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The driving factors and their interactions of fire occurrence in Greater Khingan Mountains, China

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Abstract: Fire is an important disturbance in terms of forest management. A comprehensive understanding of the relationships between the spatial distribution of fire occurrence and its driving factors are critical for effective forest fire management. To reveal biogeoclimatic and anthropogenic influences, this study introduced a geographical detector model to quantitatively examine the effects of multiple individual factors and their combinations on spatial patterns of fire occurrence in the Greater Khingan Mountains between 1980 and 2009. The geographical detector computes the explanatory power (q value) to measure the connection between driving factors and spatial distributions of fire occurrence. Kernel density estimation revealed the spatial variability of fire occurrence which was impacted by bandwidth. 30 km might be the optimal bandwidth in this study. The biogeoclimatic and anthropogenic effects were explored using topography, climate, vegetation, and human activity factors as proxies. Our results indicated that solar radiation had the most influence on the spatial pattern of fire occurrence in the study area. Meanwhile, Normalized Difference Vegetation Index, temperature, wind speed, and vegetation type were determined as the major driving factors. For various groups of driving factors, climate variables were the dominant factors for the density of fire occurrence, while vegetation exerted a strong influence. The interactions between the driving factors had a more significant impact than a single factor. Individually, the factors in the topography and human activity groups exhibited weaker influences. However, their effects were enhanced when combined with climate and vegetation factors. This study improves our understanding of various driving factors and their combined influences on fire occurrences of the study area in a spatial context. The findings of this study verify that the geographical detector is applicable in revealing the driving factors of fire occurrence.

Keywords: Fire occurrence; Driving factors; Interactions; Geographical detector; Greater Khingan Mountains

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Introduction

Fire plays a primary role in shaping fire-prone forest ecosystems (Amatulli et al. 2007; de Groot et al. 2013; Hu and Zhou 2014). Forest fires have long-term effects on species composition, structure, succession, and regeneration (Beck et al. 2011; Yi et al. 2013). Meanwhile, fires present serious threats to social systems, causing loss of life and damage to property (Syphard et al. 2012, 2013). Forest fire management requires an understanding of the spatial characteristics of fire occurrence patterns and a quantification approach for assessing the relative importance of various driving factors at a regional scale (Mundo et al. 2013).

Fire occurrence is a complex process (Yang et al. 2007). Its spatial distribution is regulated by ignition agents and the environment (Faivre et al. 2014). Fire occurrence is affected by multiple factors, such as climate, weather, vegetation, topography, and human activity. Climate is generally considered as a top-down control for fire patterns (Fan et al. 2017). Weather conditions are more important when predicting short-term fire behavior on an hourly or daily basis (Hawbaker et al. 2013) and determine the probability of ignition and spread (Littell 2018). Vegetation provides fuel in the form of live and dead plants. The flammability of the fuel is also determined by physical properties of vegetation. Topographical factors influence the spatial variability of fuel moisture and consequently affect fire occurrence (Lafon et al. 2007). Human activity factors may change the spatial patterns of fire occurrence because human-caused fires generally occur in proximity to roads and in areas with moderate road density due to accessibility (Faivre et al. 2014).

Studies have examined the driving factors of fire occurrence in various regions using quantitative methods, such as the Poisson point process model (Yang et al. 2007; Liu et al. 2012), the classification and regression tree (Flatley et al. 2011), random forest (Wu et al. 2014; Rihan et al. 2019), logistic regression (Fan et al. 2017), and Poisson regression (Faivre et al. 2014). These methods can quantitatively reveal the effects of different factors on fire occurrence. However, two challenges have been observed. First, multicollinearity is common among various explanatory variables (Verdú et al. 2012), which can generate uncertainties in quantifying the contributions of individual factors. Although the variance inflation factor (VIF) has been used to reduce the multicollinearity effects and optimize the selection of the variables for models (Chen et al. 2015, Verdú et al. 2012, Wu et al. 2014), a reliance on VIF values could cause powerful explanatory variables for fire occurrence to be missed. For instance, Wu et al. (2014) found that duff moisture content showed strong multicollinearities within the climatic variable group (VIF=43.4). However, one study indicated that duff moisture content was the most significant predictor of fire occurrence (Wotton and Martell 2005). Moreover, different VIF value have been used to select the driving factors in various studies (Chen et al. 2015; Verdú et al. 2012; Wu et al. 2014). Thus, the development of a new method that avoids multicollinearity among independent explanatory variables is needed. In addition, the need for improvements to quantitative approaches for assessing the effects of interactions has been recognized (Cary et al. 2006; Dillon et al. 2011; Falk et al. 2007). Rollins et al. (2002) suggested that topography, vegetation, and climate acted together on the spatial patterns of fire occurrences. Abatzoglou and Williams (2016) indicated that the changes in fire activity due to climate were modulated by the co-occurrence of changes in land management and human activity. There is a lack of evidence demonstrating that various factors interact to amplify or deamplify their influence on fire occurrence patterns (Flatley et al. 2011; Hawbaker et al. 2013). Using a quantitative model to identify the complex interactions among various factors that affect fire occurrence is a critical concern.

Geographical detector can describe the relationship between geographical phenomena and driving factors without any linear hypotheses or restrictions (Wang et al. 2010). Initially, this method was developed to detect control factors underlying neural tube defect incidences. In the context of medical geography, the method has been applied to assess the spatial association between dissection density and environmental factors (Luo et al. 2016), identify the relationship between planting patterns and residual fluoroquinolones in soil (Li et al. 2013), and explore the impacts of physical and socioeconomic factors of built-up land expansion (Ju et al. 2016). The geographical detector method can quantitatively characterize the separate effects of factors on geographical phenomena and avoids the multicollinearity among the driving factors. Moreover, this method can be used to quantitatively probe the interactive effects between different variables on geographical phenomena.

A large number of forest fires occurred in Greater Khingan Mountains in recent decades (Zhong et al. 2003). This area is considered a notably fire-prone region in China (Liu et al. 2012). The fire suppression policy has altered the fire regimes in this region (Chang et al. 2008). The management operations on forest fire suppression have been invested in infrastructures, such as lookout towers, fire extinguishing planes, and fire barrier systems. At present, 98% of the total area is monitored by lookout towers in the Greater Khingan Mountains, and a team of fire-inspectors is deployed during the fire season. In addition, prescribed burns have been used to reduce fuel loads at assigned locations. Three homogeneous fire environment zones have also been defined for designing fire management plans (Wu et al. 2015). The interactions among driving factors of fire occurrence across the heterogeneous region are complex. A comprehensive understanding of the relative effects of various factors on the spatial pattern of fire occurrence is necessary to improve forest management plans. Consequently, the study area offers a good opportunity to identify the influences of individual factors and their interactions on the spatial pattern of fire occurrence by using the geographical detector method.

The primary objective of this study was to quantitatively explore the spatial association between fire occurrence and the driving factors based on historical fire records and multisource biogeoclimatic and anthropogenic data. We addressed the following questions: (1) what were the driving factor and their relative importance in determining the spatial distribution of fire occurrence in the Greater Khingan Mountains? and (2) what would be the interactive influences between pairs of driving factors on fire occurrence?

