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Relative effects of climatic and local factors on fire occurrence in boreal forest landscapes of northeastern China

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HIGHLIGHTS

- We explored fire patterns and their influencing factors in Chinese boreal forests.
- Human-caused fires are clustered at areas where human population density is high.
- Lighting fires are clustered at areas where elevations are high and less populated.
- Human activity is secondary to climate as the primary fire occurrence factors.
- Management strategies might benefit from increased monitoring of human activities.

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ABSTRACT

Fire significantly affects species composition, structure, and ecosystem processes in boreal forests. Our study objective was to identify the relative effects of climate, vegetation, topography, and human activity on fire occurrence in Chinese boreal forest landscapes. We used historical fire ignition for 1966–2005 and the statistical method of Kernel Density Estimation to derive fire-occurrence density (number of fires/km^2). The Random Forest models were used to quantify the relative effects of climate, vegetation, topography, and human activity on fire-occurrence density. Our results showed that fire-occurrence density tended to be spatially clustered. Human-caused fire occurrence was highly clustered at the southern part of the region, where human population density is high (comprising about 75% of the area's population). In the north-central areas where elevations are the highest in the region and less densely populated, lightning-caused fires were clustered. Climate factors (e.g., fine fuel and duff moisture content) were important at both regional and landscape scales. Human activity factors (e.g., distance to nearest settlement and road) were secondary to climate as the primary fire occurrence factors. Predictions of fire regimes often assume a strong linkage between climate and fire but usually with less emphasis placed on the effects of local factors such as human activity. We therefore suggest that accurate forecasting of fire regime should include human influences such as those measured by forest proximity to roads and human settlements.

1. Introduction

Fire is a dominant disturbance in boreal forest landscapes, which has significantly affected the species composition, structure, and ecological processes of these forests (Bergeron et al., 2004; Bond-Lamberty et al., 2007; Flannigan et al., 2009; Lynch et al., 2004; Wang and Kemball, 2005). Fire occurrence also is increasing across the boreal forest landscape (Liu et al., 2012; Stocks et al., 1998; Wotton et al., 2010). In Chinese boreal forests, Liu et al. (2012) projected an increase in fire occurrence of 30–230% by the end of 2100. Understanding the underlying causes of fire occurrence in fire-prone boreal forest landscapes in China thus is a key issue for fire managers (Liu et al., 2012).

Among many factors related to fire occurrence, climate is often considered as regional in scale, whereas vegetation, topography, and human activity are considered local (Ali et al., 2009). Studies have reported that climate-dominate effects can be altered by local factors, especially in strongly human-affected landscapes (Ganteaume et al., 2013; Lynch et al., 2004; Niklasson and Granstrom, 2000; Syphard et al., 2007; Wallenius et al., 2004; Zumbrunnen et al., 2012). Human activity can directly affect fire through ignition or suppression (Liu et al., 2012; Zumbrunnen et al., 2011), and can indirectly induce changes in fire occurrence by modifying the spatial pattern of vegetation

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distribution and composition across the landscape (Hawbaker et al., 2013; Zumbrunnen et al., 2011). Signs of human influences on fire regimes have been detected in many forest landscapes. For example, in a European boreal forest landscape, Wallenius et al. (2004) found that between the sixteenth and twentieth centuries, numbers of forest fires greatly increased with the expansion of human settlement and population density. Therefore, the relationship between fire occurrence and its influencing factors needs to be carefully examined, especially in human-affected landscapes.

Chinese boreal forests have been heavily influenced by humans (Duan et al., 2004; Xu, 1998). Human population density in the region (15.2 persons/km^2) is higher than that of the North American boreal forest region of Canada (0.1–0.9 persons/km^2). Most of the people in Chinese boreal forests live at lower elevations near roads. Roads are widely distributed in the region and their density averages 0.24 km/km^2. Human settlement and exploitation of these forests have altered their composition, structure, and consequent fire regime in accordance with their historic variation (Wu et al., 2013; Zhou, 1991). For example, several decades of extensive logging have created a relatively fire-prone landscape by expanding a mosaic of young deciduous forests dominated by species such as birch and aspen. Such forests are widely distributed in hills and lower mountains where fires were frequently ignited by humans. Today the environmental factors influencing fire occurrence remain poorly understood across this heavily human-affected landscape.

In Chinese boreal forests, understanding the relations between fire occurrence and its causation is often focused at regional scales (e.g., the entire Chinese boreal forest (Liu et al., 2012; Tian et al., 2011; Yang et al., 2011). However, the processes determining fire occurrence are scale-dependent, meaning that relations between fire occurrence and causation observed at one spatial scale may not hold at another scale. Evaluating the relative effects of climatic and local factors at different spatial scales is thus essential (Falk et al., 2007, 2011). Accordingly, we conducted our study at two spatial scales: 1) the regional scale, i.e. the entire Great Xing'an Mountains; and 2) the landscape scale represented by each of the three forest bureaus (Xilinji, Huzhong, and Jiagedaqi).

The objective of our study was to identify the relative effect of climate, vegetation, topography, and human activity on fire occurrence in Chinese boreal forest landscapes. We asked the following three questions: (1) What are the spatial patterns of fire occurrence in the Chinese boreal forest landscape? (2) Are fire occurrence patterns predominantly affected by climate and what is the role of human activity in such human-affected forest landscapes? (3) Do the relative effects of climatic and local factors on fire occurrence differ between regional and landscape spatial scales?

2. Material and methods

2.1. Study sites selection

The Great Xing'an Mountains (50°10′N-53°33′N, 121°12′E-127°00′E), located in northeastern China, encompass approximately 8.46×10^4 km^2 (Fig. 1). This mountain range divides the plains of northeastern China to the east from the Mongolian Plateau to the west. The area has a cold, continental climate with average annual temperatures that decline from 1 °C at its southern extreme to −6 °C at its northern extreme; precipitation declines from 442 mm in the south to 240 mm in the north. More than 60% of annual precipitation falls in the summer (June to August) (Zhou, 1991).

