

WFDS simulations were designed to determine a critical CBH that allows crown fire initiation given the burning characteristics of each weather condition. A simulation domain was set up within a small area of 0.24 ha, 60 m long × 40 m wide × 30 m high (Fig. 3). For fire computations this area was divided into 120 × 80 × 60 voxels of 0.5 m resolution. Surface fuels that burn with the characteristics defined by HRRPUA, ROS, and residence time were simulated within the spatial domain. A fire ignition point was placed in the middle of the left edge of the simulation domain. Nine trees were placed systematically in a grid starting at 20 m from the left edge of the simulation domain. We arbitrarily selected 15-meter spacing between tree stems to ensure the surface fire was the only heat source contributing to crown fuel ignition. Fig. 3 shows an example of a WFDS simulation for crown fire initiation. Trees in a given simulation were set to have varying sizes (i.e., DBH, HT) but a similar CBH. For a given WFDS simulation, a target CBH was set, and nine trees with CBH within 0.25 m from the target CBH were randomly selected from the LiDAR dataset and placed in the simulation domain. Fourteen different CBH values were considered in this study, ranging from 0 to 6.5 m at intervals of 0.5 m. For each target CBH value, we developed 10 repetitions resulting in a total of 140 crown fire initiation simulations under each weather condition.

2.3.2. Horizontal fuel connectivity – crown fire propagation

WFDS simulations were designed to predict crown fire propagation from a burning tree crown to an adjacent tree crown in front of the flaming front. A simulation domain was set to 30 m long × 20 m wide × 30 m high, which resulted in 60 × 40 × 60 voxels with a 0.5 m resolution. As in the crown fire ignition simulations, surface fuels burning with the characteristics defined by HRRPUA, ROS, and residence time were simulated within the spatial domain, and a fire ignition point was located in the middle of the left edge. One source tree representing the flaming front with crown fuels expected to ignite was placed at the center of the domain and a target tree ahead of the flaming front was placed to the right (Fig. 4). Spacing between these two trees (SP) was defined as the horizontal gap distance between their crown projections (edge to edge). We simulated crown fire propagation with several SP values ranging from 0 to 3.5 m at intervals of 0.5 m. To account for wider flaming fronts formed by more than one tree, we also considered one and two additional source trees. When considering two trees forming the flaming front, one additional source tree was placed next to the first source tree on a randomly selected side. Both source trees were placed such that their crown fuels overlap to ensure a relatively continuous heat source from both trees. We arbitrarily selected a crown projection overlap of 10% the distance between both tree centers (see Fig. 4). When considering a flaming front formed by three trees, one additional source tree was placed on each side of the first source tree located at the center of the simulation domain also with a crown overlap of 10% of the tree spacing. Tree sizes were randomly selected from the LiDAR dataset for tree attributes. However, a low CBH (i.e., 0.5 m; based on initial test

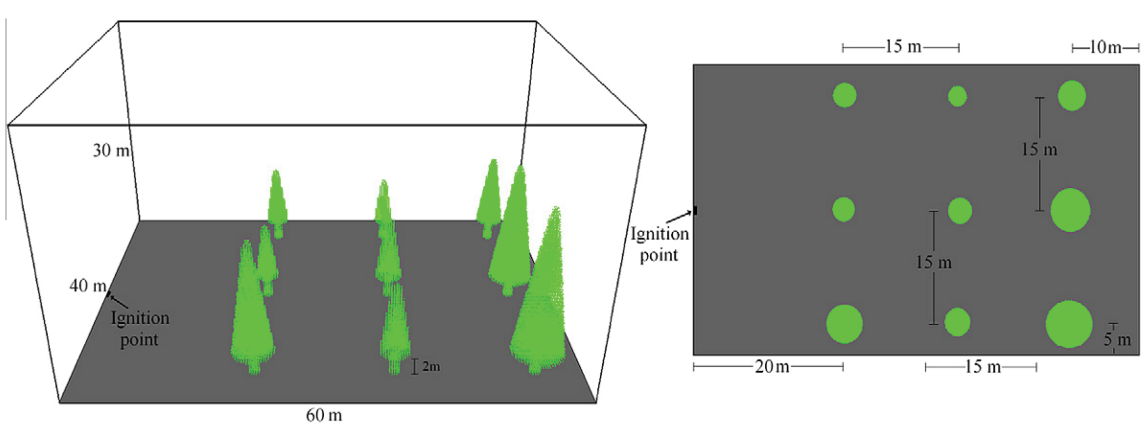

Fig. 3. WFDS simulation design for crown fire initiation showing nine trees with different dimensions but similar CBH (i.e., 2 m).

runs) was assigned to the source trees to ensure tree crown ignition, while the target tree's CBH was kept relatively high (i.e., 3.0 m; based on initial test runs) to avoid crown fire initiation from a surface fire. Ten repetitions of each fire simulation were developed, resulting in a total of 240 crown fire propagation simulations under each weather condition.

2.4. Regression Models

We calculated the percentage of dry mass loss (DML) for each tree at the end of all WFDS fire simulations to quantify the extent of tree-level burning (Murray et al., 1971). Percent DML was then converted into a binary variable to represent whether or not tree burning occurred (1 if percent DML >0.5 and 0 otherwise), and used as a response variable.

Logistic regression analysis was used to model the percent DML because of the nature of our response variable (i.e., the occurrence or not of tree burning). The multiple logistic regression model has the following form:

