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Evaluating forest fire probability under the influence of human activity based on remote sensing and GIS

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Abstract: Fires are an important factor involved in the disturbance of forest ecosystems, causing resource damage and the loss of human life. Evaluating forest fire probability can provide an effective method to minimize these losses. In this study, a comprehensive method that integrates remote-sensing data and geographic information systems is proposed to evaluate forest fire probability. In our analysis, we selected four probability indicators: drought index, vegetation condition, topographical factors and anthropogenic factors. To evaluate the influence of anthropogenic factors on fire probability, a distance analysis from fire locations to settlements or roads was conducted to see which distance was associated with a higher probability. The forest fire probability index (FFPI) was calculated to assess the probability level in Heilongjiang Province, China. According to the FFPI, five classes were identified: very low, low, moderate, high, and very high. A receiver operating characteristics (ROC) curve was used as the validation method, and the results of the ROC analysis showed that the proposed model performed well in terms of forest fire probability prediction. The results of this study provide a technical framework for the Department of Forest Resource Management to predict occurrence of fires.

Keywords: Forest fire probability; Geographic information system; Remote sensing; Natural hazards.

1. Introduction

Fire is considered to be one of the most important factors that disturb forest ecosystems (Cyr et al., 2007; Lecomte et al., 2006). Fires have both positive (Wagner and Fraterrigo, 2015) and negative (Sivrikaya et al., 2014; Somashekar et al., 2009) influences on forest ecosystems. In terms of positive aspects, fires can control understory growth (Burton et al., 2011), promote the growth of native plants and the recruitment of non-native species (Kuppinger et al., 2010). Regarding negative aspects, fires cause serious destruction to forest ecosystems, including the loss of biodiversity (Saranya et al., 2014), damage to landscape (Alencar et al., 2015), and alter vegetation structure and function (Pausas and Keeley, 2009). Additionally, forest fires can cause economic losses for people, including loss of property (Merlo et al., 2000), damage to agriculture, and even loss of human life (Pourghasemi et al., 2016). Considering the negative effects of fires, fires risks should be mitigated in some areas, and to achieve this, it is necessary to evaluate forest fire probability, which is an effective approach to monitor where and when a fire is more likely to happen (Chuvieco et al., 2014). As such, forest fire probability maps are helpful tools for forest managers, fire fighters and decision makers.

Many studies have conducted fire risk estimations in areas that are seriously affected by fires (Alonso-Betanzos et al., 2003; Brillinger et al., 2003; Chuvieco et al., 2010; Dong et al., 2005b; Yin et al., 2004). Several methods have been used to evaluate forest fire probability, such as analytical hierarchy processes (Eskandari, 2017; Sharma et al., 2012; Vadrevu et al., 2010), fuzzy logic models (Iliadis et al., 2002; Yi et al., 2013), support vector machines (Koetz et al., 2008; Zhao et al., 2011), and system dynamics (Collins et al., 2013). The development of geographical information systems (GISs) and remote-sensing (RS) data have provided a comprehensive tool to develop forest fire probability assessment methods. GIS is an effective tool to analyze complicated spatial problems (Jaiswal et al., 2003), which is widely used in forest fire probability mapping (Alemu and Suryabhagavan, 2015; Eugenio et al., 2016; Kumar et al., 2015; Said et al., 2017). RS data provide fundamental information regarding which parameters need to be considered when mapping forest fire probability, including forest structure (Lim et al., 2003), land use and land cover (Joshi et al., 2016), land surface temperature (Caselles, 2011), vegetation moisture content (Wang et al., 2013), etc. The integration of GISs and RS data is widely used in fire probability estimation, and is considered to be one of the most cost-effective and most-appropriate methods for mapping forest fire probability (Ardakani et al., 2010).

Forest fire probability depends on many environmental factors. Tree species can affect the probability of fire ignition (Pellegrini et al., 2016), where, for example, coniferous trees pose more of a fire probability than deciduous trees. Vegetation structures (Carmel et al., 2009), humidity (Huesca et al., 2009), temperature (Guangmeng and Mei, 2004), and topographical features (Satir et al., 2016) are all factors that can affect forest fire probability and provide the potential for fires to arise. Human activities (anthropogenic variables) also play an important role in the occurrence of forest fires, and they are considered to be the main ignitor of forest fires in areas with intense human activities (Adab et al., 2013).

The objective of this research was to establish a comprehensive model for mapping forest fire probability. Four influential factors were considered, including drought index, topography, vegetation condition and anthropogenic variables. The influence of human activities were analyzed based on forest fire statistics, while accurate distance values were obtained via a distance analysis.

2. Methodology

2.1 Study area

Heilongjiang Province was selected as the study area, and is located in the northern part of China between E 121° 11′ —135° 05′, and N 43° 26′ —53° 33′ with a total area of 45.19×10^4 km^2.