The vegetation of this area is representative of cool temperate coniferous forests, which here form the southern extension of the eastern Siberian boreal forest. The proportion of conifers declines from north to south, while deciduous tree species increase. The overstory species include 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*

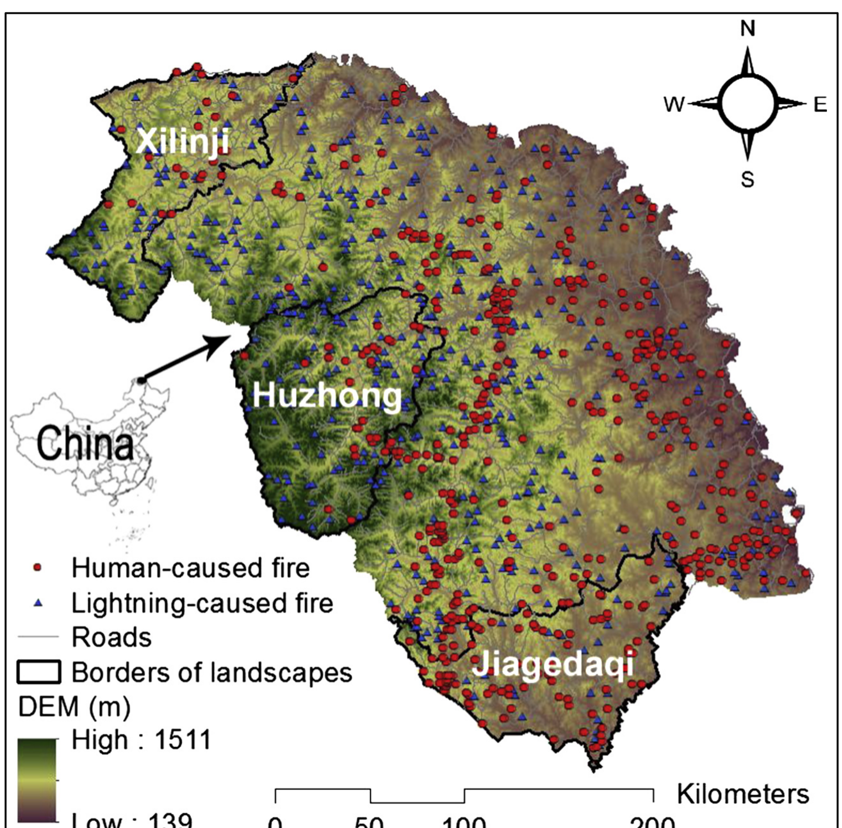

Fig. 1. Study area with historical human-caused and lightning-caused fire locations (1966–2005), roads, and DEM (digital elevation model). The spatial resolution of the DEM was 500 m.

arbutifolia), and the shrub *Pinus pumila*. Boreal conifers (mainly larch) are widely distributed late successional species that occupy moist and cool sites. Deciduous trees (e.g., birch and aspen) are early successional species that occupy the drier and better drained sites (Xu, 1998).

The Great Xinag'an Mountains are vast and covered with dense virgin forests. Historically, nomads lived in this region, and fire use was not part of their lifestyle. Boreal forests in this region were largely unexplored until the construction in the early 20th century of the first railway across the mountains (http://en.wikipedia.org/wiki/Greater_Khingan). Before then, fires were ignited primarily by lightning (Xu et al., 1997). After the founding of the People's Republic of China in 1949, a strong fire suppression policy was implemented to protect forest resources. Since then, intentional use of fire has been prohibited. Once a fire is observed, the government sends firefighters to suppress fire whenever possible. Fire thus has been effectively suppressed and fire regimes consequently have altered the region's ecology (Chang et al., 2007). In recent years fires have become smaller, but occur more frequently and intensely than before (Chang et al., 2007; Xu et al., 1997). Efficient allocation of limited fire-fighting resources also poses a great challenge in Chinese boreal forests, especially for local forest managers in this region.

The Great Xing'an Mountains encompass 10 forest bureaus. From among these, we selected three spatially independent units (Xilinji, Huzhong, and Jiagedaqi). Each unit was unique with respect to climate, topography, vegetation, and human population density (Fig. 1; Table 1). Temperature and precipitation generally increase from the northern forest bureau of Xilinjing to the southern forest bureau of Jiagedaqi. Elevations of Xilinji range from 268–1315 m and slopes average 5.9° whereas Huzhong is higher in elevation (408–1380 m) with steeper slopes that average 10.2°; Jiagedaqiis is 281 to 1017 m elevation and with slopes averaging 4.1°. As a flat landscape, the vegetation in Jiagedaqi is comprised of more meadow, shrub, and wetland vegetation than the other two bureaus. It also has the highest population density (113 people/km^2) and lowest road density (0.11 km/km^2).

2.2. Dependent variable: fire-occurrence density

2.2.1. Historical fire ignition dataset

We obtained from local forest and fire managers 1156 historical fire ignition records occurring between 1966 and 2005 in the Great Xing'an Mountains Forest Bureau. The 1156 fire records included the specific location (recorded as x, y coordinates), fire size, cause, and dates of occurrence and extinction. There were 26 fire ignitions (2%) that originated from reigniting of fire-breaks in the fire dataset. Fire-breaks are often placed at locations near roads and human settlements. The spatial distribution pattern of the 26 fires was similar to human-caused fires that largely clustered near road and human settlements, a finding verified by local fire managers through personal communication and our analysis. Therefore, we included the 26 fire ignitions as human-caused fires. Human-caused fires comprised 52% of all fires and lightning-caused fires 48%. We analyzed human-and lightning-caused fires separately.