$$P = \frac{e^{g(x)}}{1 + e^{g(x)}} \tag{2}$$

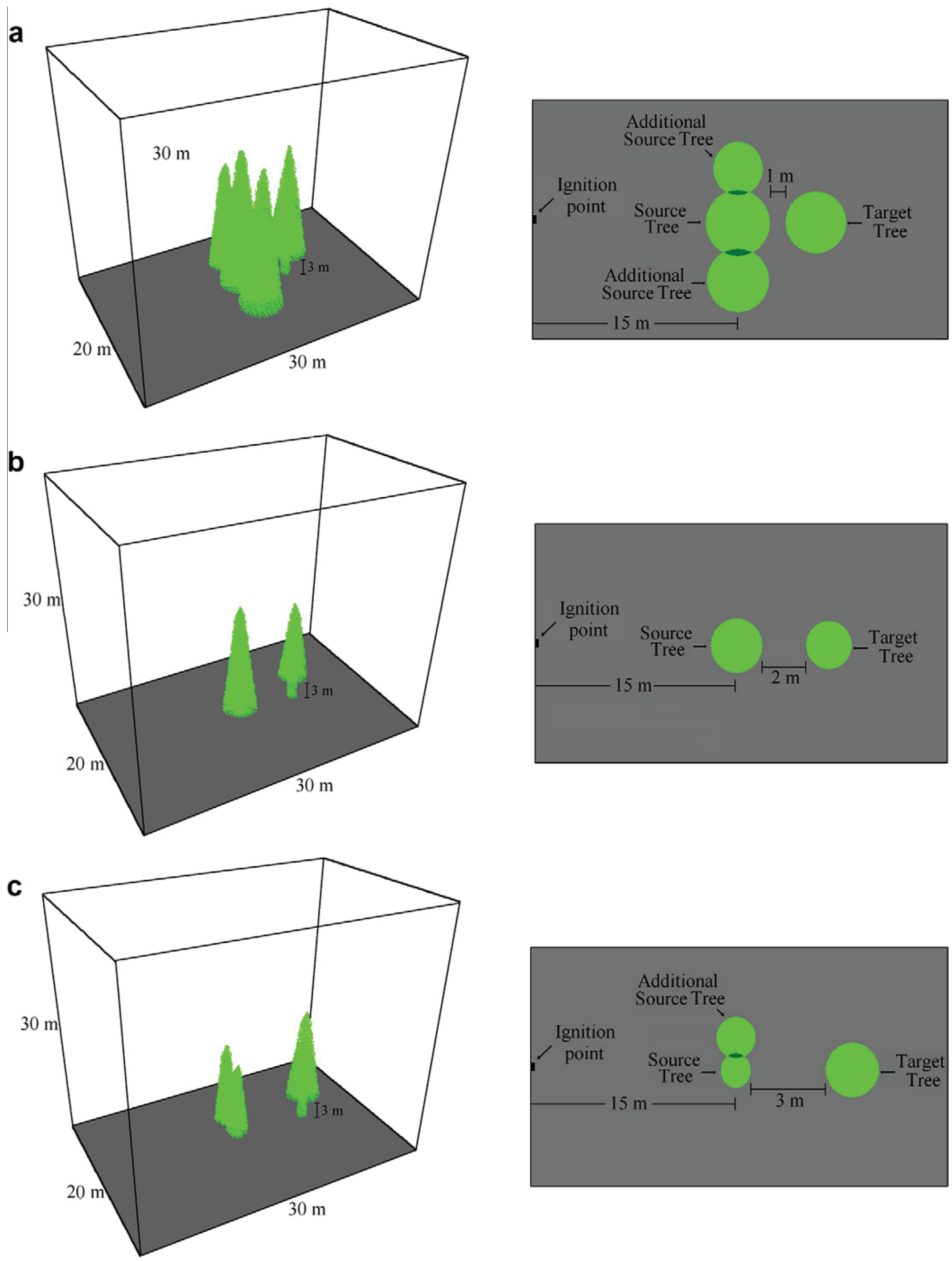

Fig. 4. WFDS simulation design for crown fire propagation. Examples show three, one, and two trees forming the flaming front (a, b, and c) and increasing spacing between the source and target tree.

with the logit function given by the equation,

$$g(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_i x_i \tag{3}$$

where, P is the probability that tree burning will occur, x_i are the independent variables, and β_i are coefficients estimated through the maximum likelihood method, which will select coefficient values that maximize the probability density as a function of the original dataset (Hosmer and Lemeshow, 2000).

In the R software platform (The R development team http://www.R-project.org), we fit a binomial generalized linear model specified by giving a two-column response using the *glm* function. To predict crown fire initiation, we considered three tree dimensions – DBH, HT and CBH – as potential independent variables. Because CW and crown length can be obtained from HT and CBH, they were not considered as potential predictors. For crown fire propagation, in addition to the three tree dimensions, we included SP as well as measures of tree density as surrogates of the flaming front size approaching the target tree (see Fig. 4) and considered them as potential predictors.

For measures of tree density, we used six distance-dependent competition indices to include trees forming the flaming front (i.e., one, two, or three source trees – see Fig. 4). Table 3 shows the distance-dependent competition indices considered in this study. CI_1 (Hegyi, 1974) and CI_2 (Braathe, 1980, as cited in Pukkala and Kolström, 1987) are size-ratio competition indices using DBH and HT as indicators of tree size, respectively. CI_3 through CI_6 are size-ratio indices employing sums of subtended angles (Rouvinen and Kuuluvainen, 1997). CI_3 is the sum of horizontal angles originating from the target tree center and spanning the DBH of the each source tree. CI_4 is the sum of the horizontal angles multiplied by the ratio of the DBH of the source trees and the target tree. CI_5 is the sum of vertical angles from the target tree base to the top of the source trees. CI_6 includes the ratio of the HT between the source trees and the target trees. These indices were developed to measure the competition level experienced by a given tree. However, their formulations effectively capture proximity and size of the flaming front by incorporating size and location of trees forming the flaming front which is related to the amount of heat released from the approaching fire and transferred to the target tree.

We calculated three model performance measures: sensitivity (proportion of ignited trees correctly predicted as such), specificity (proportion of not-ignited trees correctly predicted), and overall accuracy (proportion of ignited and not ignited trees correctly predicted as such). For model selection purposes, we started with all potential predictors, and then removed insignificant variables ($\alpha = 0.05$) to obtain a parsimonious model with high predictive quality in terms of these three performance measures.

Table 3
Distance-dependent competition indices used to obtain measures of partial tree density.

Index	Source	Equation
CI_1	Hegyi (1974)	$\sum_{i=1}^{n} d_i/(d \times dist_i)$
CI_2	Braathe (1980), cited in Pukkala and Kolström (1987)	$\sum_{i=1}^{n} h_i/(h \times dist_i)$
CI_3	Rouvinen and Kuuluvainen (1997)	$\sum_{i=1}^{n} \arctan(d_i/dist_i)$
CI_4	Rouvinen and Kuuluvainen (1997)	$\sum_{i=1}^{n} (d_i/d) \times \arctan(d_i/dist_i)$
CI_5	Rouvinen and Kuuluvainen (1997)	$\sum_{i=1}^{n} \arctan(h_i/dist_i)$
CI_6	Rouvinen and Kuuluvainen (1997)	$\sum_{i=1}^{n} (h_i/h) \times \arctan(h_i/dist_i)$

n Number of source trees forming the flaming front (i.e., one, two, three); d_i DBH of the ith source tree (cm); d DBH of the target tree ahead of the flaming front (cm); $dist_i$ horizontal distance from the ith source tree to the target tree (m); h_i height of the ith source tree (m); h height of the target tree (m).