1 Materials and Method

1.1 Study area

The Greater Khingan Mountains are situated in the Northeast China on the border with Russia (Figure 1). The study area covers a total area of 8.32×10^4 km^2 and lies between 50°33′-53°32′ N and 121°9′-127°0′ E. The elevation varies from 150 to 1500 m above sea level. A large proportion (81%) of the study area is covered by forested land. This interior region is characterized by a cool continental monsoon climate with long cold winters and short warm summers. The average annual temperature and precipitation range from -4°C to -2°C and 350 to 500 mm, respectively (Hu and Zhou 2014). The study area spans two ecozones according to the Terrestrial Ecoregions of the World (Olson et al. 2001), with conifer and mixed forests observed in the west and east, respectively. Dominant tree species include Dahurian larch (*Larix gmelini* (Rupr.) Kuzen), Scotch pine (*Pinus sylvestris* Linn. var. *mongolica* Litvinov), Korean spruce (*Picea koraiensis* Nakai), Japanese white birch (*Betula platyphylla*), two species of aspen (*Populus davidiana* Dode and *Populus suaveolens* Fisch.), and Mongolian oak (*Quercus mongolica* Fisch. Ex Ledeb.) (Fang et al. 2015).

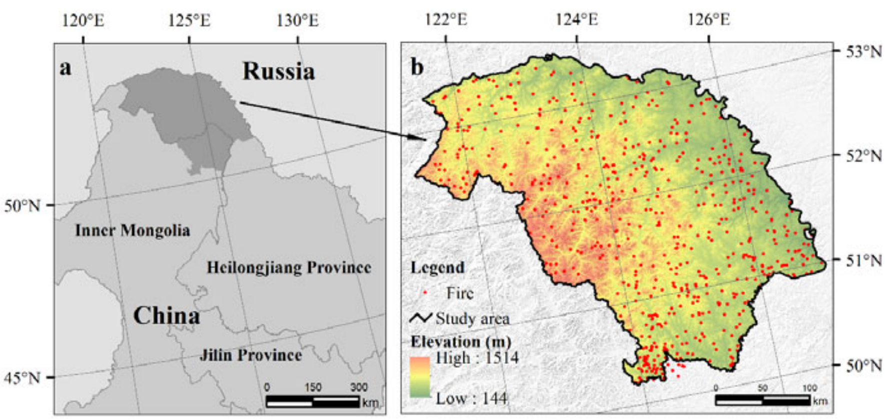

Figure 1 Map of the study area showing (a) extent of the Greater Khingan Mountains in Northeast China (dark gray area) and (b) locations of fire ignitions during 1980-2009 as displayed on top of the DEM image.

Surface fires are the main forest fires in the Greater Khingan Mountains (Xu 1998). Fire occurrences have been frequent with low intensity (Yi et al. 2013). According to the historical fire records, the fire return interval ranged from 15 to 120 years for various tree species between 1971 and 1980 (Zheng et al. 1986). The fire return interval has extended to ~500 years due to the fire suppression policy since the 1950s. Moreover, fires have become infrequent, but more intense than before (Chang et al. 2007; Liu et al. 2012). Fire occurrence obviously exhibits seasonal differences in the study area, with more ignition events occurring in the spring and fall. Therefore, two fire seasons are designated every year: from 15 March to 15 June and from 15 August to 15 November (Chang et al. 2007).

1.2 Data

1.2.1 Fire occurrence records

Fire occurrence records were collected by forest managers and provided by the forest and grass fire prevention agency of Heilongjiang Province. A total of 607 fire events were recorded during the period 1980-2009 (Figure 1). Unfortunately, these records provide incomplete information about the causes of ignitions.

1.2.2 Driving factors

Based on an extensive literature review and available data, sixteen potential driving factors were chosen for the study area (Table 1).

The elevation at a 30-arc-second (approximately 1 km²) spatial resolution was derived from the GTOPO30 digital elevation model (DEM) product (Figure 2), which was available on line through the USGS (https://earthexplorer.usgs.gov/). The aspect and slope surfaces were created by the DEM dataset using the surface toolbox of the ArcGIS 10.3 program (Figure 2). Slope was expressed in units of degrees. Aspect was divided into eight aspect classes (Figure 2). The TPI was calculated from the DEM as the difference between a cell elevation value and the average elevation of the neighborhood around that cell in a

Table 1 Driving factors used to explain the spatial pattern of fire occurrence in the Greater Khingan Mountains, China.

Category	Factor	Data source
Topography	Elevation (Faivre et al. 2014, Fan et al. 2017, Liu et al. 2012, Parisien and Moritz 2009, Prasad et al. 2008, Verdú et al. 2012, Wu et al. 2014)	Global topography data (GTOPO30)
	Aspect (Faivre et al. 2014, Parks et al. 2011, Verdú et al. 2012)	GTOPO30
	Slope (Prasad et al. 2008; Liu et al. 2012; Verdú et al. 2012; Faivre et al. 2014; Wu et al. 2014; Fan et al. 2017)	GTOPO30
	Topographic position index (TPI) (Prasad et al. 2008; Liu et al. 2012; Verdú et al. 2012)	GTOPO30
	Slope position (Prasad et al. 2008; Flatley et al. 2011)	GTOPO30
	Geomorphology	Geomorphology Map of the People's Republic of China (1:1,000,000)
Climate	Annual total precipitation (Fan et al. 2017, Liu et al. 2012, Prasad et al. 2008, Verdú et al. 2012, Wu et al. 2014)	WorldClim Version2.1
	Annual mean temperature (Liu et al. 2012, Prasad et al. 2008, Verdú et al. 2012, Wu et al. 2014)	WorldClim Version2.1
	Daily mean solar radiation (Parisien and Moritz 2009, Verdú et al. 2012)	WorldClim Version2.1
	Mean wind speed (Fan et al. 2017)	WorldClim Version2.1
Vegetation	Vegetation type (Liu et al. 2012, Parisien and Moritz 2009, Rollins et al. 2002, Wu et al. 2014)	Vegetation Map of the People's Republic of China (1:1,000,000)
	Normalized difference vegetation index (NDVI) (Hawbaker et al. 2013; Fan et al. 2017)	Global Inventory Modeling and Mapping Studies (GIMMS) 3g V1
Human activity	Population density (Faivre et al. 2014, Narayanaraj and Wimberly 2012, Prasad et al. 2008)	1-km Gridded population of China
	Distance to the nearest settlement (Liu et al. 2012; Faivre et al. 2014; Wu et al. 2014)	National Geomatics Center of China (NGCC)
	Distance to the nearest road (Faivre et al., 2014, Fan et al. 2017, Liu et al. 2012, Narayanaraj and Wimberly 2012, Wu et al. 2014)	NGCC
	Road density (Faivre et al. 2014, Fan et al. 2017, Liu et al. 2012, Narayanaraj and Wimberly 2012)	NGCC

