Defining fire environment zones in the boreal forests of northeastern China ☆

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HIGHLIGHTS

• A fire environment zone map offers a basis for designing fire management plans.
• We identified three homogeneous fire environment zones in Chinese boreal forests.
• The three fire environment zones were consistent with historical fire regimes.

ARTICLE INFO

ABSTRACT

Fire activity in boreal forests will substantially increase with prolonged growing seasons under a warming climate. This trend poses challenges to managing fires in boreal forest landscapes. A fire environment zone map offers a basis for evaluating these fire-related problems and designing more effective fire management plans to improve the allocation of management resources across a landscape. Toward that goal, we identified three fire environment zones across boreal forest landscapes in northeastern China using analytical methods to identify spatial clustering of the environmental variables of climate, vegetation, topography, and human activity. The three fire environment zones were found to be in strong agreement with the spatial distributions of the historical fire data (occurrence, size, and frequency) for 1966–2005. This paper discusses how the resulting fire environment zone map can be used to guide forest fire management and fire regime prediction.

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1. Introduction

Fire annually impacts approximately 10–15 million ha of boreal forests (Bergeron et al., 2004; Flannigan et al., 2009; Lynch et al., 2004; Stocks et al., 2002; Turetsky et al., 2011), which strongly influences ecosystem structure and function (Bond-Lamberty et al., 2007; Kang et al., 2006; Li et al., 2013; Wang and Kemball, 2005). Fire activity is increasing throughout the boreal forest region (Liu et al., 2012; Stocks et al., 1998; Wotton et al., 2010). For example, fire occurrence is predicted to increase by 140% by the end of this century in Canadian boreal forests (Wotton et al., 2010) and by 30–230% by the end of 2100 in Chinese boreal forests (Liu et al., 2012). These trends pose management challenges in boreal forest landscapes.

Fire occurrences (lightning- and human-caused) are complicated spatial point processes. For example, a single lightning-caused fire may seem to be a random event; however, studies have shown that spatial patterns of lightning-caused fires are not completely random at the landscape level (Wu et al., 2014). Rather, they are clustered (Podur et al., 2003) and have spatial distributions related to environmental variables such as climate/weather, vegetation, topography, and human activity (Diaz-Avalos et al., 2001). Spatial correlation in environmental variables thus creates areas with similar fire occurrence patterns, and fire management plans ideally should target different fire regimes predetermined by certain environmental variables distributed across a forest landscape.

Because current fire management plans (especially in China) are not discretional across forest landscapes, they may fail to capture spatial distributions determined by the environmental variables that influence fire regimes. This oversight is particularly true for fire management

based on arbitrarily defined administrative units, with boundaries often having little to do with environmental variables and fire regimes. Such administrative units thus may overlook the environmental variables most influential in determining fire regimes (Boulanger et al., 2012, 2013). Accordingly, we propose defining zones wherein environmental variables are relatively homogeneous with respect to fire likelihood and thereby improve allocation of fire management resources.

Fire attributes (e.g., occurrence, frequency, severity, and size) have been recently employed to develop fire regime/environment zones. For example, Boulanger et al. (2012) developed fire regime (HFR) zones for Canada designed to define the location and nature of fire activity across the country. Canada's HFR zones were identified by the spatial clustering of fire attributes such as fire-return interval, burn rate, and mean Julian date. Fire attribute data are generally difficult to manipulate and reconstruct (Conedera et al., 2009), however, whereas environmental data are often available to fire managers. Moreover, fire attributes are determined by environmental variables (Wu et al., 2014), which are widely integrated into many fire danger rating systems such as the Canadian Forest Fire Danger Rating System (Mansuy et al., 2014). In practice, a fire environment zone map provides timely information about areas vulnerable to fire (Chuvieco et al., 2010; Chuvieco and Congalton, 1989), allowing local fire managers to design management plans and prioritize treatment locations according to environment characteristics across a landscape (Wu et al., 2013). Areas likely to experience similarities in fire regimes using environmental variables were defined in some regions. For example, the California Department of Forestry and Fire Protection was required by law (PRC 4201-4204 and Govt. Code 51175-89) to map areas of significant fire hazards based on fuels, terrain, weather, and other relevant factors (http://www.fire.ca.gov/).

Our study aimed to identify fire environment zones by spatial clustering of the fire-regime-related environmental variables of climate, vegetation, topography, and human activity. Our specific objectives were to determine the following: (1) whether a reliable fire environment zone map can be derived by identifying the clustering of environmental variables; (2) the relative effects of environmental variables on fire regimes (occurrence, size, and frequency) among fire environment zones; and (3) how a fire environment zone map could be used for fire management. Such knowledge, we believe, would be of significant value given the increasing occurrence of fire in Chinese boreal forests (Liu et al., 2012; Yang et al., 2011).

2. Materials and methods

2.1. Study area

The study area is located on the northern and eastern slope of the Great Xing'an Mountains in Heilongjiang province in northeastern China (Fig. 1). It covers approximately 8.46×10^4 km² (50°10′ to 53°33′N and 121°12′ to 127°00′E). The terrain is hilly and mountainous with an average elevation of 573 m. This region falls within the cold temperature zone affected by the Siberian cold air mass and has a long and severe continental monsoon climate. The mean annual air temperature ranges from −6 °C to 1 °C, and the mean annual precipitation ranges from 240 mm to 442 mm, mostly falling between the months of June and August (Zhou, 1991).

The vegetation in the Great Xing'an Mountains falls within cool temperate coniferous forests, which occur at the southern extension of the Siberian boreal forest. The species includes larch (*Larix gmelini*), pine (*Pinus sylvestris* var. *mongolica*), spruce (*Picea koraiensis*), birch (*Betula platyphylla*), two species of aspen (*Populus davidiana* and *Populus suaveolens*), willow (*Chosenia arbutifolia*), and the shrub *Pinus pumila* (Xu, 1998). Boreal conifers (mainly larch) are widely distributed, late-successional species, whereas broadleaf trees (e.g., birch and aspen) are early-successional species owing to fire disturbance and timber harvesting (Xu, 1998).