2.5. Thinning Scenarios

We considered three thinning scenarios to evaluate their effects on reducing crown fire potential. Fig. 5 shows the location of all LiDAR-derived trees, and the locations of leave-trees considered in each thinning scenario in the study area. Thinning scenario I (Fig. 5b) represents the case of applying a thinning from below where primarily small suppressed and intermediate trees are removed to reduce the vertical continuity of fuels and total fuel availability. Under this thinning prescription, all small trees with a DBH less than 12.7 cm (5 inches) were assumed to be cut, piled and burned. Larger trees were considered merchantable and to be extracted for sale. Tree selection (location of cut- and leave-trees) was done manually simulating the marking process carried out by markers on the ground based on spacing between trees and tree sizes. We visually identified dense groups of trees on the stem map (Fig. 5b). Then selected the tree with largest DBH as a leave-tree and remove (mark as cut-trees) all smaller trees within a 2.5 m radius. For scenario II, cut-trees were manually selected until a target tree density of 400 leave-trees per hectare was met (Fig. 5c). For scenario III, additional cut-trees were selected among the leave-trees used in scenario II until a target tree density of 300 leave-trees per hectare was met (Fig. 5d). For the purpose of evaluating tree-level fuel connectivity on different stand conditions and tree density, the target tree densities were arbitrarily selected resulting in an average spacing of 5.0 and 5.8 m between trees for scenarios II and III, respectively.

In practice, thinning treatments can alter surface fire model, fuel moisture, and mid-flame wind speeds, but these factors were assumed constant for this analysis in all three scenarios to focus on the examination of changes in the spatial distribution of leave-trees. Consequently, for each leave-tree in each thinning scenario, we applied the crown fire initiation models to predict vertical fuel connections based on model selected tree dimensions (i.e., HT, CBH). Horizontal fuel connections among adjacent trees were predicted by applying the crown fire propagation models based on model selected predictors (i.e., tree dimensions, tree spacing and partial tree density). A flaming front area of 1.5×10 m centered at the first source tree location was used to search for additional source trees. Trees inside the flaming front area were then considered as additional source trees. Fig. 6 shows an example of a flaming front formed by three trees, a source trees and two additional source trees (dashed crown projections), used to predict crown fire propagation between the source tree and the target tree (solid crown projections). We predicted horizontal fuel connections for each pair of leave-trees in each thinning scenario.

After predicting tree-level fuel connectivity among leave-trees in the study area, we evaluated the three thinning scenarios in terms of the number of predicted vertical and horizontal fuel connections. The number of vertical connections represents the number of trees that would ignited under a given weather condition. Similarly, for a given weather conditions, the number of horizontal fuel connections represents the amount of trees that would burn after fire reaches crown fuels through vertical fuel connections.

3. Results and discussion

3.1. Regression models: Determination and Testing

3.1.1. Crown fire initiation – vertical fuel connectivity

WFDS simulation results for predicting crown fire initiation indicate that the range of CBH values that allow crown fire initiation varies with weather conditions. Table 4 shows the proportion of trees that ignited at different CBH values analyzed in this study under each weather condition. Based on these results, we limited

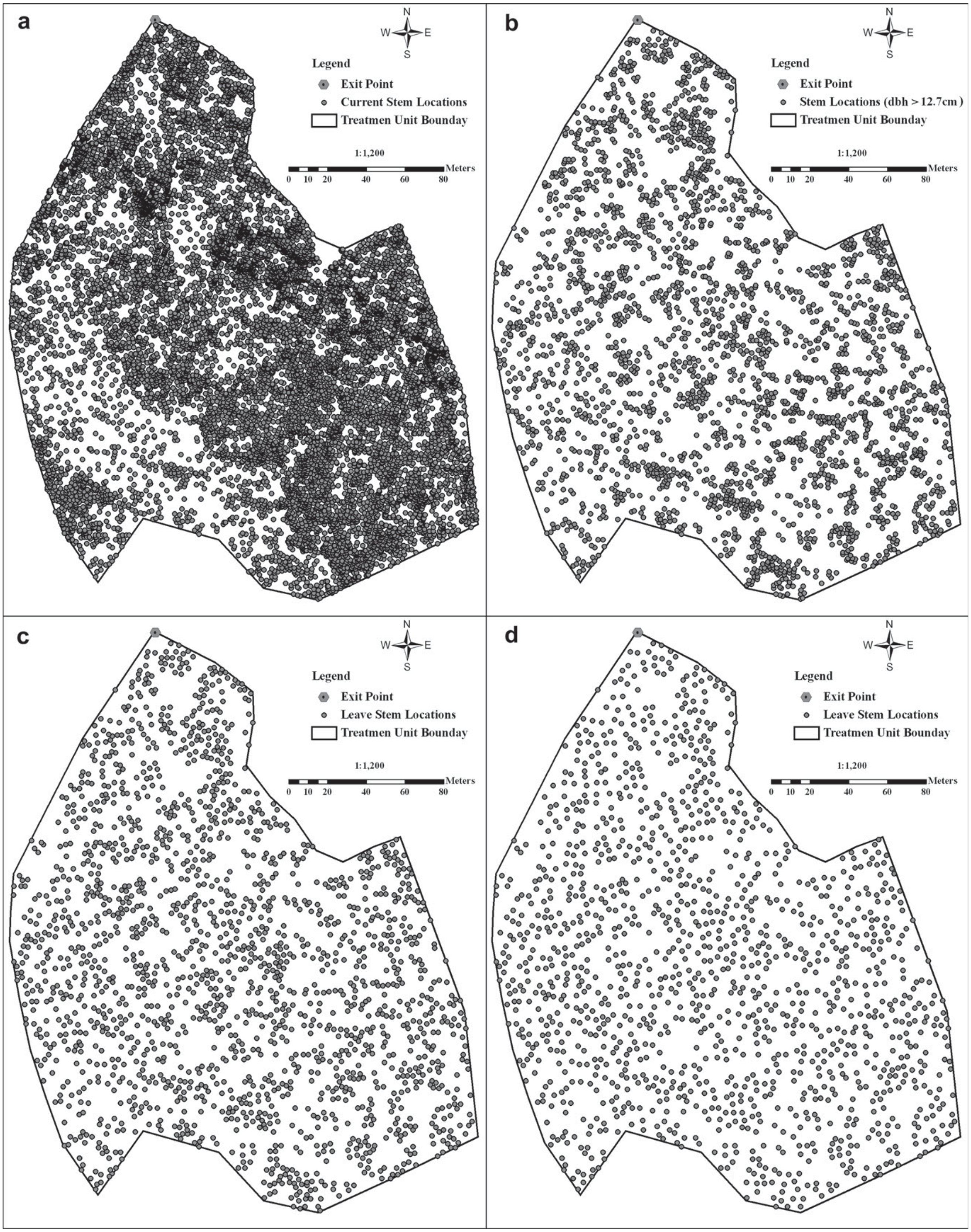

Fig. 5. LiDAR-derived stem map of trees in the study area (a), and location of leave-tree under thinning scenarios I through III, (b) through (d), respectively.