Most of human-caused fires occurred in the spring (April, May, and June), whereas most of lightning fires occurred in the spring and summer (May, June, July, and August). The annual dynamics for human- and lightning-caused fires can be found in Fig. 2.

2.2.2. Deriving continuous fire-occurrence density surfaces

To derive a continuous fire-occurrence density surface, Kernel Density Estimation (KDE) was used based on historical fire datasets of spatial ignition points (Amatulli et al., 2007; Gonzalez-Olabarria et al., 2012; Oliveira et al., 2012). In KDE, bandwidth directly influences the smoothness of the dataset in the density function. We used the cross-validation algorithm to select the appropriate smoothing bandwidths (Berman and Diggle, 1989; Diggle, 1985). Bandwidths were chosen to minimize the mean-square error criterion defined by Diggle (1985).

The KDE was based on the "density" function of the "spatstat" package in R statistical software. Fire occurrence density maps for human-caused and lightning-caused fires were derived from KDE and formed the data output at a spatial resolution of 500 m.

2.3. Explanatory variable-selection and pre-processing

Ten potential explanatory variables were selected from databases that included climate, vegetation, topography, and human activity variables (Table 2). The variables selected were chosen for their relevance to fire occurrence based on extensive literature review, local forest and fire managers' suggestions, and data availability (Achard et al., 2008; Gralewicz et al., 2012; Krawchuk et al., 2006; Oliveira et al., 2012; Wotton et al., 2010).

2.3.1. Climate data

Annual temperature and precipitation were selected as climatic variables because they influence fire occurrence by constraining fuel moisture content, and also are traditional indicators for degree of climate change (McCoy and Burn, 2005; Scholze et al., 2006; Xystrakis and Koutsias, 2013). Datasets for mean annual temperature and precipitation for 1965–2005 were generated from the 88 weather stations across northeastern China. Climatic datasets with 1-km resolution were created from AcrGIS Grids based on kriging algorithms, which produced continuous maps of mean annual temperature and precipitation.

Fuel moisture content condition has been found to be a useful predictor of fire occurrence in boreal forests (Martell et al., 1989; Wotton and Martell, 2005). We selected Fine Fuel Moisture Code (FFMC) and Duff Moisture Code (DMC), which are components of the Canadian forest fire weather index, as indicators of fuel moisture content. FFMC and DMC were determined by daily observation of temperature, precipitation, relative humidity, and wind speed and were calculated according to Van Wagner (1987). Daily meteorological data were obtained from the NECP reanalysis dataset (http://www.esrl.noaa.gov/psd).

2.3.2. Vegetation data

A vegetation cover map was derived from the Vegetation Map of the People's Republic of China (1:1,000,000) originally produced in 1982 and digitized in 2007. Vegetation types were grouped into four categories: coniferous forest (53.4% of the total area), mixed forest (4.1%), deciduous forest (12.6%), and meadow-and-other, which includes shrub land and wetland (29.4%). Because meadow constituted most of the area defined as meadow-and-other we hereafter refer to this vegetation type simply as meadow. The averaged vegetation type map was interpolated to yield a resolution of 90-m grid cells. The vegetation type composition (dominated by larch) is relatively simple in the Great Xing'an boreal forest ecosystems. Local forest managers would plant larch in

Table 1
Geography, climate, vegetation, topography, and human variables within the three forest bureaus (AMT, annual mean temperature; AMP, annual mean precipitation; CF: coniferous forest; MF: mixed forest; BF: deciduous forest; MO: meadow and other; PD: population density; RD: road density).

Forest bureau	Latitude (N)	Longitude (E)	Area (ha)	AMT (°C)	AMP (mm)	Topography (mean ± SD)		Vegetation composition (%)				Human factors	
						Elevation (m)	Slope (degrees)	CF	MF	BF	MO	PD (people/km^2)	RD (km/km^2)
Xilinji	122°11′–123°16′	52°16′–53°32′	732,092	−4.9	403	621.2 ± 147.2	5.9 ± 4.3	51.9	19.6	9.1	19.4	6	0.25
Huzhong	122°39′–124°21′	51°14′–52°25′	937,244	−4.7	500	829.4 ± 166.3	10.2 ± 6.7	76.1	0.1	3.0	20.7	5	0.28
Jiagedaqi	123°45′–126°04′	50°05′–51°12′	966,110	−1.3	500	446.1 ± 87.5	4.1 ± 3.4	18.7	0.1	37.6	43.6	113	0.11

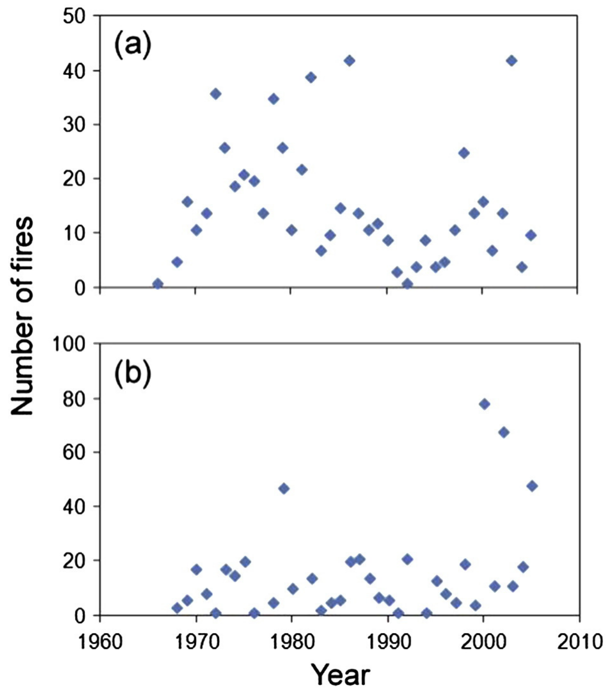

Fig. 2. The annual dynamics for human- and lightning-caused fires between 1966 and 2005 in the study area. (a) Human-caused fire; (b) Lightning-caused fire.

the burned and harvested area, and consequently the data for vegetation type within the study area was assumed to be constant during the study period.