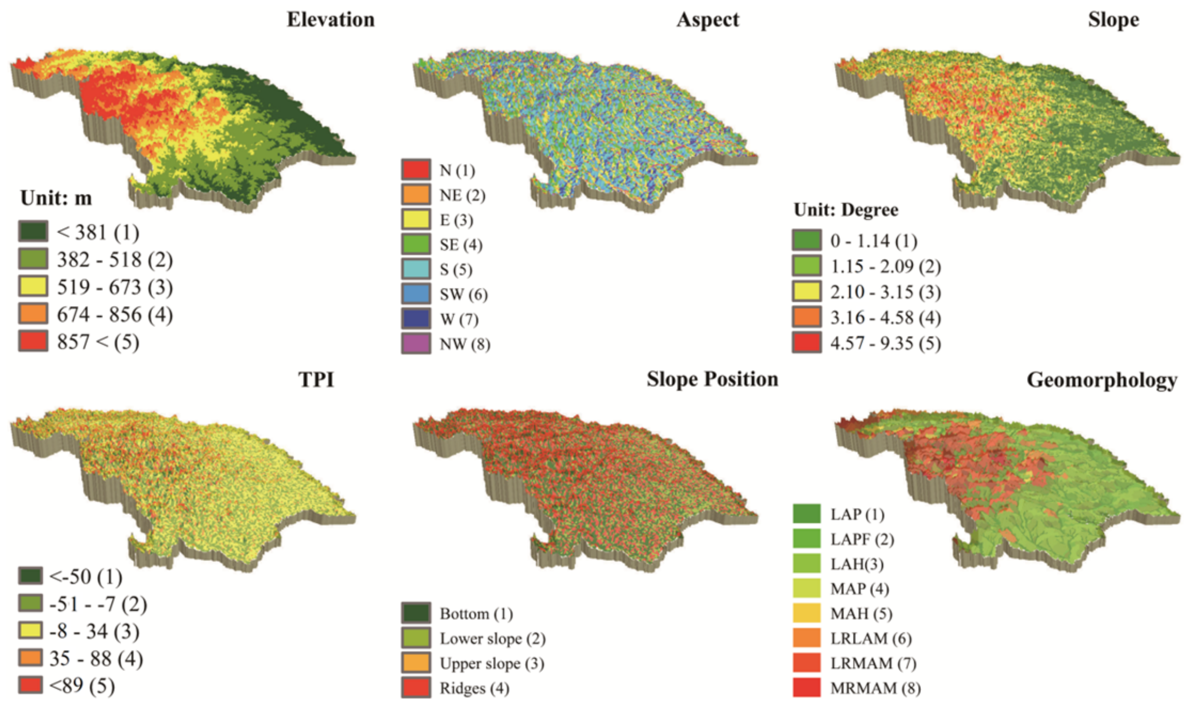

Figure 2 Spatial pattern of the topographical factors. The numbers in parentheses in the legends indicate the rank of categories for each driving factor. For the geomorphology, LAP= low altitude plain; LAPL=low altitude platform; LAH=low altitude hill; MAP=middle altitude plain; MAH=middle altitude hill; LRLAM=low relief low altitude mountain; LRMAM=low relief middle altitude mountain; and MRMAM=middle relief middle altitude mountain.

3×3 pixel window (Figure 2) (Prasad et al. 2008). SAGA 7.7 software was employed to calculate TPI. The slope position was a combination of the TPI and slope, and the landscape was classified into four categories based on the slope and TPI (Weiss 2001): ridge (TPI > 8), upper slope (-8 < TPI ≤ 8 and slope ≥ 6°), lower slope (-8 < TPI ≤ 8 and slope < 6°), and bottom (TPI ≤ -8) (Figure 2) (Prasad et al. 2008). The geomorphology was freely downloaded from the Resources and Environmental Data Cloud Platform (http://www.resdc.cn) as a polygon shapefile (Figure 2) (Cheng et al. 2011).

The annual total precipitation, annual mean temperature, daily mean solar radiation, and mean wind speed were selected as climatic variables (Figure 3). Those climate variables were masked from gridded WorldClim Version 2.1 datasets, which were interpolated at 30-arc-second (approximately 1 km^2) resolution over the period 1970-2000 (Fick and Hijmans 2017). The global WorldClim dataset was obtained from a website (http://www.worldclim.org/). The original data were monthly values of precipitation and mean temperature. Thus, monthly precipitation and mean temperature were used to calculate the annual total precipitation and annual mean temperature, respectively.

The dataset of vegetation types was acquired from a digital map originally published by the Chinese Academy of Sciences in 1982, and it was employed as a proxy dataset for the surface fuel map because the fuel conditions were difficult to describe (Fang et al. 2015). Vegetation types were represented by a number of polygons (Figure 4). The vegetation cover of the study area consists of needleleaf forests, needleleaf and broadleaf mixed forests, broadleaf forests, scrubs, marshes, meadows, and cropland. It was assumed that the vegetation within the study area was unchanged during the study period because primary tree species were planted in the burned and harvested areas by forest managers (Wu et al. 2014). The GIMMS 3g V1 NDVI dataset was available from the National Aeronautics and Space Administration Ames Ecological Forecasting Lab (https://ecocast.arc.nasa.gov/data/pub/gimms/). This dataset has a 15-day interval and spatial resolution of 1/12° (approximately 8 km^2). Maximum value composition was used to obtain the annual NDVI. Then, the NDVI was calculated based on the mean annual NDVI during the period 1982-2009 (Figure 4).

The population density, distance to the nearest settlement, distance to the nearest road, and road density were considered to represent human activity (Figure 5). Population density data were masked from the Gridded Population of China dataset at a 1 km² resolution that was also obtained from the Resources and Environmental Data Cloud Platform. The vector datasets of settlements and major roads were obtained from National Geomatics Center of China (NGCC) (http://www.ngcc.cn/) at a 1:1,000,000 scale. The transportation network included province, county, and town level roads but not local road systems. We calculated the Euclidean distance from each cell centroid of the fire density map to the nearest road and settlement. The road density was estimated at the 1 km² grid cell level.

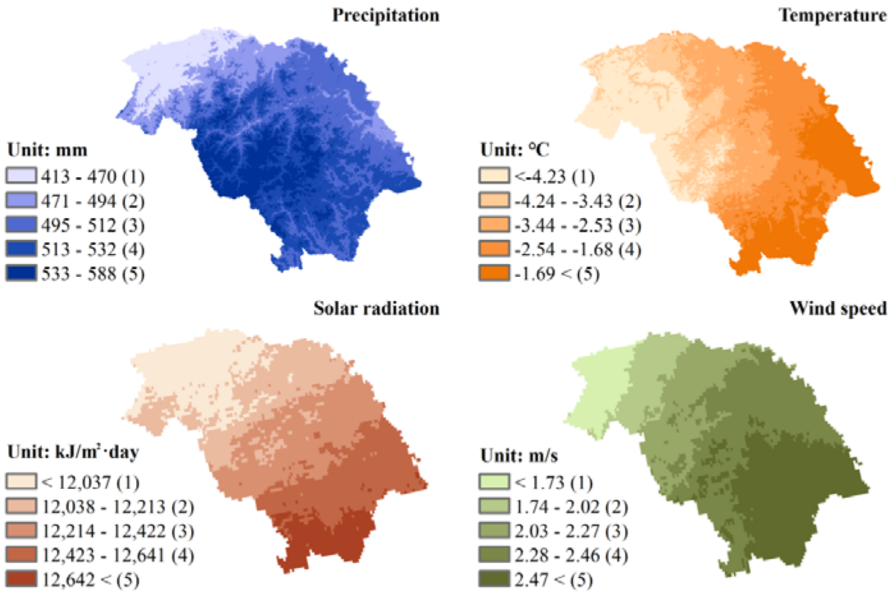

Figure 3 Spatial pattern of climate factors. The numbers in parentheses of legends indicate the rank of categories for each driving factor.

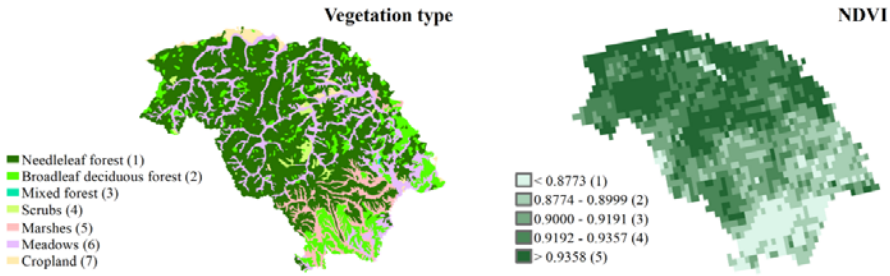

Figure 4 Spatial pattern of two vegetation factors. The numbers in parentheses of legends indicate the rank of categories for each driving factor.