Fire is one of the major disturbances in the Great Xing'an Mountains. Historically, fire regimes in this region were characterized by frequent, low intensity surface fires mixed with sparse, stand-replacing fires on relatively small areas, with a fire return interval ranging from 30 to 120 years (Xu et al., 1997; Zhou, 1991). However, the fire regimes have been changed significantly since 1950s by anthropogenic activities such as fire suppression and timber harvesting. For example, aggressive fire suppression has been conducted for more than a half century in this region (Chang et al., 2008; Xu, 1998), which has lengthened the fire cycle with the fire return interval of longer than 500 years. Currently, fires that occur in the Great Xing'an Mountains are often smaller but more severe and intense than fires that occurred before 1950s (Chang et al., 2007; Tian et al., 2005; Xu et al., 1997).

2.2. Data preparing and processing

Nine fire-regime-related environmental variables were used to conduct the analyses (Fig. 2), including climate, vegetation, topography, and human activity variables (Table 1). Previous studies indicate that these environmental variables plan a dominate role in controlling fire regimes (Achard et al., 2008; Gralewicz et al., 2012; Krawchuk et al., 2006; Oliveira et al., 2012; Wotton et al., 2010); therefore, the fire environment zones were identified through spatial clustering of the 9 environmental variables.

2.2.1. Fire data

Fire data from 1966 to 2005 were provided by the Great Xing'an Mountains Forest Fire Prevention Agency. We selected 1156 fires that had correct spatial location information (recorded as x, y coordinates) and specific fire size, cause, and date of occurrence and extinction records. We classified 26 fires induced by reignition of fire-breaks in the fire data as human-caused fires because these are spatially distributed near roads and human settlements. Approximately 52% of all fires were human-caused fires (e.g., arson, cooking fire, smoking, railway, power line), and 48% were lightning-caused fires.

2.2.2. Climate data

Climate is considered a key cause of fire. Annual temperature and precipitation were commonly suggested as climatic variables for fire regimes through their control of fuel moisture content and indicators of climate condition (Flannigan et al., 2000; McCoy and Burn, 2005; Scholze et al., 2006; Xystrakis and Koutsias, 2013). We obtained climatic data between 1965 and 2005 from 88 weather stations in northeastern China to generate the continuous surfaces of mean annual temperature and precipitation variables. We used the Kriging interpolation algorithms in ArcGIS to derive the temperature and precipitation surfaces (1 km cell size).

2.2.3. Vegetation data

Vegetation (dead and live fuel) provides the raw material for fire. Vegetation types were derived from the 1:1,000,000 Vegetation Map of the People's Republic of China (VMPRC), which was originally created in 1982 and digitized in 2007. We classified the vegetation types into four categories: coniferous forest, mixed forest, broadleaf forest, and meadow-and-other (including shrub land and wetland), with the proportions of 53.4%, 4.1%, 12.6%, and 29.4%, respectively. The VMPRC was resampled to raster data with the spatial resolution of 90 m. Historically, fires have been low and moderate intensity surface fires, and local forest managers would plant larch in the burned areas. The vegetation composition is relatively simple, and larch remains the dominate species in the Chinese boreal forests. We therefore assumed the vegetation types to be relatively unchanged over the study period in the Great Xing'an Mountains.
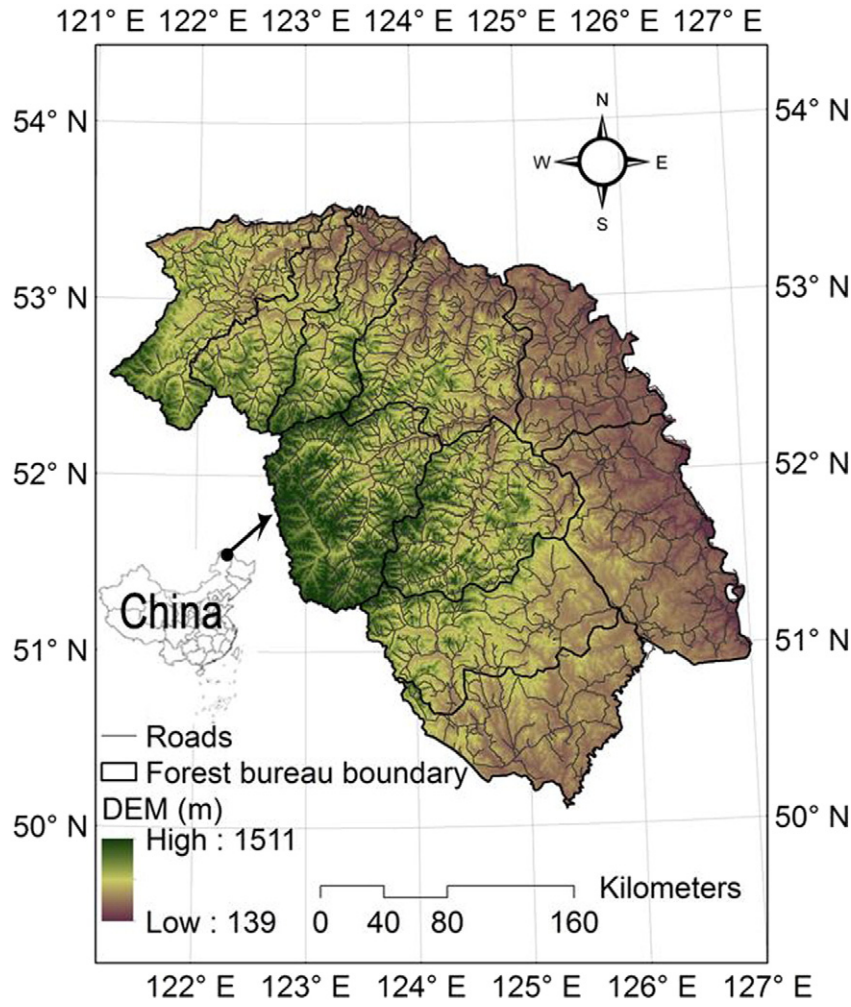
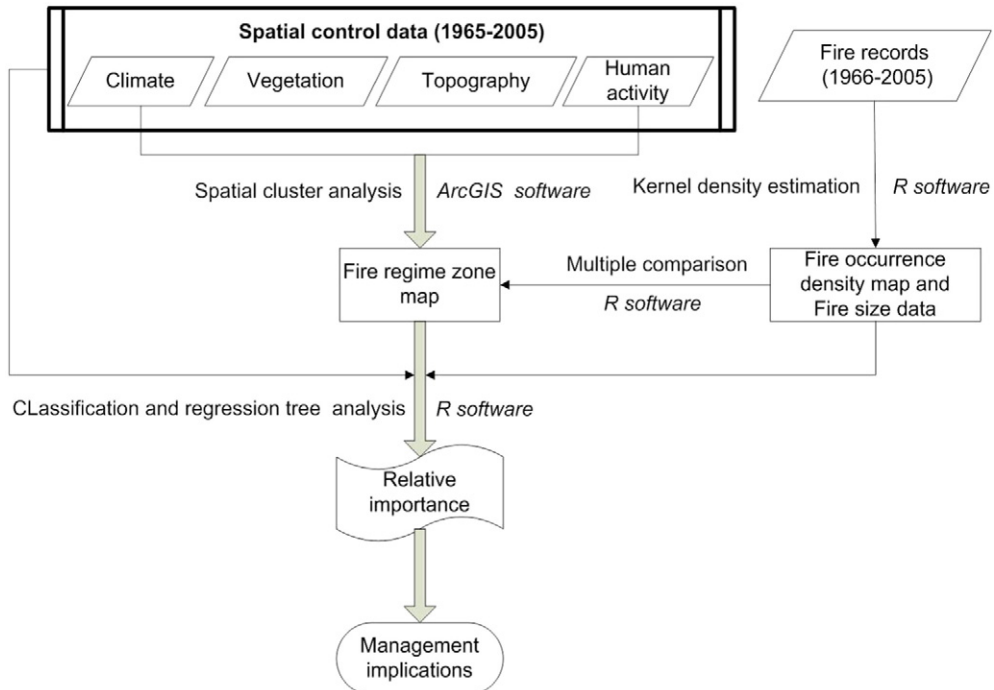**Fig. 1.** The geographic location of the study area.