2.3.3. Topography data

We used three topographic variables as factors that can potentially influence fire occurrence: elevation, slope, and aspect. A 90-m resolution grid of digital elevation model (DEM) data was generated from contour lines downloaded from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn/). The slope and aspect surfaces were derived from the DEM using the surface analysis provided in the ArcGIS Spatial Analyst tool. Aspect was further converted into an aspect index using the following formula:

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

where θ was the aspect derived from the ArcGIS "aspect" function, which ranged from 0–360. The aspect index ranged from -1 to 1, with higher values indicating higher potential solar radiation.

2.3.4. Human activity data

Human infrastructure, including roads and settlements, influences fire occurrence by determining the presence and accessibility of humans to forests (Syphard et al., 2007; Zumbrunnen et al., 2012). A digital roadway coverage (1:100,000) was obtained from the National Geomatics Center of China (http://ngcc.sbsm.gov.cn/). Proximity to roads and settlements was calculated as the Euclidean distance from each cell to the nearest road or settlement using the spatial analysis tools in ArcGIS. Most roads were built before 1990. Major roads have changed little over the past decades because of the decrease of population in this region. There were some minor changes in local roads. We assumed that the road network remained constant over the study period.

2.4. Statistical analysis

We selected 500 evenly distributed points from each of the three forest bureaus (totaling 1500 points) as the basis for data analyses. The minimum spatial distance between nearest points was approximately 4 km. The regional-scale data analysis of fire-occurrence density was based on the 1500 points, whereas the landscape scale analysis was based on the 500 points for each of the three forest bureaus. The R statistical software package was used in all analyses (R-Core-Team, 2013).

Various statistical analyses were used to determine: (1) potential collinearity within explanatory variable groups; (2) relative effects of climatic vs. local factors on fire-occurrence density; (3) the relative importance of all fire-occurrence factors in determining fire-occurrence density; and (4) spatial distributional patterns of fire-occurrence density in relation to possible causal factors.

The Variance Inflation Factor (VIF) was calculated using the "car" package in R for detecting collinearity among explanatory variables. We used the rule of thumb that when VIF > 5, then collinearity in the explanatory variables is problematic (Uriarte et al., 2012). VIF analysis indicated an absence of collinearity within topography and human variable groups. Duff moisture content showed strong collinearity within the climatic variable group (Table 2). However, climatic variables were inherently correlated. Moreover, previous studies have shown that duff moisture content is a strong predictor of fire occurrence (Wotton and Martell, 2005; Wotton et al., 2003). We therefore retained duff moisture content as a variable.

The relative grouped effects of climatic and local factors on human- and lightning-caused fire-occurrence density at regional and landscape scales were analyzed using the Random Forest (RF) model (Breiman, 2001). We first analyzed the relative effects of climatic vs. local factors on fire-occurrence density at the regional scale. We then examined effects of those factors within forest bureaus (i.e. at the landscape scale) on the variation of fire-occurrence density. We used this method to determine whether relative effects of climatic vs. local factors differed between regional and landscape scales.

Table 2
Variables used to explain fire-occurrence density after the collinearity diagnostics analysis.

Variable	Abbreviation	Data Source	Units	Variance inflation factor
Topography factors				
Elevation	Elev	National Geomatics Center of China	Meter	1.3
Aspect	Asp	Derived from elevation	N/A	1.0
Slope	Slope	Derived from elevation	Degree	1.3
Human factors				
Distance to nearest road	DisRd	National Geomatics Center of China	Meter	1.0
Distance to nearest settlement	DisSet	National Geomatics Center of China	Meter	1.1
Vegetation type	Veg	Vegetation map of the People's Republic of China	Class 1–4	
Climate factors				
Mean annual precipitation	Prep	China Meteorological Data Sharing Service system	mm	29.9
Mean annual temperature	Temp	China Meteorological Data Sharing Service system	°C	6.3
Fine fuel moisture content	FFMC	Calculated based on algorithm described by Van Wagner (1987), daily meteorological data were downloaded from NCEP_Reanalysis data	Dimensionless (range: 0–101)	2.3
Duff moisture content	DMC	The same as FFMC	Dimensionless (range: >0)	43.4

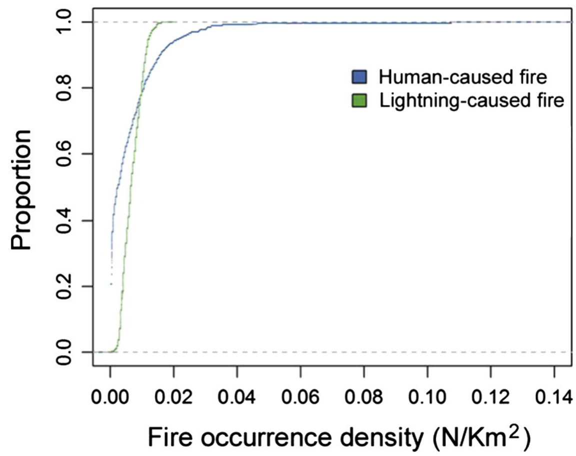

Fig. 3. Empirical cumulative distributions for human-caused and lightning-caused fire-occurrence densities.