1.3 Analysis

1.3.1 Fire occurrence density

The location of fire ignition was not a precise geographical position as it was the post-fire record. A continuous surface is able to minimize the effect of fire location uncertainty (Amatulli et al. 2007). Kernel density estimation (KDE) was employed to model the distribution of fire occurrences in the Greater Khingan Mountains in this study. The KDE method takes into account the symmetric probability density function for each point location to produce a smooth cumulative density function (Amatulli et al. 2007). The normal distribution function has been selected in the study. The size of bandwidth considerably influences the surface of the spatial fire pattern. Several methods were introduced to define the appropriate size of bandwidth in this study, including mean random distance (Riva et al. 2004; Koutsias et al. 2004), Silverman's rule of thumb (Silverman 1986), Scott's rule of thumb (Scott 1992), cross-validation (Diggle 1985), and likelihood cross-validation (Loader 1999). Bandwidth parameters derived from various methods were calculated using the 'spatstat' package in R statistical software. Fire occurrence surface of KDE were formed the data output at a spatial resolution of 1 km.

1.3.2 Effects of driving factors

The effects of driving factors on fire occurrence density were examined using the geographical detector. This method is suitable for study area with strong spatial heterogeneity (Wang et al. 2016). According to the principle of the geographical detector (Figure 6), fire occurrence density should exhibit a spatial pattern similar to that of a driving factor responsible for fire occurrence (Wang et al. 2010). Geographical detector belongs to analysis of variance scope (Wang and Xu 2017). Unlike the traditional regression model, the geographical detector method has no linear assumptions or restrictions, such as the homogeneity of variances or independent error. Therefore, it is not necessary to consider multicollinearity among the explanatory variables since their effect intensity is tested separately (Zhan et al. 2017). The method can detect implicit interrelationships between driving factors and fire occurrence density with respect to the explanatory and response variables (Xu 2017). The geographical detector includes four detectors: the factor detector, risk detector, interaction detector and ecological detector. In this study, the first three detectors were selected in the analysis.

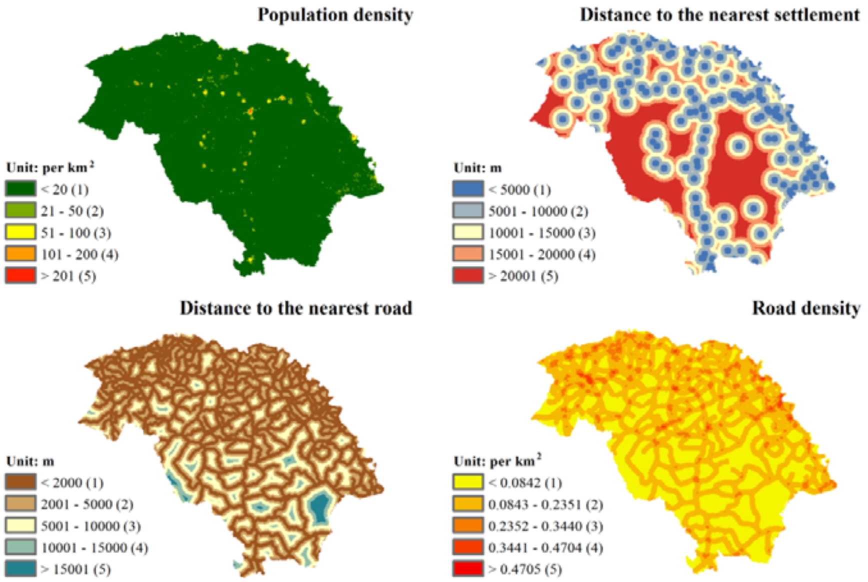

Figure 5 Spatial pattern of four human factors. The numbers in parentheses of legends indicate the rank of categories for each driving factor.

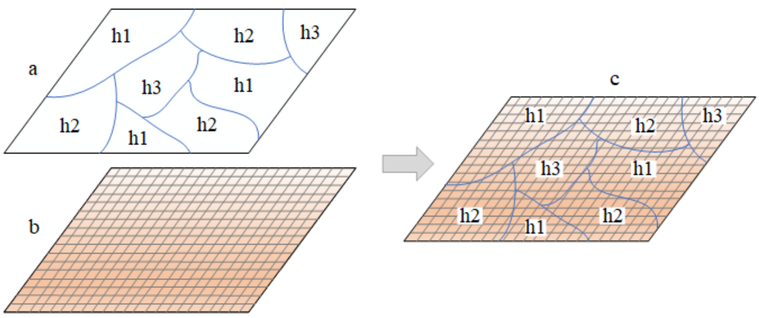

Figure 6 Illustration of the geographical detector, including (a) the classified map representing the driving factor x_i; (b) the grid layer representing the response variable y; and (c) the overlay of driving factor x_i and response variable y. There are three categories denoted by h_1, h_2 and h_3 (L=3) for driving factor x_i; eight units (N=8) in the study area; and there are three, three and two units for categories h_1, h_2 and h_3, respectively (N_{h1}=3, N_{h2}=3, and N_{h3}=2).

The geographical detector can accommodate explanatory variables that are categorical variables (e.g., vegetation type) and quantitative variables (e.g., elevation). However, quantitative variables should be segmented into various categories. The aspect, slope position, geomorphology and vegetation type were categorical variables with eight, four, eight, and seven classes each, respectively. A portion of quantitative variables, i.e., elevation, slope, TPI, precipitation, temperature, solar radiation, wind speed, NDVI, and road density, were segmented into five categories each using the natural break method. The rest of quantitative variables, i.e., population density, distance to the nearest settlement, and distance to the nearest road were also segmented into five categories based on spatial variation. The selection of five categories to discrete quantitative variables was based on reported applications of geographical detector review. There were fewer categories in the study area, which might lead to an inefficient ability to reflect the spatial heterogeneity of fire occurrence. In contrast, there were more categories that could scatter the data. The natural break method can help identify the minimum and maximum variance within and among intervals. The polygons or pixels with the same attribute were aggregated as a category for a driving factor. Each polygon or continuous pixels with same the attribute were considered to be a unit. Categorized attributes of all driving factors were extracted for each cell of fire occurrence density. The density values of all cells and their attributes of all driving factors were inputted into the geographical detector software which was obtained from http://www.geodetector.org/.

In the geographical detector model, the factor detector was used to quantify the degree of the separate effect of each driving factor on the observed spatial pattern of fire occurrence density. The factor detector is used to explore driving factors by comparing the variances of fire occurrence density in different categories with the variance of fire occurrence density over the entire study area. If a factor is a determinant of fire occurrence density, then the dispersion variance of the fire occurrence area of each category is small; otherwise, the variance between categories is large. Initially, the effect of a factor was generally measured by the power of determinant (PD) value in the factor detector (Wang et al. 2010). The PD value was recently renamed the q statistic and is defined as follows (Wang et al. 2016):

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2 \tag{1}$$

$$\sigma^2 = \frac{1}{N-1}\sum_{m=1}^{N}\left(y_m - \overline{y}\right)^2 \tag{2}$$

$$\sigma_h^2 = \frac{1}{N_h - 1}\sum_{k=1}^{N_h}\left(y_{h,k} - \overline{y_h}\right)^2 \tag{3}$$

where N represents the number of units in the study area for a certain driving factor; σ^2 represents global variance of fire occurrence density in the entire study area; h=1, 2, 3, ... , L, with L representing the number of categories of the driving factor, i.e., L is 8 for aspect (Figure 2) and L is 5 for temperature (Figure 3); N_h represents the number of units in category h; σ_h^2 represents the local variance of category h; y_m represents the value of the m^{th} unit from the entire study area; y is the global mean of y over the entire study area; $y_{h,k}$ represents the value of the k^{th} unit of y in category h; and $\overline{y_h}$ represents the local mean of y in category h. The value of q is typically within the range [0,1], with values close to 1 indicating that a factor has a strong influence on fire occurrence density and values close to 0 indicating a weak influence on fire occurrence density. Therefore, the q value represents the determinant power or relative importance of a factor. The corresponding p-value is based on a noncentral F-distribution (Wang et al. 2016).