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The forest-covered area in the study area is 16.44×10^4 km^2, which accounts for 36.38% of the total area (Fig. 1). Heilongjiang Province experiences a continental monsoon climate with an extremely cold and dry winter, a windy spring and autumn, and a short, mild and moist summer. The average annual temperature is between -5 ^{o}C and 4 ^{o}C. The average precipitation varies in the region, being higher in the eastern part and lower in the western part. Sixty percent of the precipitation is concentrated between June and August, while precipitation in the winter accounts for only 17% of the annual total. Abundant vegetation cover and climatic conditions such as strong winds and droughts make the study area susceptible to fires. The fire season is from March to November. Forests are considered natural resources to support the economic development in the province, and the occurrence of fires can cause great damage to these forest resources. Statistics show that 528 fires have occurred during the past 10 years, and the total burned area reached 13.8×10^4 hm^2. As a hectare of trees lost to fire can cause a loss of 4398.93 yuan (Zhang et al., 2001), the total economic losses reached 607 million yuan. Due to these enormous losses, the study area is considered as an important area for forest fire prevention in China.

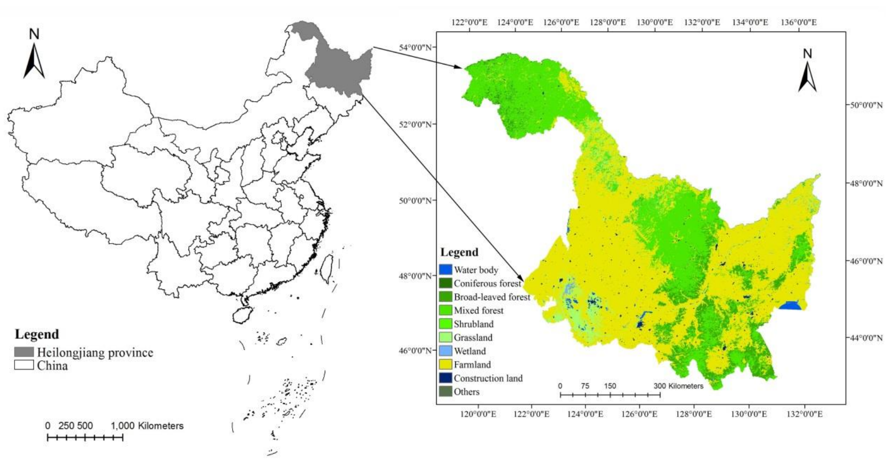

Figure 1: Location and land cover types of Heilongjiang Province

2.2 Index system

Several influencing factors were considered to assess forest fire probability. The indicators selected in the study are shown in Table 1.

Table 1. Indicators employed to evaluate fire probability in Heilongjiang Province

Influence factor	Variables	Data source
Drought index	Percentage of precipitation anomaly	Monthly precipitation data from meteorological stations
Topographical factors	DEM	ASTER
	Slope	Calculated from DEM
	Aspect	Calculated from DEM

Vegetation condition	Fractional vegetation cover	Calculated based on MOD13Q1
	Vegetation type	MCD12Q1
Anthropogenic factors	Distance from settlement (km)	Settlements obtained by a visual-interpretation method based on Landsat TM data
	Distance from road (km)	Roads were digitized from the traffic map

2.2.1 Drought index

The percentage of precipitation anomaly (PPA) is an important indicator that represents the distribution and variation of drought (Wei and Ma, 2003). To calculate PPA, monthly precipitation data were obtained from 83 meteorological stations (Fig. 3) in Heilongjiang province from March to November. An inverse distance weighted interpolation method was used to generate the spatial data. Fires are more likely to arise under drought conditions. The calculation formula of PPA was:

$$D_p = \frac{P-\bar{P}}{\bar{P}} \times 100\% \quad (1)$$

where D_p was the PPA, P was the amount of precipitation during the fire season, and $\bar{P}$ was the multi-year average precipitation during the fire season.

2.2.2 Topographical factors

Topography is often measured in terms of elevation, slope and aspect (Jung et al., 2013). Elevation is highly associated with moisture, temperature, wind and vegetation structure (Lin et al., 2013); therefore, it has an important influence on fire occurrences. Slope is a key parameter that influences the spread of fires (Weise and Biging, 1997). Aspect affects the amount of received solar energy, which results in different degrees of fuel moisture levels (Adab et al., 2013). These topographical factors were obtained from ASTER (the Advanced Spaceborne Thermal Emission and Reflection radiometer) and GDEM (Global Digital Elevation Model) Version 2.

2.2.3 Vegetation conditions

The vegetation conditions were measured using the vegetation types and the fractional vegetation cover (FVC). According to existing research (Deng et al., 2012), vegetation types were classified into five grades, where coniferous forests are considered as very high probability, mixed forests, broad-leaved forests and shrublands as high probability, grasslands as moderate probability, farmlands as low probability, and other vegetation types are considered as very low probability. The vegetation types were obtained from the MODIS land cover type product MCD12Q1.