CBH values considered in the development of regression models to emphasize modeling efforts on CBH values effectively covering the full range of responses (0–100% crown fire initiation) and avoid over-estimation of models' predictive quality. For example, under the average weather conditions, crown fire initiation was predicted for 100% of trees with CBH of 1.5 m, hence for all trees with smaller

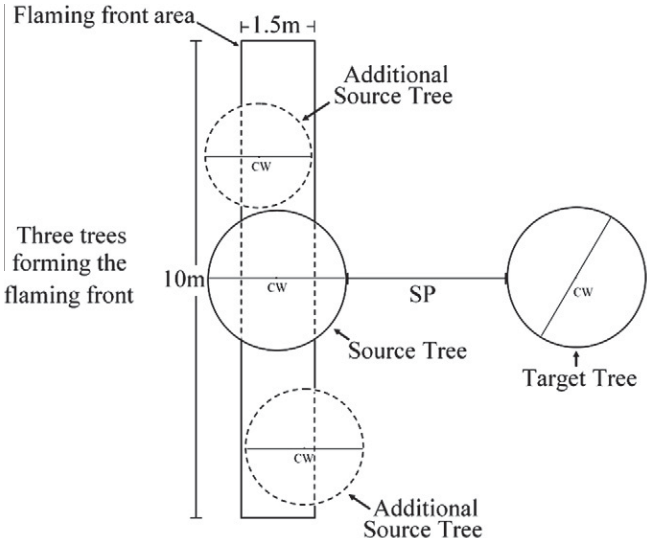

Fig. 6. Schematic of the flaming front area used to estimate crown fire propagation between a source tree and a target tree.

Table 4
Percentage of trees expected to ignite for each target crown base height (CBH) value considered in the crown fire initiation simulations under both weather conditions.

CBH (m)	Average conditions (%)	Severe conditions (%)
0.0	100	100
0.5	100	100
1.0	100	100
1.5	100	100
2.0	93	100
2.5	89	100
3.0	33	100
3.5	15	100
4.0	11	89
4.5	0	78
5.0	0	44
5.5	0	19
6.0	0	19
6.5	0	0

Table 5
Correlation matrix showing the relationship between tree attributes and their relationship with percent dry mass loss (DML).

	DBH (cm)	HT (m)	CBH (m)	DML (%)
DBH (cm)	–	0.828	0.187	0.054
HT (m)		–	0.195	0.085
CBH (m)			–	−0.727

CBH values. Contrarily, crown fire initiation did not occurred at trees with CBH values of 4.5 m, and thus did not occur for trees with larger CBH values. Simulation results from trees with CBH smaller than 1.5 m and larger than 4.5 m do not contribute to explain the variability in the simulation results, and including these results would only inflate the predictive quality of the models. Consequently, we considered trees with CBH from 1.5 to 4.5 m for the average weather conditions, and trees with CBH from 3.5 to 6.5 m for the severe weather conditions.

Tree height is the tree attribute directly measured using LiDAR data and because it was used to estimate DBH (Eq. (1)), HT and DBH present a strong correlation (Table 5). On the other hand, CBH is not well correlated with either DBH or HT. CBH is the tree attribute most strongly correlated with percent DML ($r = -0.723$). This negative correlation indicates that as CBH increases, the probability of crown tree ignition decreases.

For both weather conditions, the selected logistic regression model included HT and CBH as independent variables. As CBH directly affects the amount of heat transfer from the surface fire to crown fuels, it is a significant predictor of crown fire initiation. Although, HT is not strongly correlated with percent DML, its inclusion in the logistic model indicates it is a significant variable for predicting the binary response of crown fire initiation. This could be explained because HT is directly proportional to CW, which is related to the crown base area being heated from the surface fire. Thus, trees with larger crown base areas absorb radiative and convective heat from the surface fires for longer periods of time than trees with smaller crown base areas. Interaction between CBH and HT was also tested but it was insignificant for both weather scenarios.

The logit function associated with the final crown fire initiation prediction models for the average and severe weather conditions are presented in Eq. (4) and (5), respectively.

$$g(x) = 5.98838 + (0.19224 \times \mathrm{HT}) - (2.86137 \times \mathrm{CBH}) \quad (4)$$

$$g(x) = 10.93897 + (0.24285 \times \mathrm{HT}) - (2.84814 \times \mathrm{CBH}) \quad (5)$$

The difference in the intercept coefficient value between both models reflects the difference in the surface fire burning conditions, where a tree is less likely to ignite under the average weather conditions than the severe conditions. In concordance with our assumption of crown fire ignition (percent DML > 0.5), we also assumed ignition will occur when the predicted probability $P > 0.5$. The resulting performance measures for both crown fire initiation models have similar prediction quality with overall accuracy levels of approximately 87% and 86% for the average and severe conditions, respectively (Table 6). Sensitivity and specificity indicate similar ability to predict ignited and not-ignited trees in both weather conditions.

3.1.2. Horizontal fuel connectivity – crown fire propagation

WFDS simulation results for crown fire propagation show that weather conditions largely affect the ranges of tree spacing that allow fire propagation between adjacent trees. Under the average weather conditions, fire did not propagate when SP between trees was larger than 1.0 m (Table 7). This is mainly because of the

Table 6
Logistic regression models' performance for predicting vertical fuel connectivity (crown fire initiation) under average and severe weather conditions.

Average weather conditions			
	Regression result not-ignited	Regression result ignited	Accuracy = 0.8714
WFDS predicted not-ignited	331	41	Sensitivity = 0.8450
WFDS predicted ignited	40	218	Specificity = 0.8898
Severe weather conditions			
	Regression result Not-ignited	Regression result Ignited	Accuracy = 0.8619
WFDS predicted not-ignited	270	47	Sensitivity = 0.8722
WFDS predicted ignited	40	273	Specificity = 0.8517

Table 7
Percentage of adjacent trees burned through crown fire propagation for each target spacing (SP) under both weather conditions.

SP (m)	Average conditions (%)	Severe conditions (%)
0.0	55	100
0.5	40	100
1.0	20	89
1.5	0	67
2.0	0	56
2.5	0	22
3.0	0	33
3.5	0	0

Table 8
Correlation matrix of the six competition indices and their relationship with percent DML.

	CI_1	CI_2	CI_3	CI_4	CI_5	CI_6	% DML
CI_1	–	0.936	0.828	0.912	0.794	0.896	0.298
CI_2		–	0.815	0.804	0.836	0.932	0.350
CI_3			–	0.819	0.969	0.829	0.486
CI_4				–	0.726	0.902	0.275
CI_5					–	0.825	0.494
CI_6						–	0.343

relatively low wind speed used in these weather conditions (see Table 2). On the other hand, under the severe weather scenario where wind speed is about 60% higher than the average condition, fire propagated in some cases where SP was 3.0 m. These results are in concordance with literature indicating that wind speed is one of the most important drivers of crown fire propagation (Rothermel, 1983). Similar to the simulation results from the crown fire initiation, we limited the range of SP considered in the development of regression models to emphasize modeling efforts on SP values effectively covering the full range of responses (0–100% crown fire propagation) and avoid over-estimating the predictive quality of the models. We considered SP from 0.0 to 1.5 m and from 0.5 to 3.5 m for average and severe weather conditions, respectively.