The risk detector was used to search for the fire-prone areas in the Greater Khingan Mountains. In this study, risk is identified by magnitude of average fire occurrence density in a category for a certain driving factor. Meanwhile, the risk detector can be used to examine whether the density of fire occurrence was significantly different between any two categories for each factor based on a t-test.

The interaction detector was used to identify whether any two driving factors impart synergistic effects on the spatial pattern of fire occurrence density in the Greater Khingan Mountains. The interaction between two driving factors x_i and x_j is assessed by comparing values of interaction q_{ij} with values of q_i and q_j, where q_{ij} is the power of determinant for a new factor created by overlaying factors x_i and x_j (Figure 7). There may be three primary types of interaction relationships, including combined weakened effects, combined enhanced effects, and completely independent effects on spatial patterns of fire occurrence. In detail, the interaction detector can define seven

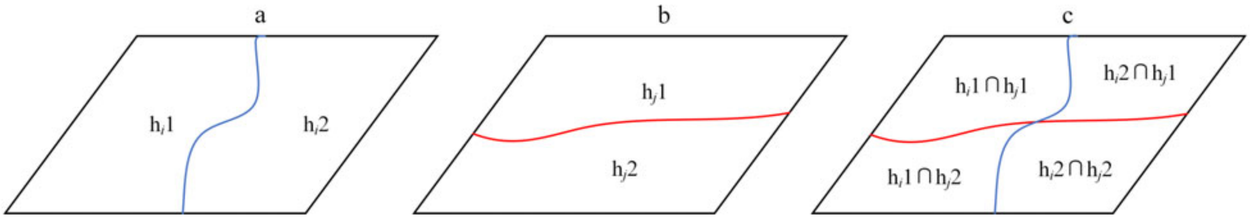

Figure 7 Illustration of the interaction effects using the geographical detector method: (a) layer of driving factor x_i; (b) layer of driving factor x_j; (c) a new layer created by overlaying driving factors x_i and x_j $(x_i \cap x_j)$. Then, the q value of the new factor is calculated vis Eq. (2).

interaction relationships (Table 2).

2 Results

2.1 Fire occurrences modeling

The bandwidth parameters estimated from mean random distance, likelihood cross-validation, cross-validation, Scott's rule of thumb, and Silverman's rule of thumb are 5853 m, 11,168 m, 12,770 m, 31,635 m, and 32,562 m, respectively. To perform a visual-subjective evaluation, KDE was applied using seven alternative bandwidths, those of 5 km, 10 km, 15 km, 20 km, 25 km, 30 km, and 35 km (Figure 8). The maximum densities for various surface decrease with bandwidths increasing. There are scattered patterns of fire occurrences using a less than or equal to bandwidths of 15 km. Meanwhile, the fire ignition density explicitly presents spatial patterns of fire occurrence variability when the bandwidths are over 20 km. Koutsias et al. (2004) suggested that an appropriate bandwidth produced density estimates whose values tend to follow a normal distribution. Therefore, a Kolmogorv-Smirnov test was used to test whether the estimates follow a normal distribution. Results of the test indicated that the bandwidth of 30 km was appropriate to be estimated fire occurrence density in the study area.

2.2 Sensitivity of the geographical detector to bandwidths of KDE

In order to understanding sensitivity of the geographical detector for different smooth surfaces, factor detector was applied to various fire density surfaces which were derived from seven alternative bandwidths of KDE (Figure 9). The q values of all the driving factors are statistically significant (p<0.01) for various fire density surfaces. Most of the q values for single driving factor tended to increase with increasing bandwidths, with exception of those for geomorphology and four human activity factors. The q values and ranks of geomorphology showed distinctly instable for fire density surface derived from various bandwidths. The bandwidths of KDE primarily impact on explanatory power of driving factors. Note that the factors with relatively high q values displayed similar ranks when factor detector was applied for fi re density surfaces at the bandwidths of 30 and 35 km. Taking into account appropriate bandwidth and the sensitivity of geographical detector to bandwidths, the fire density surface derived from 30 km bandwidth was used for the following analysis.

Table 2 Seven potential interactions between pairs of driving factors and the relationships between individual q values and the interactive q value of any two factors (Xu 2017).

Interaction relationship	Description
Nonlinear weakness	q (A ∩ B) < q (A) and q (B)
Univariate weakness	q (A ∩ B) < q (A) or q (B)
Weakness	q (A ∩ B) < q (A) + q (B)
Enhancement	q (A ∩ B) > q (A) or q (B)
Bivariate enhancement	q (A ∩ B) > q (A) and q (B)
Nonlinear enhancement	q (A ∩ B) > q (A) + q (B)
Independent	q (A ∩ B) = q (A) + q (B)

Note: the symbol '∩' denotes the interaction between A and B.

2.3 Factor detector

The factor detector was used to determine the relative influence of single driving factors on the incidence of fire. Solar radiation shows the biggest q value (0.2381) among all factors, indicating that it is the most influential factor on fire occurrence density over the period 1980-2009. The q values of four other factors (NDVI, temperature, wind speed, and vegetation type) were relatively high with values ranging from 0.1044 to 0.1756. We consider these five variables with q values greater than 0.1 as being the major driving factors determining the spatial patterns of fire occurrence in the study area. It is notable that all major determinants are climate and vegetation factors. The contribution of topographic and human activity factors is clearly lower than the contribution of climate and vegetation factors. To compare the relative influence of the topographic, climatic, vegetation, and human activity variables on the spatial pattern of fire occurrence, we calculated the average q values for various groups of driving factors. In descending order, the average q values of climate, vegetation, topography, and human activity factors are 0.1470, 0.1400, 0.0169, and 0.0070, respectively.

2.4 Risk detector

We used the risk detector to investigate the density of fire occurrences for various categories of the major driving factors in the Greater Khingan Mountains (Table 3). The highest density of fire occurrence (0.0113 per km²) was found in a region with greater than 12,641 kJ/m²·day (rank 5) of solar radiation. A relatively high density of fire occurrence (greater than 0.01 per km²) was observed in a category where the NDVI is less than 0.8773 (rank 1) and in mars hes vegetation types (rank 5). The fire occurrence density increases with increasing solar radiation in the study area. In contrast, the fire density increases with decreasing NDVI. Furthermore, significant differences in the magnitude of the average fire occurrence density are common in various categories for the major driving factors.

2.5 Interaction detector

The interaction detector was used to examine the combined effects of two factors on the density of fire occurrence in the Greater Khingan Mountains (Figure 10). In total, 120 pairs of interactions existed between any two factors in this study. All interaction relationships showed either bivariate or nonlinear enhancement. The interactive q value of solar radiation and wind speed was the biggest (0.3476), whereas the q values of the interactions between solar radiation

Table 3 Power of determinant of all selected driving factors for the spatial pattern of fire occurrence density.