Fig. 2. The overall study steps of this study.

Table 1
Environmental variables used to identify fire environment zones.

Environmental variables	Abbreviation	Data source	Units
Elevation	Elev	National Geomatics Center of China	Meters
Aspect	Asp	Derived from elevation	Indexes[a]
Slope	Slope	Derived from elevation	Degrees
Distance to nearest road	DisRd	National Geomatics Center of China	Meters
Distance to nearest settlement	DisSet	National Geomatics Center of China	Meters
Road density	RdDen	Derived from DisRd	km/km^2
Vegetation type	Veg	Vegetation Map of The People's Republic of China	Classes 1–4
Mean annual precipitation	Prep	China Meteorological Data Sharing Service system	mm
Mean annual temperature	Temp	China Meteorological Data Sharing Service system	°C

[a] An index value ranging from −1 to +1 (see Eq. (1)).

2.2.4. Topographic data

Topography directly influences vegetation composition and fuel structure and often determines where and why fires occur and spread (Dillon et al., 2011). We employed elevation, slope, and aspect as topography variables. We downloaded the contour lines from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn/) and used them to derive the digital elevation model (DEM; 90 m cell size). We employed the spatial analyst tool in ArcGIS to extract the variables of slope and aspect from the DEM. The degree of slope ranged from 0 to 90, and values for aspect ranged from 0 to 360. We calculated an aspect index using the map algebra expression of raster calculator in ArcGIS as:

$$\text{Aspect index} = -\cos(\theta \times 2 \times \text{PI}\ ()/360), \qquad (1)$$

where θ is aspect derived from the ArcGIS "aspect" function. The aspect index ranges from −1 to 1, with higher values indicating higher potential solar radiation.

2.2.5. Human activity data

Human activities, such as those reflected by roads and settlements, influence fire occurrence probability by controlling accessibility of human-derived ignition sources to forests (Liu et al., 2012; Syphard

et al., 2007; Zumbrunnen et al., 2012). Proximity to roads and settlements were used as human activity variables, extracted from the 1:100,000 roadway coverage provided by the National Geomatics Centre of China (http://ngcc.sbsm.gov.cn/). We calculated Euclidean distance from each cell to nearest road or settlement under the spatial analysis environment of ArcGIS. Given that most roads were built before 1990, we assumed that the road network remained constant over the study period.

2.3. Identifying fire environment zones

Fire environment zones were identified using spatial clustering analysis of the 9 environmental variables using the "Grouping analysis" tool in ArcGIS 10.1. This analysis connects sampling units into distinct, spatially defined regions that maximize both within-group (cluster in our study) similarities and between-group differences based on the considered variables, which in our study were the 9 environmental variables. More information on the "Grouping analysis" tool can be obtained from ArcGIS Resource Center (http://resources.arcgis.com/en/help/).

We resampled the climate, vegetation, topography, and human activity data to raster-based data with the spatial resolution of 500 m and converted the raster-based data into point-based data. The point
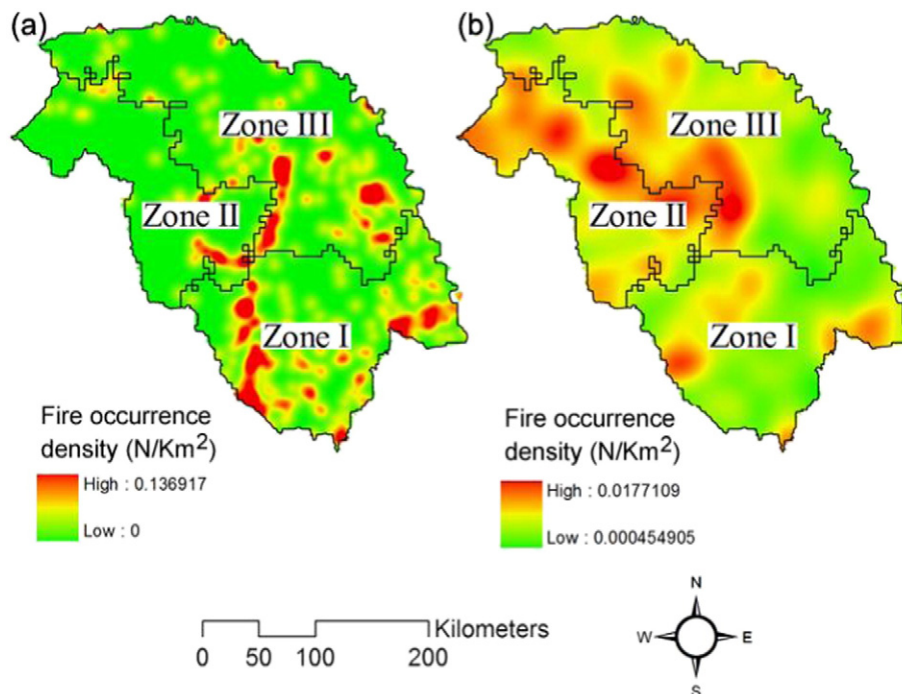
Fig. 3. Kernel smoothed intensity estimated from the fire occurrence data reported from 1966 to 2005. The smoothing scales (bandwidths) in the kernel density estimator for human-and lightning-caused fires were 4183.4 m and 12,550.3 m. (a) Human-caused fire, (b) lightning-caused fire.

data became the sampling unit used for the spatial clustering analysis to identify fire environment zones. In the "Grouping analysis" tool, an R^2 value was computed for each variable (environmental variable in this study) to reflect how much of the variation in the original variable data was retained after the grouping process. A variable with the highest R^2 value indicates that this variable divides the study region into groups most effectively. The R^2 is computed as:

$$(TSS-ESS)/TSS, \tag{2}$$

where TSS is the total sum of squares and ESS is the explained sum of squares. TSS is calculated by squaring and then summing deviations from the global mean value for a variable. ESS is calculated the same way, except deviations are group by group; every value is subtracted from the mean value for its group, then squared and summed.