The six measures of partial tree density present strong correlation among each other because of the similarities in their formulation (Table 8). These competition indices were evaluated individually along with the other potential predictors to avoid colinearity issues. In general, competition indices are not strongly correlated with percent DML. The indices more correlated with the response variable presented r values of about 0.49.

For both weather conditions, the selected logistic regression model included HT, SP as independent variables. Also competition indices CI_1 and CI_3 were retained in the models for the average and severe weather conditions, respectively (Eq. (6) and (7)).

$$g(x) = -5.3475 + (0.2855 \times \mathrm{HT}) - (2.1397 \times \mathrm{SP}) + (2.2222 \times \mathrm{CI}_1) \tag{6}$$

$$g(x) = -6.9064 + (0.3194 \times \mathrm{HT}) - (3.2356 \times \mathrm{SP}) + (69.4118 \times \mathrm{CI}_3) \tag{7}$$

Based on the models' coefficients, the probability of crown fire propagating from a source tree to a target tree increases as the target tree's height increases. As expected, the probability of crown fire propagation decreases with increasing spacing between trees. The larger the flaming front, as measured by CI_1 and CI_3, the larger the probability of crown fire propagation. The resulting performance measures for the crown fire propagation model under the average conditions show an overall predictive quality of 80% (Table 9). Sensitivity and specificity measures show that the model better predicts cases where fire does not propagate through adjacent trees than when fire propagates (85% vs. 71%). For the severe weather conditions, the model has an overall predictive quality of about 93% and similar sensitivity and specificity levels (Table 9). The lower predictive quality of the model for average weather conditions might be explained by the fact that even with zero spacing between trees, fire propagated only to 55% of target trees (see Table 7). If trees with overlapping crowns (negative SP values) where included in the analysis to obtain fire propagation to 100% of target trees, predictive quality is likely to increase.

From the results of WFDS fire simulations for both weather conditions, we observed variability in crown fire propagation among trees with similar dimensions as well as trees with an approaching

Table 9
Logistic regression models' performance for predicting horizontal fuel connectivity (crown fire propagation) under average and severe weather conditions.

Average weather conditions			
	Regression result not-ignited	Regression result ignited	Accuracy = 0.8000
WFDS predicted not-ignited	64	11	Sensitivity = 0.7111
WFDS predicted ignited	13	32	Specificity = 0.8533
Severe weather conditions			
	Regression result not-ignited	Regression result ignited	Accuracy = 0.9381
WFDS predicted not-ignited	93	7	Sensitivity = 0.9369
WFDS predicted ignited	7	104	Specificity = 0.9300

Table 10
Tree-level fuel connectivity results from the logistic regression models under both weather conditions for each thinning scenario.

Thinning scenario	Weather conditions	Number of trees	Crown fire initiation		Crown fire propagation		
			Number of trees ignited	Percentage of trees ignited	Number of connected clusters	Average connection per tree	Average trees per cluster
I	Average	2645	99	3.75	82	7.28	32.26
	Severe		536	20.26	38	10.49	69.60
II	Average	1840	76	4.13	109	4.29	16.88
	Severe		393	21.36	73	5.27	25.20
III	Average	1380	66	4.78	211	2.63	6.54
	Severe		289	20.94	158	3.09	8.73

crown fire of similar size (represented by the number and size of trees forming the flaming front). Similarly, fire simulation results present variability in crown fire initiation among trees of similar sizes (i.e., HT and CBH). This variability is likely to be explained by micro fire–fuel, fire–atmosphere interactions considered and modeled in WFDS simulations. Although we could theoretically extract measures of these interactions from the WFDS simulation results (such as resulting flame height, and wind profile) and include them as predictors in our logistical regression models, it would be impractical to obtain this type of information on the ground.

3.2. Evaluation of Alternative Thinning Scenarios

The tree-level fuel connectivity results from applying the logistic regression models to each of the three thinning scenarios are presented in Table 10. For all thinning scenarios, the number of

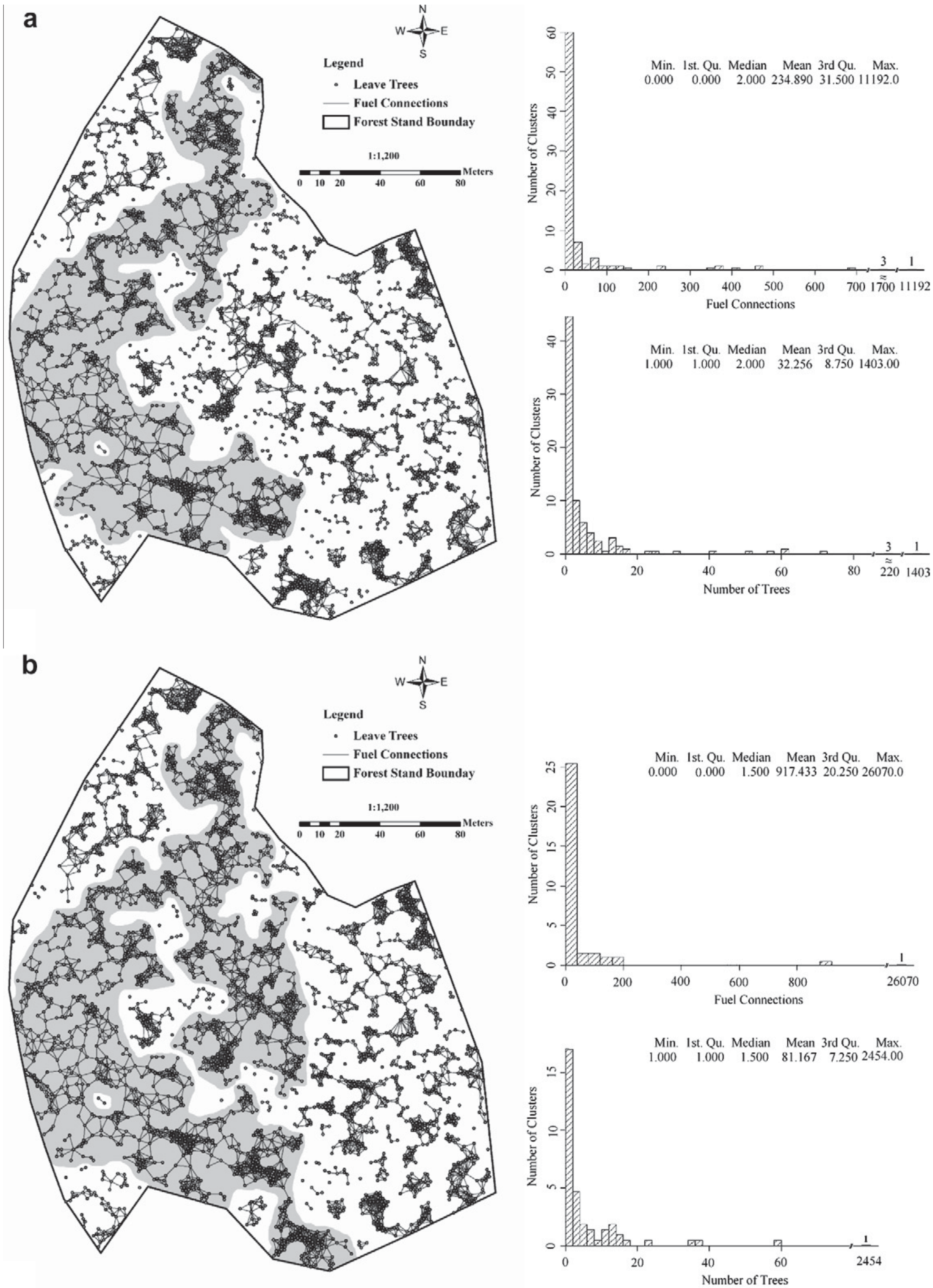

Fig. 7. Location and size of clusters formed by predicted tree-level fuel connections for thinning scenario I under average (a) and severe (b) weather conditions.