Factor	q	Factor	q
SolRad	0.2381	DisSet	0.0195
NDVI	0.1756	Slope	0.0083
Temp	0.1454	PopDen	0.0041
WinSpd	0.1084	TPI	0.0035
Veg	0.1044	Aspect	0.0031
Prec	0.0960	RdDen	0.0027
Elevation	0.0458	DisRd	0.0018
GeoMop	0.0367	SloPos	0.0010

Note: Factors with underlines are considered to be major driving factors. SolRad = daily mean solar radiation; NDVI = normalized difference vegetation index; Temp = annual mean temperature; WinSpd = mean wind speed; Veg = vegetation type; Prec = annual total precipitation; GeoMop = geomorphology; DisSet = distance to the nearest settlement; PopDen = population density; TPI = topographic position index; RdDen = road density; DisRd = distance to the nearest road; and SloPos = slope position.

and elevation and distance to the nearest settlement exceeded 0.3. Over 70% of the interactions exhibited nonlinear enhancement. For instance, the q value of the NDVI was 0.1756 and that of the wind speed was 0.1084. The sum of the individual q values of NDVI and wind speed (0.2840) was lower than the interactive q value between the NDVI and wind speed (0.2960). Nevertheless, the interactions between climate and vegetation driving factors commonly showed bivariate enhancement, except the interaction between wind speed and solar radiation and NDVI, which exhibited nonlinear enhancement. For instance, the q value of solar radiation was 0.2381,

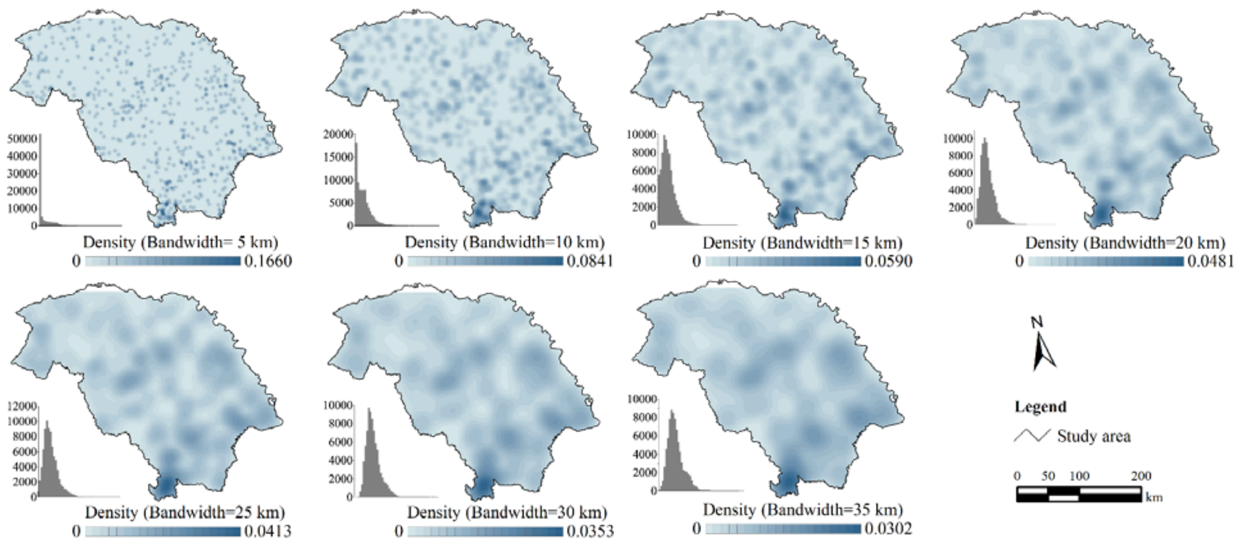

Figure 8 Fire occurrence density using the Kernel density estimation at various bandwidths in the Greater Khingan Mountains.

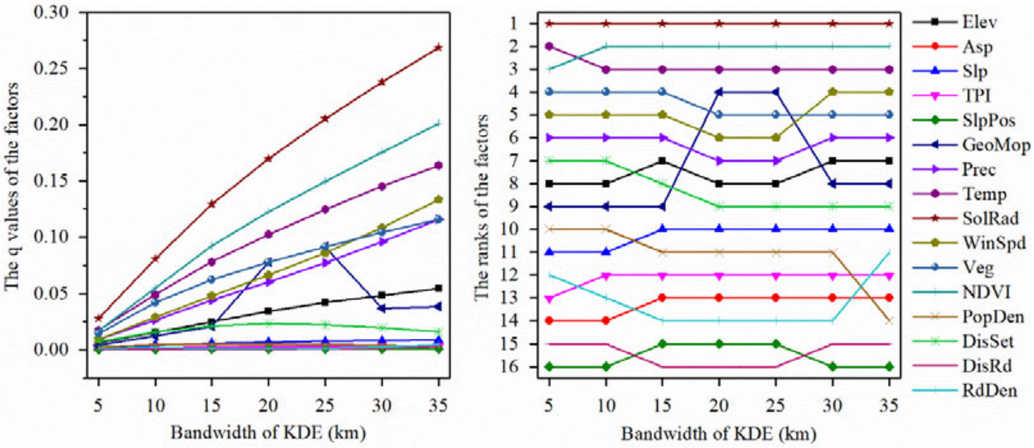

Figure 9 Sensitivity of q values and the ranks of the factors to fire density surfaces at various bandwidths. (KDE, Kernel density estimation)

	SolRad	**NDVI**	**Temp**	**WinSpd**	**Veg**	Prec	Elevation	GeoMop	DisSet	Slope	PopDen	TPI	Aspect	RdDen	DisRd
NDVI	0.2864														
Temp	0.2971	0.2687													
WinSpd	0.3476	0.2960	0.2222												
Veg	0.2722	0.2287	0.2054	0.1983											
Prec	0.2725	0.2454	0.2290	0.1524	0.1985										
Elevation	0.3053	0.2374	0.2187	0.1876	0.1597	0.1618									
GeoMop	0.2938	0.2255	0.1648	0.1722	0.1430	0.1645	0.0628								
DisSet	0.3041	0.2261	0.1582	0.1625	0.1615	0.1620	0.0669	0.0508							
Slope	0.2549	0.1897	0.1596	0.1229	0.1115	0.1062	0.0500	0.0395	0.0250						
PopDen	0.2481	0.1872	0.1503	0.1142	0.1220	0.1039	0.0523	0.0410	0.0221	0.0124					
TPI	0.2466	0.1838	0.1555	0.1179	0.1081	0.1055	0.0562	0.0380	0.0216	0.0112	0.0079				
Aspect	0.2440	0.1782	0.1515	0.1116	0.1109	0.1007	0.0529	0.0428	0.0266	0.0123	0.0088	0.0071			
RdDen	0.2514	0.1880	0.1526	0.1118	0.1187	0.0979	0.0635	0.0593	0.0404	0.0150	0.0104	0.087	0.0065		
DisRd	0.2512	0.1852	0.1503	0.1109	0.1139	0.0967	0.0592	0.0542	0.0323	0.0131	0.0065	0.075	0.0054	0.0036	
SlpPos	0.2405	0.1777	0.1485	0.1113	0.1070	0.1013	0.0551	0.0372	0.0203	0.091	0.0054	0.0038	0.045	0.0044	0.0035

Figure 10 All q values for interactions between any two driving factors on the spatial pattern of fire occurrence. Uncolored cells denote bivariate enhancement, and gray cells denote nonlinear enhancement. Factors with boldface are major driving factors. SolRad=daily mean solar radiation; NDVI=normalized difference vegetation index; Temp=annual mean temperature; WinSpd=mean wind speed; Veg=vegetation type; Prec=annual total precipitation; GeoMop=geomorphology; DisSet=distance to the nearest settlement; PopDen=population density; TPI=topographic position index; RdDen=road density; DisRd=distance to the nearest road; and SloPos=slope position.

while that of NDVI was 0.1756. The q value of the interaction between solar radiation and NDVI was 0.2864, which was higher than that of either factor alone (solar radiation or NDVI) but lower than the sum of the individual q values of solar radiation and temperature (0.4137).