The k-nearest neighbor (KNN) algorithm was used to define neighbor relations among points, based on the nearest 8 points using the Euclidean distance algorithm to calculate distance from each point to neighboring points (the straight-line distance between points). The KNN algorithm is appropriate for clustering point data, and points in the same cluster are those nearest to each other. That is, a point will only be included in a cluster with the KNN algorithm when at least one other cluster member is a KNN. If we choose 8 for the number of neighbor parameters, for example, every point in a cluster will be within 8 nearest neighbors of at least one other point in the same cluster.

The spatial clustering approach first constructed a connectivity graph to characterize the neighborhood relationships among points (environmental data). From the connectivity graph, a minimum spanning tree was built to summarize the similarity between points. The tree was pruned to minimize the dissimilarity in the resultant clusters, while avoiding singletons (clusters with only one point). The minimum spanning tree was divided by this pruning process until the number of

clusters specified was obtained. Here, the Calinski–Harabasz pseudo F-statistic was employed to determine the number of clusters. Larger F-statistic values indicate solutions that perform better at maximizing both within cluster similarities and between cluster differences than do smaller values. The Calinski–Harabasz pseudo F-statistic is computed as:

$$\frac{\left(\dfrac{R^2}{n_c-1}\right)}{\dfrac{1-R^2}{n-n_c}}, \tag{3}$$

where: $R^2 = \frac{SST-SSE}{SST}$, SST is a reflection of between-group difference, and SSE reflects within-group similarity:

$$SST = \sum_{i=1}^{n_c}\sum_{j=1}^{n_i}\sum_{k=1}^{n_v}\left(V_{ij}^k - \overline{V^k}\right)^2 \quad SSE = \sum_{i=1}^{n_c}\sum_{j=1}^{n_i}\sum_{k=1}^{n_v}\left(V_{ij}^k - \overline{V_1^k}\right)^2$$

where:

n	the number of features,
n_i	the number of features in the group i,
n_c	the number of classes (groups),
n_v	the number of variables used to group features,
V_{ij}^k	the value of the kth variable of the jth feature in the ith group,
$\overline{V^k}$	the mean value of the kth variable, and
$\overline{V_1^k}$	the mean value of the kth variable in the group i.

2.4. Deriving fire occurrence density surfaces

The fire occurrence density surfaces were derived from the kernel density estimation (KDE) method, a nonparametric statistical method
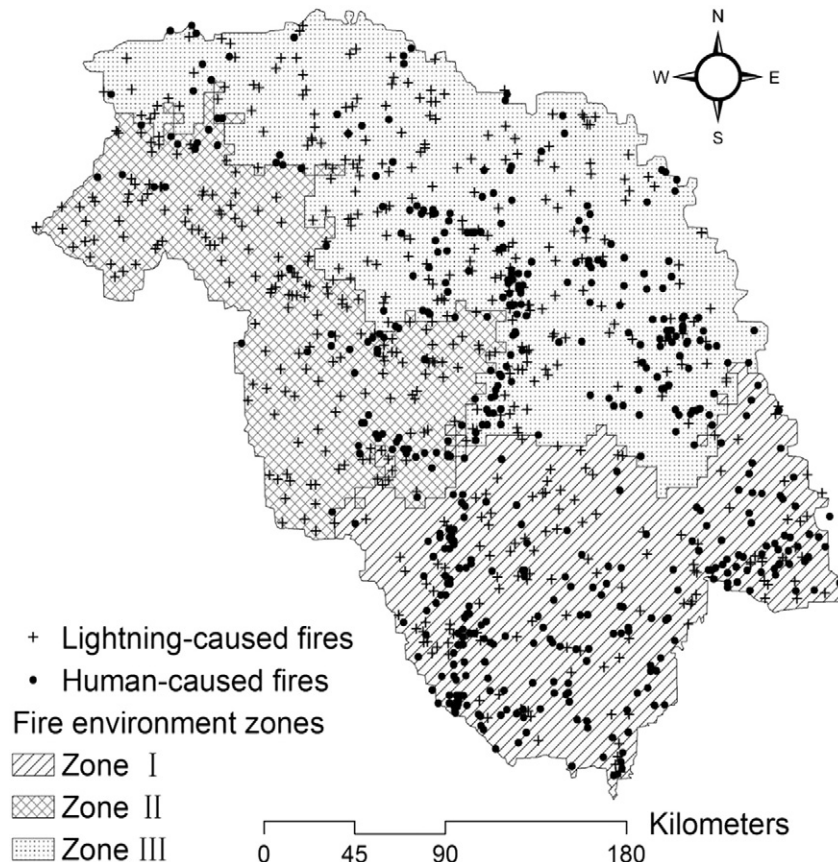

Fig. 4. Three fire environment zones as derived by the spatial cluster of environmental variables.

widely used to convert point-based fire data into raster to illustrate continuous fire occurrence density surfaces (Amatulli et al., 2007; Gonzalez-Olabarria et al., 2012; Oliveira et al., 2012). Using a dataset of ignition points as input, KDE can estimate the ignition probability of any location across the study area based on the location of observed fire events (Gonzalez-Olabarria et al., 2012).

The bandwidth selection strongly impacts the aggregation level of the data in the kernel density estimation. A narrower bandwidth produces a finer mesh density; a larger bandwidth produces a smoother distribution density and results in less variability between areas (Amatulli et al., 2007). Several approaches have been proposed for selecting an optimal bandwidth for kernel density estimation, including the KNN algorithm, cross-validation algorithm, and subjective choices (Kuter et al., 2011). In this study, the bandwidth was determined by

the cross-validation algorithm (Berman and Diggle, 1989; Diggle, 1985), which minimizes the mean-square error according to the criterion defined by Diggle (1985).