trees expected to ignite under the average weather conditions is smaller than under the severe weather conditions because of the less intense surface fire. About five times more trees are expected to ignite under the severe weather conditions than the average conditions. As thinning intensity increases, fewer small trees with low CBH are left in the forest stand, and thus the number of trees expected to ignite decreases under both weather conditions.

Fuel connections between pairs of adjacent trees were also predicted by applying the crown fire propagation prediction models. As crown fire propagates only through nearby adjacent tree crowns (i.e., SP $\leqslant$1 m and 3 m under the average and severe weather conditions, respectively), fuel connections between adjacent trees are predicted, which in turn form clusters or groups of connected trees throughout the forest stand. The spatial distribution and size of

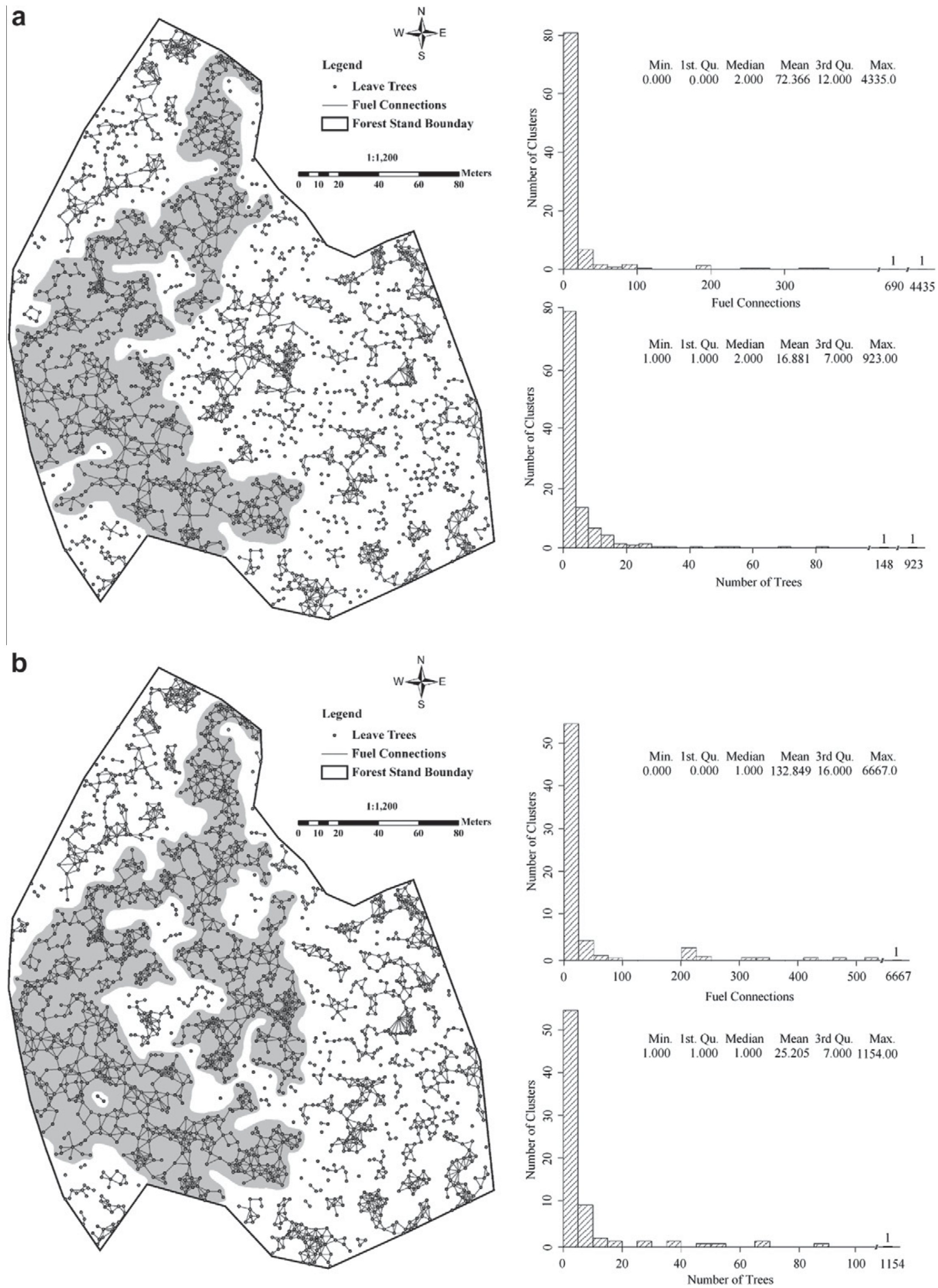

Fig. 8. Location and size of clusters formed by predicted tree-level fuel connections for thinning scenario II under average (a) and severe (b) weather conditions.

these clusters of connected trees predicted under each weather condition for thinning scenarios I through III, are shown in Figs. 7 through 9, respectively.

For thinning scenario I, the crown fire propagation model for each tree in the stand under the average weather conditions predicted 82 clusters of connected trees (Fig. 7). Each cluster is formed by an average of 32.26 tree-level fuel connections and each tree's crown fuels are connected to an average of about seven adjacent trees. When severe weather conditions are considered, crown fire can propagate over a larger distance between adjacent trees. The model thus predicted a larger number of average fuel connections per tree compared with the average conditions (Table 10), which resulted in fewer and larger clusters of connected trees. The number of clusters predicted under the severe weather conditions is