We also used importance values of the RF variable to rank the individual factors based on the strength of their relation to fire-occurrence density at the regional and landscape scales. The RF algorithm estimates the importance value of a variable by looking at how much prediction errors increase when data for that variable are permuted while all others are left unchanged (Liaw and Wiener, 2002; Thompson and Spies, 2009).

The RF models showed that climate and human activity were the most important in influencing fire occurrence. We therefore further used the RPART model to better understand the nature of relations between fire-occurrence density and climate and human activity. The RPART analysis is a non-parametric technique that recursively partitions a dataset into subsets that are increasingly homogeneous with regard to the response. The RPART models were constructed using the "rpart" package in R. We used the 10-fold cross-validation method to prune tree models to derive the smallest trees using an error within 1 standard error of the minimum error (Yang et al., 2008).

Table 3
Variance of fire occurrence densities explained by climatic and local variable groups at the regional scale (%). The calculation of percent variance explained was based on an out-of-bag estimation in the random forest model.

Fire types	Climatic variables pooled	Local variables pooled
Human-caused fires	63.2	34.1
Lightning-caused fires	86.1	49.5

3. Results

3.1. Overall characteristics of fire-occurrence density patterns

Median values of fire-occurrence density (number of fires/km^2) for human-caused and lightning-caused fires were 0.002 and 0.006, respectively. Human-caused fire-occurrence density ranged from 0.0 to 0.137 and averaged 0.006. The lightning-caused fire occurrence densities ranged from 0.001 to 0.018 with an average of 0.007 (Fig. 3).

The kernel-smoothed fire-occurrence densities estimated from reported fire ignitions between 1966 and 2005 identified the locations of "hotspots" of fire occurrence. Human-caused fire occurrence was highly clustered at the southern part of the region, where human population density is high (comprising about 75% of the area's population). In the north-central areas where elevations are the highest in the region and less densely populated, lightning-caused fires were clustered (Fig. 4).

3.2. Relative effects of climatic vs. local factors on fire-occurrence density

At the regional scale, results of RF analysis showed that the climatic factors combined were significantly stronger than local factors combined in explaining fire-occurrence density in all the random forest models. Climatic factors jointly accounted for 63.2% and 86.1% of variance in human-caused and lightning-caused fire-occurrence densities, respectively. Local variables jointly explained 34.1% and 49.5% of variance in human-caused and lightning-caused fire-occurrence density, respectively (Table 3).

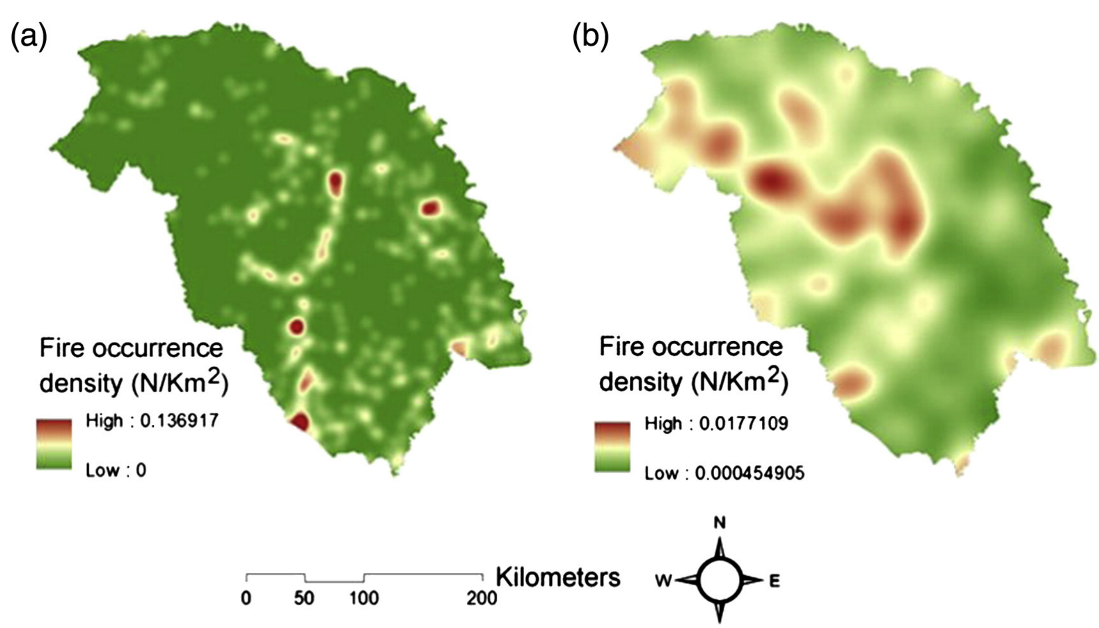

Fig. 4. Kernel smoothed intensity estimated from the fire occurrence data reported from 1966 to 2005. The smoothing scales (bandwidths) in the kernel density estimator for human- and lightning-caused fires were 4183.4 m and 12,550.3 m. (a) Human-caused fire; (b) Lightning-caused fire.

Table 4
Variance of fire occurrence densities explained by climatic and local variable groups at the landscape scales (%). The calculation of percent variance explained was based on an out-of-bag estimation in random forest model.

Fire types	Xilinji		Huzhong		Jiagedaqi	
	Climatic variables	Local variables	Climatic variables	Local variables	Climatic variables	Local variables
Human-caused fires	42.3	22.0	44.1	22.3	63.0	49.6
Lightning-caused fires	82.3	68.6	78.8	19.4	70.8	51.4

Patterns of fire-occurrence density explained by climatic vs. local factors at the landscape scale were similar to those at the regional scale (Tables 3, 4). But climate effects at the landscape scale were less than those at the regional scale, except for the highly populated forest landscape of Jiagedaqi (Table 4).