We used the "spatstat" package in R to conduct the KDE while deriving the human- and lightning-caused fire occurrence density surfaces. The fire occurrence surfaces were raster-based maps (500 m cell size) (Fig. 3).

2.5. Statistical analysis

The statistical analyses were conducted to explore the following: (1) differences of fire occurrence and size among the three fire environment zones; and (2) relative effects of environmental variables on fire
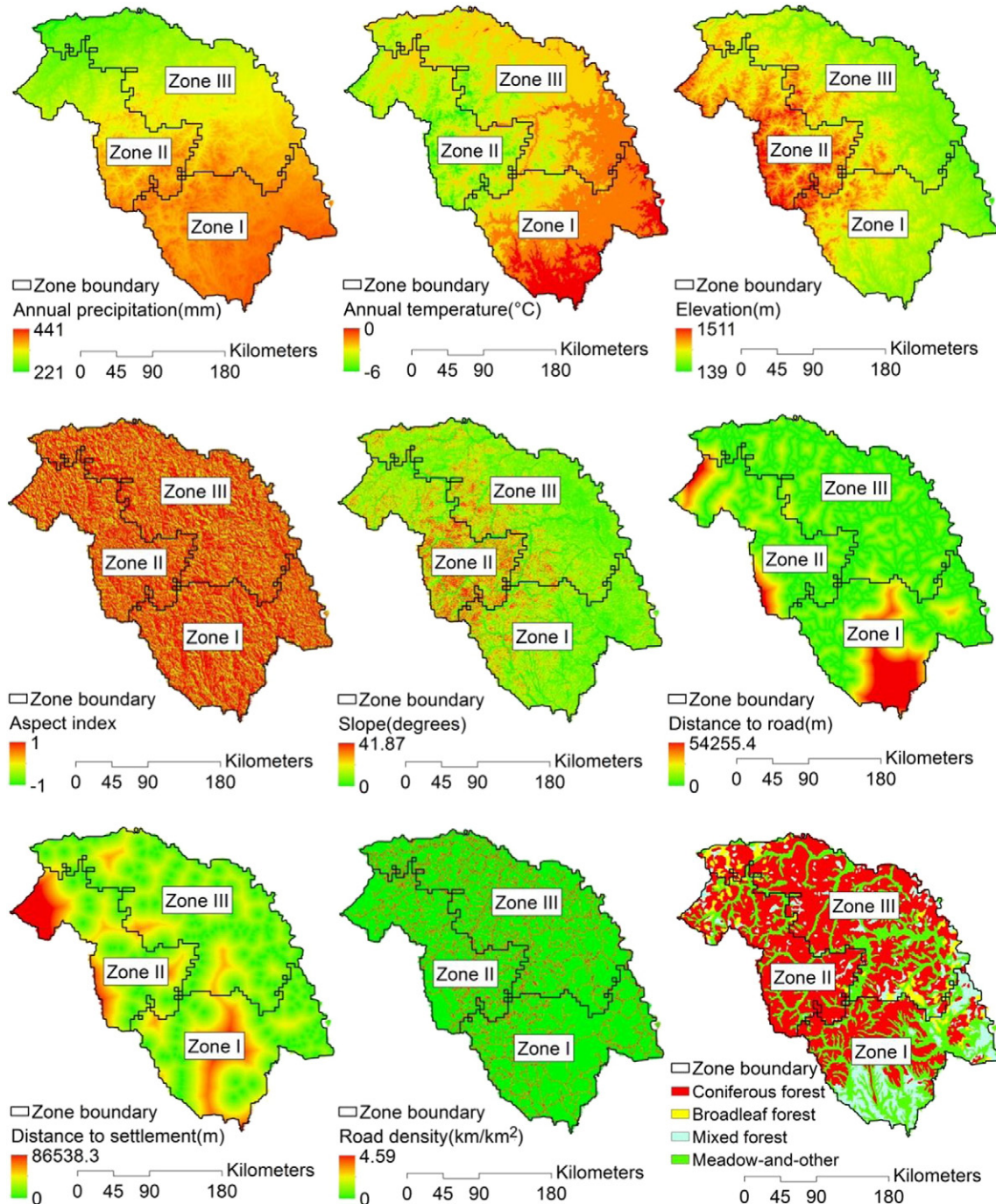

Fig. 5. Spatial distribution characteristic of environmental variables under three fire environment zones. Aspect index value ranging from −1 to +1 (see Eq. (1)).

occurrence and size within each of the three fire environment zones. The R statistical software was used in all analyses (R-Core-Team, 2013).

We converted the raster-based data of fire occurrence density surface and the 9 environmental variables (with a spatial resolution of 500 m) to point-based data. To avoid the spatial autocorrelation issue, we extracted points from the point-based data by constraining the distance between the nearest two points to 5 km. As a result, the point-based samples used in statistical analyses of fire occurrence density numbered 1052, 782, and 1397 for fire environment zones I, II, and III, respectively.

The fire size and frequency data were derived based on historical fire records, which included the specific location (recorded as x, y coordinates), fire size, cause, and dates of occurrence and extinction. We mapped all the fires as points based on their coordinates from the fire records and assigned values of fire size accordingly. The environmental variables of each fire were extracted from the raster-based environmental data with a spatial resolution of 500 m.

The Duncan test with the "laercio" package in R was used to examine differences of fire occurrence density and fire size and frequency patterns among the fire environment zones. The fire occurrence analysis was based on the point-based samples extracted from the fire occurrence density surface. We divided the fire sizes into four classes (<100, 100–1000, 1000–10,000, and >10,000 ha) and analyzed how the frequency distribution of the size classes varied among fire environment zones. We then used the fire environment zones as the units to analyze the difference of fire size and frequency. Because the Duncan multiple comparison test effectively identifies significant differences among multiple treatments, it was used in our fire regime analyses to determine whether three or more means differed significantly (Lee et al., 2008).