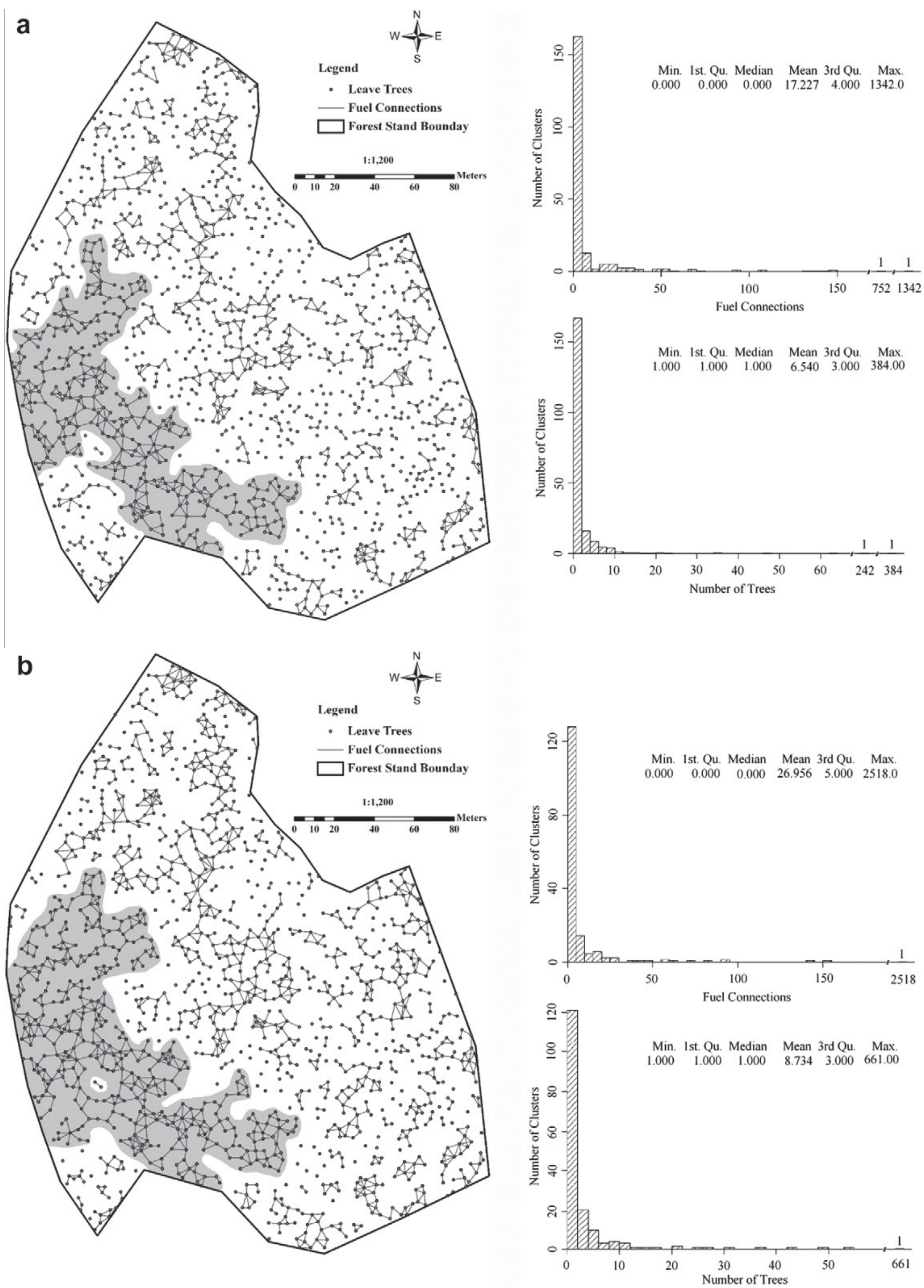

Fig. 9. Location and size of clusters formed by predicted tree-level fuel connections for thinning scenario III under average (a) and severe (b) weather conditions.

about 30% of those predicted under the average conditions, and the average cluster is formed by about 2.5 times as many trees, where trees are connected to about 30% more adjacent trees. Under both weather scenarios, most clusters are formed by less than 20 connected trees, but there are a few large clusters connecting a large number of trees. For example, 5% of the clusters connect about 95% of the entire trees in the stand, and the largest cluster connects about 60% and 90% of trees under the average and severe weather conditions, respectively (shaded areas show the largest cluster in Fig. 7).

For thinning scenario II, the crown fire propagation models predicted a larger number of smaller clusters than those predicted for thinning scenario I because the more intensive thinning intensity left fewer and larger trees in the stand. Under the average weather conditions there are almost 30% more clusters as those predicted under the severe conditions; however, clusters under severe conditions are much larger and trees are connected to more adjacent trees (Table 10). The same pattern of few clusters connecting most trees in the stand observed in thinning scenario I appears in thinning scenario II under both weather conditions (Fig. 8). The largest cluster connects approximately 55% and 70% of the trees under the average and severe weather conditions, respectively (shaded areas in Fig. 8). For thinning scenario III, the number of clusters under both weather conditions is about twice as many as those predicted for thinning scenario II. However, cluster size is about one third of those in scenario II averaging 6.54 and 8.73 trees under the average and severe weather conditions, respectively (Table 10). The largest cluster is also much smaller than those for the previous thinning scenarios connecting about 36% and 59% of the remaining trees under the average and severe weather conditions (shaded areas in Fig. 9).

3.3. Capturing Spatial Variability of Fuels

The results of the tree-level fuel connectivity prediction models from the three thinning scenarios suggest that as thinning intensity increases crown fire potential decreases, as represented by the number of vertical and horizontal fuel connections. Consistent conclusions can be obtained using the widely-used existing fire behavior model such as FlamMap (Finney, 2006) to predict crown fire potential for the study unit. However, as mentioned before, existing models are designed for stand-level predictions and ignore spatial variability of fuels within stands, which can have a significant effect on changing fire behavior. For example, for the same thinning prescription, a given combination of cut-trees might result in minimal crown fire propagation through adjacent tree crowns because of relatively large spacing among leave-trees

Table 11
Tree-level fuel connectivity results under the severe weather conditions for six alternative combinations of leave-trees under the same thinning intensity.

Leave-tree selection	Crown fire initiation			Crown fire propagation			
	Number of trees ignited	Percentage of trees ignited	Horizontal fuel connections	Number of connected clusters	Average connections per cluster	Average connection per tree	Average trees per cluster
Manual	289	20.94	4259	158	26.96	3.09	8.73
Random 1	297	21.52	6302	140	45.01	4.56	9.86
Random 2	291	21.09	6326	137	46.18	4.58	10.07
Random 3	292	21.16	6532	145	45.04	4.73	9.52
Random 4	265	19.20	6438	150	42.92	4.67	9.20
Random 5	283	20.51	6214	152	40.88	4.50	9.08

Table 12
Summary statistics for average stand attributes obtained after six alternative combinations of leave-trees.