3 Discussion

3.1 Determinants of fire occurrence

Previous study has shown that the q value is sensitive to the classification of quantitative variables but has not found an explicit relationship between q values and the classification method (Ju et al. 2016). Studies suggested that optimal classification algorithms and prior knowledge were needed to categorize the quantitative variables, which would improve the efficiency of the geographical detector (Wang et al. 2010; Xu and Zhang 2014). Hu et al. (2011) suggested that it be difficult to present the actual spatial associations between driving factor and geographical phenomena using an arbitrary classification approach. In this study, the natural break method and consideration of spatial variations were defined with optimal algorithms to categorize the quantitative variables. The natural break method generated the greatest similarity and differences within each and among various categories. With uneven human population distribution and characteristics of accessibility, the spatial variations were considered helpful to classify human activity factors. Therefore, our methods demonstrated are liability for discretizing quantitative variables.

The factor detector suggested that climate variables presented the greatest contribution to the spatial pattern of fire occurrence over the entire study area, followed by vegetation and topography, while human activity factors contributed the least. These findings are consistent with those of a previous study in which climate and vegetation were demonstrated to be the primary drivers underlying fire occurrence (Hawbaker et al. 2013). We expected that climate variables would have a strong influence on fire occurrence in the forest ecosystems at a regional scale. Wu et al. (2014) indicated that the density of fire occurrence was greatly affected by climate factors at regional and landscape scales in this area. Climate influences fire regimes through modulating fuel abundance, fuel flammability, or both (Abatzoglou and Williams 2016; Littell et al. 2018). It has been shown that climate factors are not only a strong driver of spatial distributions but also affect the temporal patterns of fires (Flatley et al. 2011). Consequently, long-term climate trends play a top-down control role in fire disturbances in forest ecosystems. Climate is the most important determinant, suggesting that climate change may lead to future change in the spatial pattern of fire occurrence in the study area. Liu et al. (2012) predicted that the fire occurrence density in the boreal forest of Northeast China could increase by 30%-230% by the end of the 2100s due to climate change. Moreover, climate change might substantially increase the occurrence of lightning-ignited fires in summer (Fan et al. 2017). The greater importance of biogeoclimatic factors compared to human activity factors reflect non-human-caused fires that dominate the spatial pattern of fire occurrence in the study area during the period 1980-2009. This agrees with previous study in this region. One study indicated that the number of lightning-caused fires accounted for more than 60% of fire incidents (Chen et al. 2015).

An unexpected finding was that solar radiation had the strongest influence on the spatial pattern of fire occurrences among all the driving factors in the Greater Khingan Mountains. Generally, potential solar radiation derived from slope and aspect has been used as a topographic variable for revealing fire regimes (Dillon et al. 2011; Parisien et al. 2013; Fang et al. 2015; Stralberg et al. 2018). In this study, solar radiation interpolated from weather station observations was regarded as climate variable. Observed solar radiation has been used as a predictor for fire suitability (Parisien and Moritz 2009). However, this study lacked attention to the impacts of solar radiation on the spatial pattern of fire occurrence. In the study of Verdú et al. (2012), solar radiation was discarded because strong multicollinearity was found between solar radiation and temperature. Our finding suggests that solar radiation should not be ignored. Solar radiation influences the moisture content of fuel via variations in slope and aspect (Zumbrunnen et al. 2012). Meanwhile, forest fuels can ignite due to the focused solar radiation effect (Baranovskiy and Yankovich 2015). The q values of temperature indicated that the driving factors have a considerable influence on the spatial pattern of fire occurrences. Solar radiation and temperature were more important than precipitation, implying that the study area was energy limited (Meyn et al. 2007). In general, temperature directly affects fuel moisture. High temperature reduces deal fuel moisture, and so as the fires occurrence. Our result suggested that wind speed has a substantial influence for long-term fire occurrence. The study area is characterized with high wind speed condition, which increases the flammability because of desiccation of fuel. Moreover, wind in term of fire weather also has a large effect on fire occurrence. Fan et al. (2017) reported that fire occurrences were generally accompanied by stronger winds in the fire season. According to the statistical data, 80% of the major fire events occurred along with a force of 5 (19-24 mph) wind speed in the study area (Hu 2011). Precipitation exhibited a weaker effect on spatial pattern of fire occurrence than other climate factors. Annual precipitation mainly falls in summer which is considered to be outside of the fire seasons in the Greater Khingan Mountains. However, precipitation could exert a major control on other term of the fire regime, such as burned area (Holden et al. 2018).

Studies have suggested that vegetation factors significantly affect fire occurrence (Liu and Wimberly 2015; Parisien et al. 2014; Rollins et al. 2002). Vegetation factors reflect the inherent variability of fuel physical properties, including composition, loading, moisture, and flammability. This study found that the NDVI and vegetation type had a considerable influence on the spatial pattern of fire occurrences. Generally, NDVI could be used to describe vegetation classes at a broad scale. The minimum NDVI value in the study area was 0.84, which suggested that the range of NDVI variation was not significant enough to be used to identify vegetation classes. Previous studies have shown that NDVI is well correlated with live fuel moisture content (Chuvieco et al. 2004; Yebra et al. 2008), which depends on vegetation physiological characteristics (Myoung et al. 2018). Correspondingly, the moisture content of dead vegetation is highly related to atmospheric variability (Yebra et al. 2008; Myoung et al. 2018). Therefore, we suggest that NDVI represents the spatial variability of live fuel moisture conditions in the study. Along with the results of the risk detector, there is a clear negative relationship between the NDVI and fire density (Table 4). Fuel moisture is a strong predictor of fire occurrence and significantly affects the occurrence of fires in the Chinese boreal forest region (Fan et al. 2017). Vegetation type is related to fuel composition. Marshes and broadleaf forests displayed a higher average density of fire ignition than the other vegetation types. The study area is located in a cold temperate zone, and low temperatures lead to frozen ground in the study area in the fire season (spring and autumn), while marsh plants are converted into withered grass. The main tree species in the broadleaf forests of this area are deciduous. Fuels such as forest litter and fallen leaves accumulate. Meanwhile, precipitation is insufficient in the fire season, resulting in decreasing fuel moisture. Therefore, both vegetation types are relatively flammable during the fire season. As driving factors that underlie the spatial pattern of fire occurrence, live moisture content is obviously more important than composition (Table 4) because live fuel is abundant across all vegetation types in our study area (Fang et al. 2015).

Topographical variables impact runoff, wind direction, and solar radiation, which in turn influence flammability through fuel moisture and production (Flatley et al. 2011). In the Greater Khingan Mountains, however, the average q value of the topographical factors was 0.0169, indicating that the topographical factors had a marginal effect on the spatial pattern of fire occurrences at a regional scale. Individual topographical factors play a limited role in the entire study area. The explanatory powers of slope and aspect were consistently ranked as the least important factors in determining fire occurrence based on a random forest model (Wu et al. 2014) since the study area has a relatively flat terrain and presents low spatial variation in the terrain. According to our results, the study area is located in a fire-prone climatic setting that may have weaker topographical patterns of fire than an area in a less fire-prone environment because climate modulates impacts of single topographical variable on spatial pattern of fire occurrence at regional scale (Flatley et al. 2011). However, topography may act as a local- and micro-scale driving factor on fire occurrence. A previous study reported that lightning-caused fires cluster in the Huzhong forestry bureau, which has the highest elevations in the Greater Khingan Mountains (Wu et al. 2014).