To avoid autocorrelation, which is common in environmental data, we used the classification and regression tree (CART) analysis method to assess the relative importance of environmental variables in controlling fire occurrence and size (Lee et al., 2009; Lentile et al., 2006). The CART analysis is non-parametric and allows spatially autocorrelated data (Calbk et al., 2002; Collins et al., 2007). In this study, the "rpart" package in R software was used to conduct CART analysis, in which any monotonic transformation of the independent variables should make no difference. A change in a variable that preserves the number of unique split points has no impact with respect to the bias; therefore, tree models in CART are not affected by transformations on the explanatory variables (Zuur et al., 2007). The "rpart" analysis was conducted separately on data from each of the three fire environment zones. We pruned the tree models using the 10-fold cross-validation method to derive the smallest trees within 1 standard error of the minimum error (Wu et al., 2013; Yang et al., 2008). In the "rpart" analysis, measuring variable importance is the sum of the goodness of split measures for each split in which it was the primary variable, plus goodness (adjusted agreement) for all splits in which it was a surrogate. In the printout, the variable importance values were scaled to sum to 100 and the rounded values obtained, omitting any variable with a proportion <1% (R-Core-Team, 2013).

3. Results

3.1. Characteristics of fire environment zones

Three fire environment zones were identified by the spatial cluster of environmental variables. Fire environment zone I occurred in the southern part of the study area, zone II in the northwest, and zone III in the northeast (Fig. 4). The environmental characteristics of the three zones were verified by local forest and fire managers through personal communication.
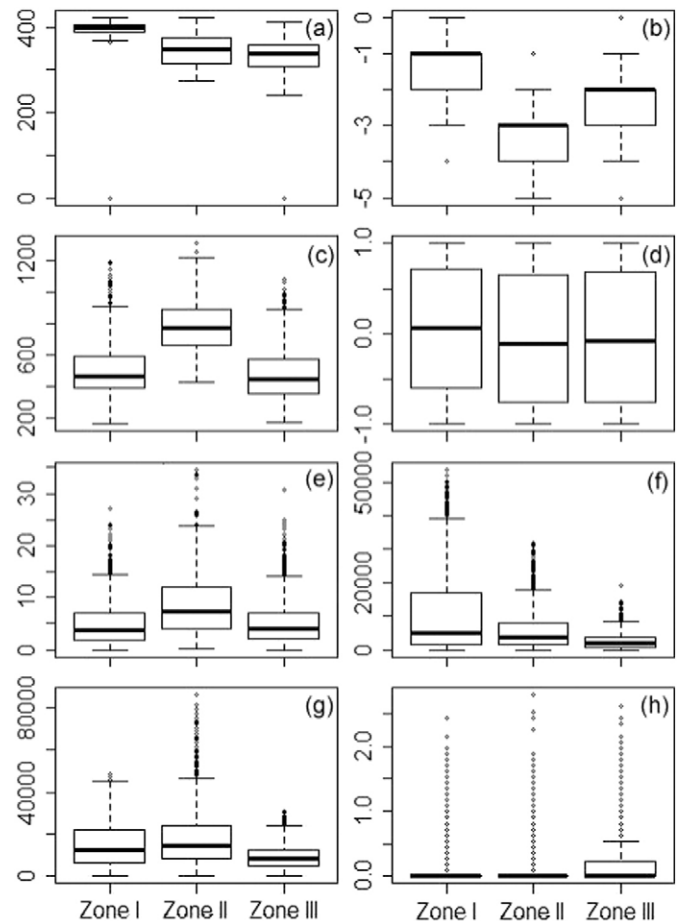
The mean annual temperature (°C) and precipitation (mm) generally decreases from south to north in our study area. Specifically, zone I (−1.15 °C) has a slightly warmer mean annual temperature than

zone II (−3.09 °C) and zone III (−2.14 °C). The mean annual precipitation declines from 396.99 mm in zone I to 333.23 mm in zone III. Zone I is relatively flat, spanning elevations from 164 to 1185 m with slopes averaging 5°. Zone II occurs at higher elevations (425–1305 m) with slopes averaging 8.45°. The terrain of zone III is intermediate and extends from 178 to 1078 m elevation with slopes averaging 5.12°. Because of its flatness, zone I comprises more meadow, shrub, and wetland vegetation than zone II and zone III. The distance to the nearest roads and settlements in zone III is the major environmental variable difference compared to zones I and II. Other environment variables (e.g., climate, topography, and vegetation) are intermediate between zone I and zone II (Figs. 5 and 6; Table 2).

3.2. Comparing fire occurrence and size patterns among fire environment zones

The historical fire occurrence density (both human- and lightning-caused fires) varied significantly among the three fire environment zones ($p < 0.01$). Human-caused fires burned with the highest density in zone I, whereas lightning-caused fires burned with the highest density in zone II. Fires in zone III were relatively complex mixes of human- and lightning-caused fires (Fig. 7).

The average fire size in the three fire environment zones were 7789.1, 1749.9, and 2680.1 ha, respectively. The historical fire size differed significantly among the three fire environment zones ($p < 0.01$) (Fig. 8). Zone I had the lowest and highest frequency for small (<100 ha) and extreme large fires (>10,000 ha) compared with zones

Fig. 6. Characteristics of environmental variables under three fire environment zones. (a) Mean annual precipitation (mm); (b) mean annual temperature (°C); (c) elevation (m); (d) aspect (−1 to + 1 index value); (e) slope (degrees); (f): distance to nearest road (m); (g) distance to nearest settlement (m); (h) road density (km/km²).

Table 2
Characteristics of vegetation composition under three fire environment zones.

Environment zones	Coniferous forest	Broadleaf forest	Mixed forest	Meadow-and-other
Zone I	37.7%	20.3%	3.0%	39.0%
Zone II	67.8%	5.4%	4.1%	22.7%
Zone III	60.4%	8.8%	5.3%	25.5%

II and III. Zone II (0.4%) had the lowest frequency of extreme large fires compared with zone I (6.5%) and zone III (1.9%) (Fig. 9).

3.3. Relative importance of environmental variables in controlling fire occurrence and size among fire environment zones

The distance to nearest settlement, elevation, and mean annual precipitation were always the most important variables explaining occurrence of human-caused fires. The elevation, mean annual precipitation, and mean annual temperature were always the most important factors explaining occurrence of lightning-caused fires. Slope and aspect were least important in controlling both human- and lightning caused fires. Vegetation type in zone I was more important than that in zones II and III. Elevation and distance to nearest settlement were more important in zone II. The relative importance of environmental variables was complex and indistinguishable in zone III (Table 3).

The relative importance patterns of environmental variables determining fire size differed significantly among the three fire environment zones. Fire size in zone I was generally related to variables of aspect, road density, distance to nearest settlement, and vegetation type. Elevation played a dominate role in zone II, and zone III was mainly controlled by elevation and vegetation type (Table 4).