Leave-tree selection	Tree attribute	Range of values					
		Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Manual	HT	7.79	12.20	15.02	15.49	17.94	33.05
Random 1		7.93	12.32	14.95	15.50	18.13	32.09
Random 2		7.93	12.33	14.96	15.48	18.09	32.09
Random 3		7.79	12.44	15.04	15.62	18.14	33.05
Random 4		7.79	12.44	15.15	15.56	18.10	33.05
Random 5		7.79	12.45	15.06	15.55	18.11	29.59
Manual	DBH	12.70	15.39	19.35	21.53	25.13	60.85
Random 1		12.70	15.57	19.19	21.54	25.38	60.85
Random 2		12.70	15.57	19.24	21.51	25.36	60.85
Random 3		12.70	15.86	19.43	21.79	25.75	60.85
Random 4		12.70	15.68	19.40	21.67	25.48	60.85
Random 5		12.70	15.63	19.37	21.58	25.46	58.07
Manual	CBH	0.00	5.35	6.96	7.05	9.03	15.08
Random 1		0.00	5.50	7.16	7.11	8.93	15.08
Random 2		0.00	5.54	7.16	7.12	8.93	15.08
Random 3		0.00	5.51	7.23	7.18	9.08	15.08
Random 4		0.00	5.61	7.22	7.23	9.12	14.81
Random 5		0.00	5.61	7.27	7.28	9.11	15.08
Manual	CW	2.34	3.66	4.51	4.65	5.38	9.91
Random 1		2.38	3.70	4.48	4.65	5.44	9.63
Random 2		2.38	3.70	4.49	4.65	5.43	9.63
Random 3		2.34	3.73	4.51	4.69	5.44	9.91
Random 4		2.34	3.73	4.54	4.67	5.43	9.91
Random 5		2.34	3.73	4.52	4.67	5.43	8.78

(i.e., SP larger than 3.5 m), while an alternative combination of cut-trees might lead to fire propagating through most leave-trees because of small trees spacing.

To illustrate the importance of capturing the spatial variability of fuels (i.e., tree locations) within stands, we compared alternative combinations of leave-tree locations under the same thinning intensity. We applied the fuel connectivity predictive models under the severe weather conditions to the manually selected leave-tree locations considered in thinning scenario III, as well as five alternative combinations of randomly selected leave-trees. In these latter random combinations, a given leave-tree was selected by (i) indexing all 2645 trees in the stand, (ii) generating a random number from 1 to 2645, and (iii) selecting the tree indexed with the selected random number as a leave-tree. A combination of random leave-trees was completed when 1380 distinct leave-trees were selected.

The results of the predicted fuel connectivity show that the spatial distribution of leave-trees can have a considerable effect on crown fire potential in terms of the number of fuel connections between adjacent pairs of remaining trees (Table 11). Tree-level fuel connectivity among the five combinations of random leave-tree locations is relatively similar. However, all these combinations have about 50% more fuel connections than the combination of manually selected leave-tree location (Table 11). Combinations of random leave-trees also have a larger number of average fuel connections per tree compared with the combination of manually selected leave-trees (approx. 4.5 vs. 3.0, see Table 11). All these alternative combinations of leave-trees have practically the same aggregated stand values (Table 12). Consequently, predictions of crown fire potential using existing fire behavior models will also be very similar. Determining crown fire potential by predicting tree-level fuel connectivity can provide more a detailed assessment of fire hazard than existing stand-level fire behavior models (e.g., FlamMap) which can improve the evaluation of alternative fuel treatments effects on changing fire behavior.

Although the models developed in this study have relatively high predictive quality for estimating tree-level crown fire initiation and propagation, based on the models' prediction agreement with results from WFDS fire simulations, their performance depends largely on the accuracy of the input tree locations and sizes. There are a number of ways to obtain tree locations varying from traditional field measurements and GPS devises to advanced remote sensing technologies such as high-resolution aerial photos (Hirschmugl et al., 2007), multispectral imaging (Popescu and Wynne, 2004), and LiDAR (Maltamo et al., 2004). The algorithms used to develop LiDAR-derived stem maps in our study area have correctly identified only about 53% of field sampled trees in LEF when considering all tree classes (Suratno et al., 2009). However, stem detection accuracy increases significantly on dominant trees. In similar forest conditions to those of our study area, the stem detection algorithm provided an accuracy of about 90% when considering only dominant trees (Rowell et al., 2006). As we considered only dominant trees with DBH larger than 12.7 cm, we expect similar stem map detection accuracy.

Additionally, the relatively high predictive quality of the developed regression models is measured based on tree-level fire behavior as modeled by WFDS and not on the observation of real fires. Therefore, the models ability to predict tree-level fire behavior on real fires is likely to differ. Although it is theoretically possible to measure fire behavior at the tree-level on the ground, the inability to predict the exact location of fire beforehand makes obtaining this type of data practically impossible. As a result, we need to rely on advanced physics-based numerical fire behavior model such as WFDS to simulate tree-level fire initiation and propagation.

4. Conclusions

Advanced physics-based numerical fire behavior models coupled with high precision vegetation mapping technologies have enabled us to consider individual tree-level fuel characteristics in understanding fire behavior and evaluating the effects of alternative thinning in reducing crown fire hazards.

To facilitate practical application of the three-dimension, fine-scale fire behavior model, such as WFDS, we demonstrated methods to develop regression models to predict tree-level vertical and horizontal fuel connectivity using a fire simulation domain with tree arrangements. We also applied the regression models to evaluating various thinning treatments in terms of the number of trees that can ignite and the number of trees through which fire can propagate after reaching canopy fuels under a given weather condition. The developed regression models should be applied to areas with weather parameters similar to the weather conditions considered in this study. Applying these models to drier, hotter and windier areas would likely result in underestimating the number of trees that would ignite and the distance over which fire can propagate through adjacent crowns.

We evaluated the effectiveness of alternative thinning treatments for reducing crown fire potential more precisely than existing stand-level fire behavior models by applying tree-level fuel connectivity predictive regression models. These regression models can also be implemented into algorithms to optimize the selection of individual tree removal at the stand level, so the combination of leave-trees with the most efficient reduction of crown fire potential is selected for a given thinning intensity. The number of tree-level fuel connections, or other measures of fuel connectivity such as the average number of fuel connections per tree or average trees forming a cluster of connected tree fuels, can be used as indices to optimize the allocation of thinning treatments for altering fire behavior and reducing fire spread at the landscape level.

Further research needs to be conducted to expand and test the applicability of our approach. Our work is just a first step, testing the feasibility of building regression models that can be applied to forest stands on the basis of detailed three-dimensional fire model simulations. There are many aspects relating to modeling fire that we did not evaluate here. For example, three-dimensional models such as WFDS are sensitive to the voxel resolution used in the simulations; we did not test whether our outcomes would have been different with smaller cell sizes. Similarly, a more exhaustive set of WFDS fire simulation should be designed to include additional weather factor and vegetation characteristics. Tree-level fire behavior should be simulated for a range of values of FMC, ambient temperature and wind speed to better account for variability existing in the real environment. Regression models including these additional factors as predictors of crown fire initiation and propagation can then be applied to different areas under any weather conditions.

Acknowledgement

We would like to thank Dr. Carl Seielstad, director of the National Center for Landscape Fire Analysis at the University of Montana, for providing the LiDAR data used in this project.

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