Studies have suggested that human activities alter the fire regime through fire ignition or suppression (Yang et al. 2007; Faivre et al. 2014). However, our results indicate that human activity factors had the lowest influence on the spatial pattern of fire occurrence in the Greater Khingan Mountains. Hu and Zhou (2014) reported that fire frequency and burned area of human-caused fires decreased significantly in this area over the period

Table 4 Average fire occurrence densities for each category of various major impact factors. The numbers in the first line represent the categories (ranks) for these driving factors.

Factors	1	2	3	4	5	6	7
SolRad	0.0042	0.0054	0.0066	0.0078	0.0113	-	-
NDVI	0.0107	0.0078	0.0068	0.0056	0.0053	-	-
Temp	0.0051	0.0059	0.0056	0.0077	0.0092	-	-
WindSpd	0.0055	0.0040	0.0054	0.0071	0.0080	-	-
Veg	0.0059	0.0084	0.0052	0.0068	0.0102	0.0066	0.0053

Note: SolRad=daily mean solar radiation; NDVI=normalized difference vegetation index; Temp=annual mean temperature; WinSpd=mean wind speed; Veg=vegetation type.

1967-2006, which implies that the influences of human activity factors on fire regimes have gradually weakened. In particular, a catastrophic fire burned a total area of approximately 1.3×10^4 km^2 in the study area in 1987 (Chang et al. 2007); since then, fire management and prevention have been more vigilant and enforced (Chang et al. 2007; Fan et al. 2017). Forest harvesting has also been strictly limited due to experiments in the Natural Forest Protection Project since 1998. This restriction has significantly reduced open sparks from logging machines and smoking loggers. Additionally, a number of protected areas have been established, such as the Huzhong National Natural Reserve, Nanwenghe National Natural Reserve, and Panzhong National Natural Reserve, greatly decreasing the impacts of anthropogenic disturbances in these protected areas.

The identification of zones of high fire risk in fire-prone areas is important. The results of the risk detector can provide useful information regarding fire occurrence density in various categories, and the distribution of the identified fire occurrence hotspots can offer effective benefits for optimizing the allocation of fire management resources (Gonzalez-Olabarria et al. 2012; Wu et al. 2014). According to the risk detector results (Table 4), management strategies should focus on known high-density zones, such as areas with high solar radiation and temperature and low NDVI. Moreover, significant differences typically occur among various categories for each major factor, which further reinforces that the fire occurrence spatial pattern is heterogeneous among the driving factors.

3.2 Interactions between pairs of factors on fire occurrence

Complex interactions generally exist in the driving factors that influence of fire occurrence patterns (Schoennagel et al. 2004). Thus, identifying how climate, topography, vegetation, and human activity factors mutually interact is important because these results are necessary for the management or prediction of fire occurrence. The geographical detector model fills a critical gap by providing a framework to quantitatively measure the interactions between pairs of driving factors, and this capability provides unique insight into the study of the spatial pattern of fire occurrence. Our study indicates that all interactions between pairs of driving factors had an enhancing influence on the spatial pattern of fire occurrence in the Greater Khingan Mountains. We found no case of independent or weakening interactions. This finding suggests that relative to the influence of individual factors, the interactions between driving factors played a more important role in shaping the spatial pattern of fire occurrence. The results of the interaction detector reveal that despite the weak influence of single topographical and human activity factors, the effects of interactions between any two groups should not be ignored. This work supports previous results that the interaction among climate, vegetation, topographical, and human factors together determine the spatial pattern of fire occurrence (Rollins et al. 2002; Hawbaker et al. 2013). Therefore, we suggest that comprehensive effects among various factors should receive greater attention rather than any single factor alone when forest managers make policy for fire management.

It has been demonstrated that interactions between top-down and bottom-up controls could result in a nonlinear relationship between fire activity and fire-induced ecological consequences (Peters et al. 2004). In the Greater Khingan Mountains, over 70% of the interactions between pairs of driving factors exhibited nonlinear enhancement, which mainly involves topography and human activity factors. According to Table 2, nonlinear enhancement is stronger than bivariate enhancement. Although single topographic and human activity factors have weak effects on the density of fire ignition events, these factors contributed more strongly to the spatial pattern of fire occurrence when they interacted with climate and vegetation factors, which indicates the importance of both group's factors. Human activities could play an important role in certain areas of the Greater Khingan Mountains. For instance, the Jiagedaqi District is located at the southwestern study area, which has the strongest fire occurrence density. It is the administrative center of the Greater Khingan Mountains Prefecture and has the highest human population density. Fire ignition records show that human activities are the main cause of fire occurrence in the Jiagedaqi District. Meanwhile, it is characterized by the higher solar radiation and temperature than elsewhere, which promotes the ignition of the biomass of broadleaf forests. Achard et al. (2008) found that two-thirds of fires were caused by the joint occurrence of climate anomalies and human disturbance in the Russian boreal forest. Timber harvesting and human activities in protected areas and forestlands have been restricted in the study area. However, with economic development, human activities correlate with infrastructure and built-up land expansion changes local climate patterns as a result of the enhanced interactive effect on fire activity. One study demonstrated that anthropogenic climate change, such as human caused increase in temperature and vapor pressure deficit, nearly doubled fire area in comparison to area burned expected from natural climate variability in the western US forest ecosystem (Abatzoglou and Williams 2016). Hu and Zhou (2014) suggested that high temperatures improve residents' awareness of fire safety regarding increased fire risk. The strength of topographic factors on the spatial pattern of fire occurrence trends varied according to the climatic context in the southern and central Appalachian Mountains (Flatley et al. 2011). Topographic relief and drainage can redistribute land surface heat and moisture, which are from solar radiation and precipitation, respectively. Massifs and vegetation reduce wind speed and change the wind direction. In additionally, wind reduces fuel moisture which can be characterized by NDVI. Therefore, appropriate climate and vegetation factors combined with topography and human activities further improve the explanation of the spatial pattern of fire occurrences in the Greater Khingan Mountains.

The interactive relationships between pairs of climate and vegetation factors in the study area generally exhibited bivariate enhancement, which is a weaker enhancement than nonlinear enhancement. In other words, climate and vegetation factors appropriately enhanced each other when driving the distribution of fire occurrences. This condition is likely due to the strengths of the linkages among climate and vegetation factors. The long-term climate determines the spatial pattern of major vegetation types (Liu and Wimberly 2015), i.e. climate controls the spatial distribution of fuels and fuel loads. Therefore, interactions between climate and vegetation factors merely enhance the effects of each factor on fire occurrence density.

4 Conclusions

The geographical detector is an effective method for analyzing the driving factors of spatial variations in fire occurrence density. In particular, the method is useful for quantitatively characterizing the interactions between a complex set of factors of fire occurrence. Our study shows that solar radiation plays the greatest role in fire occurrence in the Greater Khingan Mountains, followed by NDVI, temperature, wind speed, and vegetation type. According to variable groups, climate and vegetation variables rather than topography and humans are primary determinants of the spatial pattern of fire occurrence at a regional scale. Any pair of factors had a stronger influence on the spatial pattern of fire occurrence than any single factor. The interactions between most of the climate and vegetation factors generally showed bivariate enhancement whereas the interactions that involved topographical and human activity factors showed a nonlinear enhancement. Although the topographical and human factors alone had a weak influence on the spatial pattern of fire occurrence, this influence was enhanced when combined with climate and vegetation factors. The results offer a perspective for understanding the driving factors of the spatial patterns of fire occurrence. The approach of this study can be helpful to forest managers when implementing fire polices based on the influence of climate, vegetation, topography and human activities and their interactions.

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