4. Discussion

Fire attributes (e.g., frequency, size, and severity) were widely used in many previous studies to derive fire regime/environment zones, but the development of zones using environmental parameters has not been reported. Understanding the spatial characteristics of fire environmental variables is the basis for fire management (e.g., fuel treatment) and prediction, and these data are often obtained by forest and fire managers. In practice, local managers can design a highly individualized approach to manage fires according to the spatial distribution characteristics of the environmental parameters across a forest landscape. For example, some regions (zones) are characterized by high

elevation and consequently management activities should include more intense monitoring of lightning fires in these regions.

The three fire environment zones defined by our study were in strong agreement with the spatial distribution patterns of recorded historical fire occurrence and size from 1966 to 2005 in Chinese boreal forests. This agreement indicates that our analytical method through spatially clustering of environmental variables (climate, vegetation, topography, and human activity) can capture the spatial variation of fire regimes. Our study thus confirms that fire activity is not a spatially random process, but can be explained and modeled by considering the controlling environmental variables (Podur et al., 2003; Vazquez and Moreno, 2001).

We used the KNN spatial constraint algorithm to define neighbor relations of climate, vegetation, topography, and human activity variables to derive three fire environment zones. Several cluster analysis algorithms have been proposed over the last decades, each of which might lead to different clusters (Boulanger et al., 2012; Gordon, 1996). Although the KNN algorithm in this study makes fire environment zoning relatively straightforward, it might overlook the relative importance (spatial weight) of climate, vegetation, topography, and human activity variables. Further development of a clustering algorithm (e.g., create spatial weights matrix) may improve zoning of environments and subsequently refine fire environment zones.

The remarkable characteristic of fire environment zone I is higher temperature compared to that in zone II and zone III. Fire environment zone II is primarily located at high elevations. The distances to nearest roads and settlements in zone III are the major environmental variables that differed from zones I and II. Our study provides evidence that fire regimes are strongly linked to climate, vegetation, topography, and human activity characteristics across forest landscapes. For example, human-caused fire occurrence was clustered in zone I where human population density is high, and variables of road density and distance to nearest road were important in controlling fire size. Lightning-caused fires were the highest in zone II where elevations are the highest and most distant from settlements. Fire size was highly related to elevation in zone II.

The strong effect of elevation on both human- and lightning-caused fires and the weak effect of road density on human-caused fire occurrence are noteworthy. The strong effects of elevation may be explained by the spatial characteristics of vegetation in our study area. In Chinese boreal forests, dense and heavily branched shrubs of dwarf Siberian Pine (*P. pumila*) are common at high elevations (especially elevations > 800 m), and the harvest of their nuts is the main economic activity of local people. Consequently, both
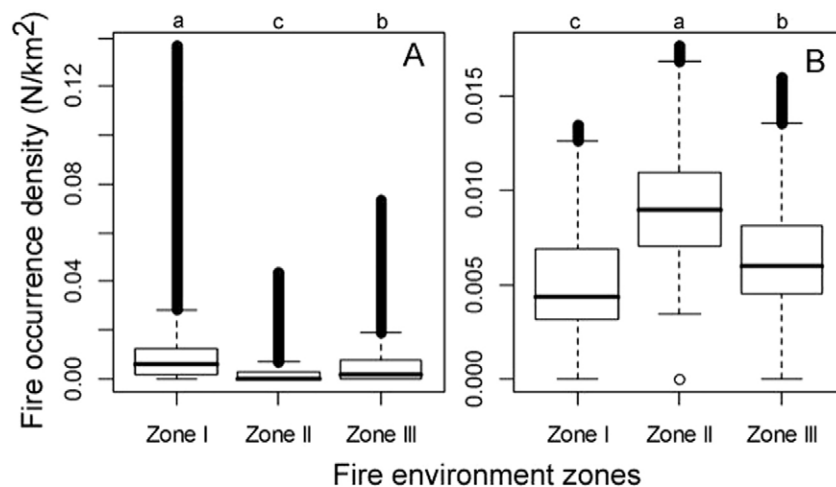
Fig. 7. Comparison of historical fire occurrence densities (1966–2005) among three fire environment zones. Letters (a, b, and c) indicate the significance difference ($a = 0.05$) among fire environment zones. (A) Human-caused fire; (B) lightning-caused fire. The significance of difference in historical fire occurrence density (1966–2005) among three fire environment zones was tested using the Duncan test with the "laercio" package in R software.

human- and lightning-caused fire occurrence densities are high in areas where elevations are high. The spatial variation of roads is lower than other environmental variables in Chinese boreal forests. We assumed that the spatial pattern of roads can partially explain the weak effect of road density on fire occurrence compared with other human factors such as distance to nearest settlements.

The three fire environment zones were derived based on the spatial clustering of climate, vegetation, topography, and human activity variables between 1965 and 2005. Although environmental conditions are relatively constant in the Great Xing'an Mountains compared with elsewhere in China, our findings should be carefully assessed in other forest landscapes or regions due to the extreme variability and uncertainty in environments. For example, land use or climate change can alter relevant environmental variables, and former fire attributes are less likely to dominate in a future changing landscape (Boulanger et al., 2013, 2014).

The delineation of fire environment zones may have important implications for refining fire suppression strategies and fire response policies (Boulanger et al., 2012, 2014; Yin et al., 2004). Specifically, delineation of fire environment zones can potentially help forest managers identify where monitoring and fire watch towers are needed. In our study, we identified three fire environment zones and described their natural and anthropic environment. These defined zones, in turn, can be used by fire managers to design different management plans for each fire environmental zone according to differences in the relative effects of environmental variables on fire regimes in each zone (e.g., occurrence and size). For example, human-caused fires are primarily distributed in fire environment zone I, characterized by flat terrain and a high human population. In this zone, management activities could advantageously include more intensive monitoring of human activities than in other areas. In contrast, zone II, characterized by high elevations and, distant from settlements, thus making fires larger and more difficult to detect and suppress. Accordingly, managers in this zone could use those areas for ecological restoration by allowing some small fires. This strategy thus would move the current monolithic use of fire suppression toward biodiversity or other management goals compatible with fire.