3.3. Relative importance of climatic and local factors in influencing fire-occurrence density

Importance values calculated from the RF showed that fine fuel and duff fuel moisture contents were most important at both landscape and regional scales. The importance of temperature was not as strong as expected at the landscape scale. The distance to nearest settlement and distance to nearest road were more important at landscape scale than at regional scale in explaining fire-occurrence densities. Vegetation type, slope, and aspect were least important. As expected, elevation was generally important in explaining lightning-caused fire-occurrence density (Figs. 5 and 6).

3.4. Partition of fire-occurrence density in relation to climatic and human factors

The RPAR model of human-caused fire-occurrence density produced 8 terminal nodes. The first partition was based on duff moisture contents (DMC) below 37. The lowest levels of human-caused fire-occurrence density occurred when DMC was lower than 37 and with distance to nearest settlement (DisSet) larger than 6877 m. The high levels of human-caused fire-occurrence density occurred when distance to nearest settlement (DisSet) was less than 13,000 m, fine fuel moisture content (FFMC) below 88, and distance to nearest road was less than 34,000 m (Fig. 7).

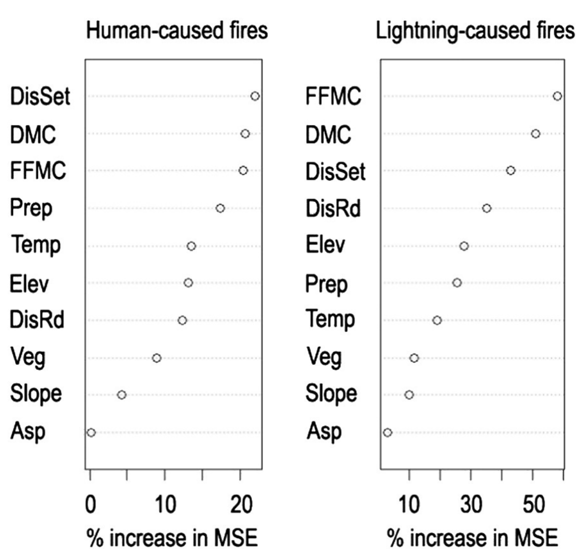

Fig. 5. Percent increase in mean square error (MSE) for variables in the random forest models for human-caused and lightning-caused fires at the regional scale. The MSE was calculated using a permutation test in the random forest model. DisSet: Distance to nearest settlement; DMC: Duff moisture content; FFMC: Fine fuel moisture content; Prep: Mean annual precipitation; Temp: Mean annual temperature; Elev: Elevation; DisRd: Distance to nearest road; Veg: Vegetation; Asp: Aspect.

The RPAR model of lightning-caused fires produced 12 terminal nodes. The majority lightning-caused fires were in areas with low duff moisture content. The first split partitioned the data based on duff moisture content (DMC) above 36. High levels of lightning-caused fire-occurrence densities associated with DMC greater than 27. The lowest lightning-caused fire-occurrence density occurred at elevations below 697 m when DMC was below 39 (Fig. 8).

4. Discussion

We evaluated human- and lightning-caused factors that influenced fire-occurrence densities based on historical fire data collected between 1966 and 2005 in Chinese boreal forests. Among the variables considered, we found that climatic factors had the greatest influence on fire-occurrence density at both regional and landscape scales and both human- and lightning-caused fires. This result is consistent with findings from other boreal forests (Flannigan et al., 2009; Gillett et al., 2004; Stocks et al., 1998). However, we found that human activity factors (e.g., distance to nearest settlement and road) also were important in predicting fire occurrence. These findings reinforce claims that, despite the strong influence of climatic factors, effects of human factors should not be ignored (Achard et al., 2008; Ganteaume et al., 2013; Syphard et al., 2007; Yang et al., 2007).

Of the climatic factors we considered, fine fuel and duff fuel moisture contents, and precipitation were consistently the major factors influencing fire occurrence at both regional and landscape scales. Fine fuel moisture was a stronger predictor for the human-caused fires and duff moisture content was strong in predicting the expected number of lightning-caused fires in Chinese boreal forest region (Martell et al., 1989; Wotton et al., 2003). This also concurs with previous boreal forest studies (Bessie and Johnson, 1995; Johnson et al., 2001; Keeley and Fotheringham, 2001). Effects of air temperature were generally less important at the regional scale, and they were less so at the landscape scale. This suggests that, under a warming climate, higher temperatures alone may not lead to increased fire frequency (Bergeron et al., 2001; Fauria and Johnson, 2008). The weak effect of temperature on fire frequency supports results from North American boreal forests (Fauria and Johnson, 2008; Lynch et al., 2004). For example, Lynch et al. (2004) suggested that warmer/drier climatic conditions have not necessarily increased fire occurrence in Alaskan boreal forests.

In our study, the response of fire-occurrence density to temperature was strongly constrained by patterns of local factors such as human activity and elevation. We found that fire-occurrence density was spatially clustered even in locations with high air temperatures. For example, human-caused fire occurrence was clustered at the south of the region (e.g., Jiagedaqi) where human population density is high (comprising about 75% population of the area), whereas lightning-caused fires were highest in the north of the region where less densely populated (e.g., Huzhong). In the landscape of Huzhong, the elevation is higher than elsewhere and ignitions are frequently caused by lightning. Predictions of fire regimes often assume a strong linkage between climate and fire but usually with less emphasis placed on the effects of local factors such as human activity (Liu et al., 2012; Wotton et al., 2010). Our study shows a close relation between humans and the occurrence of fire. Therefore, where spatial patterns of human activity are available, they