Another possible application of our study results is to predict spatially explicit future fire regimes. Prediction of fire regimes is often conducted using administration-based or ecoregion-based land units (Flannigan et al., 2005; Wotton et al., 2010); however, ecoregion-based prediction units often fail to capture the spatial patterns of fire regimes across forested landscapes. For example, Boulanger et al. (2012)
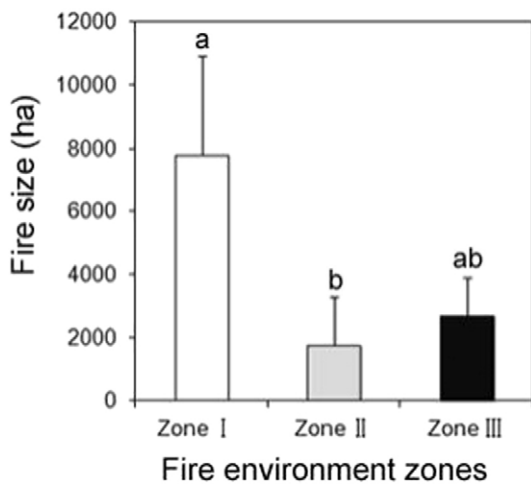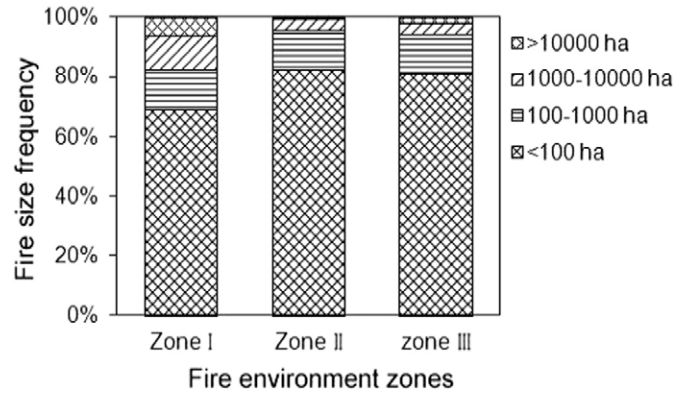

Fig. 9. Frequency distribution (%) of fire sizes among three fire environment zones.

found that using ecozone-based units in Canada led to an overgeneralization of fire regime estimates, which in turn resulted in less captured variation than using defined fire regime zones. The use of fire regime zones as basic fire-management units thus may provide a better fit and more precise and spatially explicit representation of future fire activity than that provided by predefined ecological units (Boulanger et al., 2012, 2014). Our study also provides evidence of fire regime variation among zones, and fire environment zone data, where available, could be used to gain insight into likely changes in fire activity.

Due to data availability, we employed only temperature and precipitation as climatic variables. Previous studies have shown that weather variables such as wind and relative air humidity also play important roles in controlling fire regime (e.g., rate of spread) (Carvalho et al., 2008). For example, weather is often considered a key cause of fire occurrence through its control of fuel moisture content and related probabilities of lightning ignition (Williams, 2005; Zumbrunnen et al., 2011). Effects of human activity on fire regimes were quantified with variables of proximity to settlements and roads, but the responses of fire regimes to human activities can be complex. Human activity often changes or destroys the spatial pattern of vegetation distribution and composition (Hawbaker et al., 2013; Zumbrunnen et al., 2011), which strongly determines fire types (e.g., surface or crown fire); therefore, human-induced effects on fire regimes may not be linearly related to proximity to roads

Table 3

Relative importance of environmental variables in controlling fire occurrence in the three fire environment zones. The relative importance values of the environmental variables were calculated with the "rpart" package in R software. The importance values ranged from 0 to 100 and summed to 100.

Fire types	Environmental variables	Fire environment zones		
		Zone I	Zone II	Zone III
Human-caused fires	Mean annual precipitation (mm)	8	15	32
	Mean annual temperature (°C)	12	8	9
	Elevation (m)	26	28	13
	Aspect (−1 to + 1 index value)[a]	0	3	2
	Slope (degrees)	6	7	7
	Distance to nearest road (m)	8	8	6
	Distance to nearest settlement (m)	23	25	25
	Road density (km/km^2)	1	5	5
	Vegetation type	16	1	1
Lightning-caused fires	Mean annual precipitation (mm)	31	28	29
	Mean annual Temperature (°C)	11	12	22
	Elevation (m)	24	24	27
	Aspect (−1 to + 1 index value)[a]	1	7	1
	Slope (degrees)	5	7	8
	Distance to nearest road (m)	11	4	4
	Distance to nearest settlement (m)	9	13	6
	Road density (km/km^2)	1	3	0
	Vegetation type	6	1	3

[a] An index value ranging from −1 to +1 (see Eq. (1)).

Fig. 8. Comparison of historical fire sizes (1966–2005) among three fire environment zones. Letters (a, b, and c) indicate the significance difference ($a = 0.05$) among fire environment zones. The significance of difference in historical fire size (1966–2005) among three fire environment zones was tested using the Duncan test with the "laercio" package in R software.

Table 4
Relative importance of environmental variables in controlling fire size in the three fire environment zones. The relative importance values of the environmental variables were calculated with the "rpart" package in R software. The importance values ranged from 0 to 100 and summed to 100.

Environmental variables	Fire environment zones		
	Zone I	Zone II	Zone III
Mean annual precipitation (mm)	6		
Mean annual temperature (°C)	1		4
Elevation (m)	11	100	66
Aspect (−1 to + 1 index value)[a]	33		
Slope (degrees)			1
Distance to nearest road (m)	13		2
Distance to nearest settlement (m)			2
Road density (km/km^2)	23		
Vegetation type	13		25

[a] An index value ranging from −1 to +1 (see Eq. (1)).

and settlements. Despite these limitations, our study results have potential application to landscape fire management.

5. Conclusions

The high complexity and variability in environmental variables across space and time often limit the efficiency of administrative boundary-based fire management plans. We identified three fire environment zones based on the clustering of 9 environmental variables in Chinese boreal forests. The three zones defined by our study generally agree with the spatial distribution patterns of historical fire data (occurrence, size, and frequency) from 1966 to 2005, and therefore our results can be applied to a range of forest and fire management activities.

Nevertheless, some uncertainties remain regarding the fire environment zones identified. For example, fire regime is a function of the occurrence, frequency, area burned, intensity, severity, and seasonality of fires. Our fire environment zones were tested only with historical fire occurrence and size data, and how well these defined fire environment zones capture the characteristics of other fire attributes (e.g., fire severity) is largely unknown. The merit of applying our results to other regions therefore requires further evaluation because of the large variability and uncertainty resulting from high environmental variability.

Acknowledgments

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