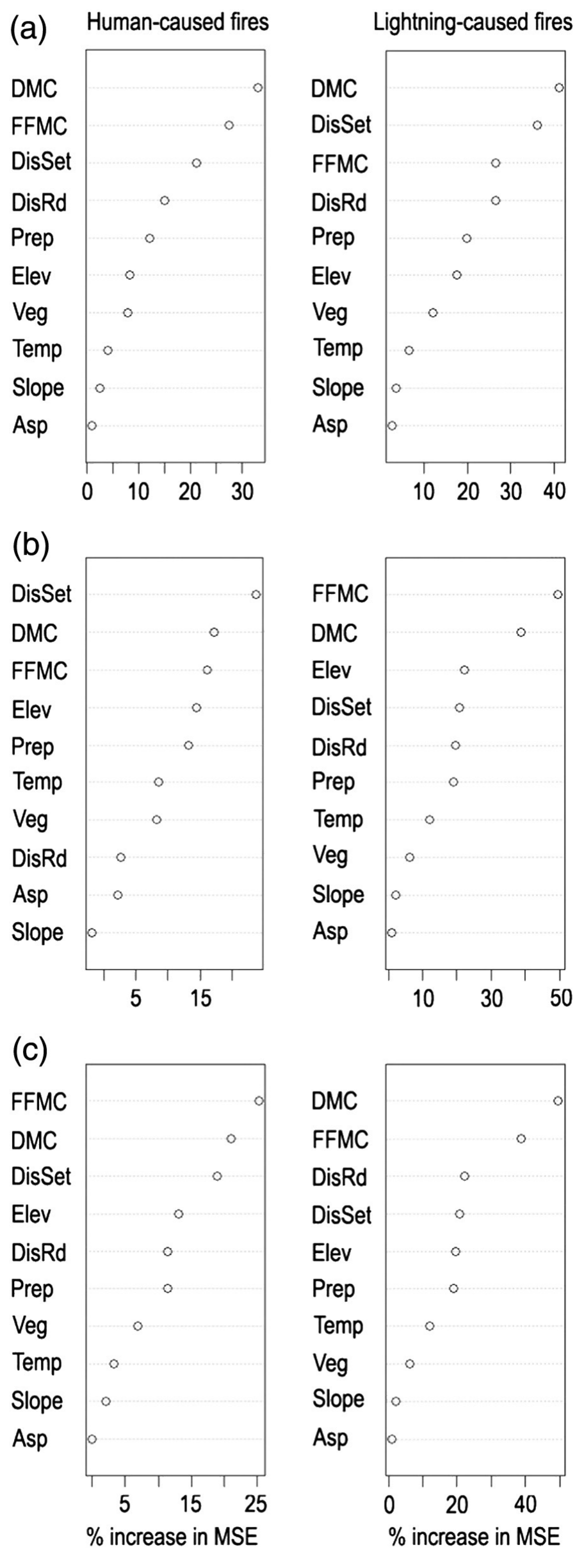

Fig. 6. Percent increase in mean square error (MSE) for variables in the random forest models for human-caused and lightning-caused fires at the landscape scale. (a) Xilinji; (b) Huzhong; (c) Jiagedaqi. DisSet: Distance to nearest settlement; DMC: Duff moisture content; FFMC: Fine fuel moisture content; Elev: Elevation; Prep: Mean annual precipitation; Temp: Mean annual temperature; Veg: Vegetation; DisRd: Distance to nearest road; Asp: Aspect.

potentially can be used to adjust spatial patterns of fire occurrence (Miranda et al., 2012). The identification of fire occurrence hotspots can provide useful information for more effective allocation of fire management resources (Gonzalez-Olabarria et al., 2012; Yang et al., 2007).

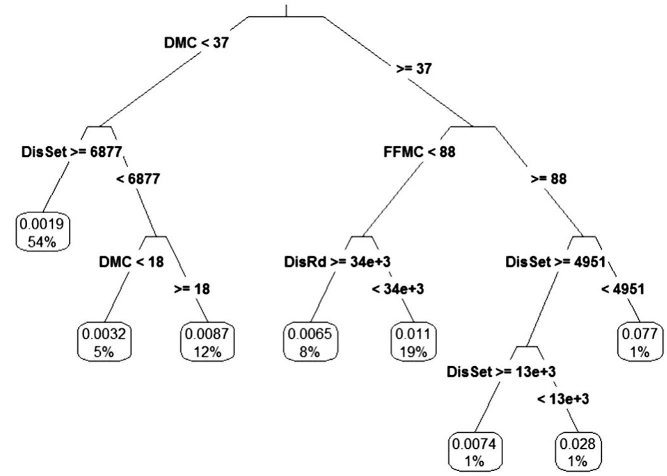

Fig. 7. Partitioning of human-caused fire-occurrence density in relation to climate and human factors at the regional scale. Each box at the terminal nodes shows the mean fire occurrence density value (top) and the percent of area (bottom). The unit of the values in the small boxes is number of fires/km^2. DMC: Duff moisture content; DisSet: Distance to nearest settlement; FFMC: Fine fuel moisture content; DisRd: Distance to nearest road.

Management strategies accordingly might benefit from increased monitoring of human activity in known hotspots.

These findings are in agreement with the hypothesis that, in human-dominated landscapes, fire occurrence is primarily related to human factors (Zumbrunnen et al., 2011). The strong relation between human activity and fire also has been reported in other boreal forests. For example, Achard et al. (2008) suggested that, in Russian boreal forest, up to one-third of fire impacts (i.e. their areal extent) could be attributed to climate anomalies alone, with the remainder resulting from the joint occurrence of human disturbance and climate anomalies. In our study area, changes in the composition, structure, and fuel load accumulation of the forest are widely affected by timber harvest and fire suppression. For example, timber harvest produced a spatial mosaic of young and small fire-susceptible trees (birch and aspen). Aggressive fire suppression carried out for over a half century has produced high fuel accumulations. Consequently, forest harvesting and fire suppression have altered fire regimes in this region (Chang et al., 2007; Li et al., 2006). Studies have indicated that historical fire regime was characterized by

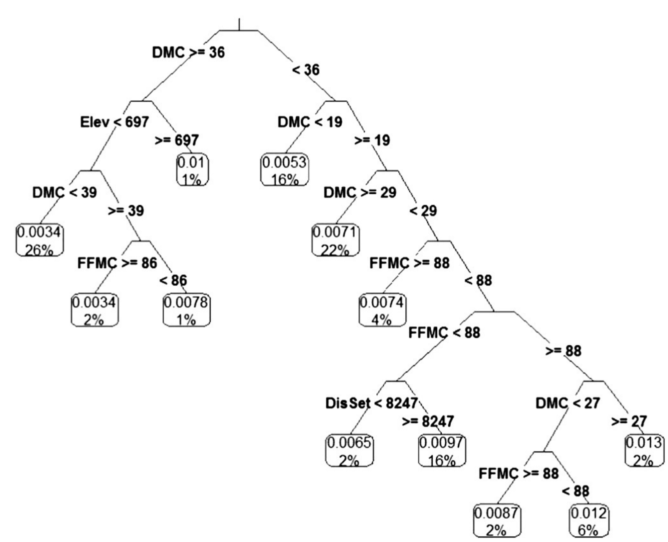

Fig. 8. Partitioning of lightning-caused fire-occurrence density in relation to climate and human factors at the regional scale. Each box at the terminal nodes shows the mean fire occurrence density value (top) and the percent of area (bottom). The unit of the values in the small boxes is number of fires/km^2. DMC: Duff moisture content; Elev: Elevation; FFMC: Fine fuel moisture content; DisSet: Distance to nearest settlement.

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). Currently, fires have been infrequent with a fire return interval about 500 years (Chang et al., 2007), but these often burn as intensely and larger fires (Chang et al., 2008).

The areas with greater lightning-caused fire-occurrence density can be explained by the distribution of elevation across Chinese boreal forests. For example, within the Huzhong bureau where elevations are the highest in the region, fires were clustered. There, slope and aspect were always ranked as the least important factor in determining fire-occurrence density (Figs. 5 and 6). Generally, steep slopes imply greater topographic roughness and are more difficult for humans to access (Guyette et al., 2002; Yang et al., 2007). Yang et al. (2007) found that in the oak forests of the U.S. Missouri Ozarks, more fires occurred on gentler than on steeper slopes. In our study area, most fires occurred in areas with slopes <4° (Liu et al., 2012).

Some studies have suggested that the weak effects of vegetation type may be because vegetation is generally not a limiting factor in boreal forests (Johnson and Larsen, 1991). Because forests were largely dominated by larch in our study area, spatial composition was relatively simple and spatial variation therefore was comparatively low. In the study of Liu et al. (2012), their deciduous forests and meadows were characterized by relatively high fire frequency. The spatial variation of deciduous forests in our study area is low and these forests are mainly distributed across relatively flat terrain close to settlements or roads. In contrast, the spatial variations of topography and human factors are higher. Therefore, we assumed that the explanatory power of topography and human factors eroded the explanatory power of vegetation.

A possible limitation to our study may have been that small-scale spatial variation in weather may not have been accurately represented. Because spatially and temporally explicit historical fire weather data were not available, we did not examine relations between fire-occurrence density and weather factors such as wind speed, number of continuous days without rain, and relative humidity. However, fire occurrence is directly affected by those factors (Carvalho et al., 2008). Another limitation of our study was related to human activity factors, which only considered distances to nearest settlement and roads. Some other human-related factors such as population density are important in explaining fire-occurrence density. The expansion in population density can affect forest landscape directly through land-use change, timber harvesting, and fire management (Hawbaker et al., 2013; Zumbrunnen et al., 2011). The variables we used may not be linearly related to the many possible human-induced changes occurring in a landscape. For example, in some agroforestry landscapes, one of the major ways for humans to affect the landscape configuration (land use pattern) is through converting forest into agricultural land. Consequently, the human-induced landscape configuration changes can alter fire regimes greatly. Moreover, our spatial dataset approach using different spatial resolutions (cell size) ranged from 90 m to 1 km. We aggregated the spatial resolution of all the variables into 500 m. Therefore, the spatial variation of some variables was averaged, which may have resulted in loss of sensitivity in factors related to spatial aggregation. Consequently, the explain ability (importance) of some variables (e.g., vegetation type) could be affected in our study.

In the Great Xing'an Mountains, changes (climate, vegetation, topography, and human activity) are not as pronounced as elsewhere in China where rapid increases in population lead to drastic changes in natural landscapes. However, further assessment is also needed in evaluating the application of our results to other regions because of the large variability and uncertainty resulting from high environmental heterogeneity in predictions of fire-occurrence pattern. Especially, a direct assessment of temporal changes of environments would improve our understanding the changes of fire regimes. The temporal correlations analysis can reveal whether changes in environments precede or postdate changes in fire regimes. This is especially true for landscapes that experienced significant temporal changes in environments and fire regime patterns.

5. Conclusions

Fires are not randomly distributed in the Chinese boreal forests. Human activity is secondary to climate as the primary fire occurrence factors at regional and landscape scales. Climate effects at the landscape scale were generally less important than those at the regional scale. The identified fire occurrence hotspot where most ignitions occur provides useful information for prioritizing management locations.

Human activity factors vary in space and change over time. Human factors will likely be modified in the future through increased settlement, road network expansion, and other development processes in a rapid developing region. Therefore, building useful and flexible models of future fire occurrence should be based on the scenarios of changes in human activity factors as well as climate change.

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