FVC represented the vegetation density, where high FVC values indicated areas with high probabilities of fire. FVC was calculated by:

$$FVC = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \quad (2)$$

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where NDVI was the Normalized Difference Vegetation Index, and $NDVI_{\min}$ and $NDVI_{max}$ represented its minimum and maximum values, respectively. NDVI was obtained from the MODIS vegetation index product MOD13Q1 every 16 days. Eighteen NDVI data from March to November in 2017 were downloaded, and the mean values were calculated and used in the FVC calculation.

2.2.4 Anthropogenic factors

Settlements were obtained with a visual-interpretation method based on Landsat TM data. Roads were obtained based on a traffic map of the study area, which included national roads, provincial roads and country roads (Fig. 2).

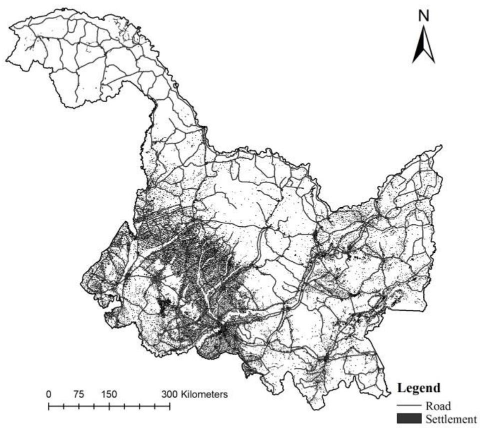

Figure 2: Roads and settlements in the study area

For anthropogenic variables, numerous studies have used the distance from roads and settlements to represent the influence of human activities (Dong et al., 2005a; Hernandez-Leal et al., 2009; Sağlam et al., 2008). The key point of this method is how far the distance from roads and settlements should be set with regards to high or low forest fire probability. A distance analysis was employed to see which distance has the highest associated fire probability. Fire numbers and density were calculated for every integer kilometer from settlements and roads. The fire density was calculated as follows:

$$D_i = \frac{N_i}{A_i} \tag{3}$$

where D_i was the fire density in the i^{th} range, N_i was the number of ignition events in the i^{th} range, and A_i was the area of the i^{th} range.

To finish this process reasonably, field data from 2000 to 2005 were employed, including coordinates, ignition locations, time, burned area, fire reason, vegetation type in the burned area and other information of each forest fire that occurred during this period (Fig. 3). According to the field data, 992 forest fires occurred from 2000–2005. Among those fires, 234 were caused by lightning strikes, and the other 758 fires (76.41% of the total) were caused by human activities. This clearly indicated that human activities are one of the most important causes of forest fires. According to the

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purpose of this study, human-caused fires were used in the model construction and validation. Seventy percent (531) of human-caused fires were used in the distances analysis. The rest (227) were used as validation data for the subsequent forest fire probability evaluation.

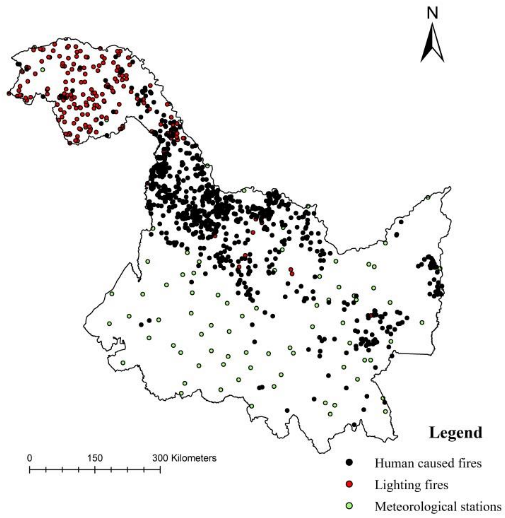

Figure 3: Forest fire locations and Meteorological stations in the study area

2.3 Forest fire probability model

2.3.1 Indicator weights

An analytic hierarchy process (AHP) method, which is commonly used in GIS-based analyses (Al-Abadi et al., 2016), was employed to obtain the weight of each indicator. AHP is an effective method to rank decision alternatives. A numerical score can be developed to rank each decision alternative. In forest fire probability estimation, every indicator can be considered as a single information layer for the comprehensive analysis. The relative importance of each indicator to fire probability is the main reference point when setting the weights. Vegetation conditions were considered with the highest importance which provide the fuels of fires(Deng et al., 2012). Anthropogenic factors were considered with second importance which is the main ignition of the study area(Jia, 2018).

2.3.2 Models

The variables were divided into five probability ranks: very low, low, moderate, high and very high, as shown in Table 2. The PPA, topographical factors and FVC were divided into five classes using a natural breaks method in ArcGIS.

Table 2. Ranks and weights of the influence factors and variables

Influence factor	Weight	Variables	Weight	Rank of fire probability	Description of fire probability

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Drought index	0.15	PPA	1	1,2,3,4,5	Very low, low, moderate, high, very high
Topographical factors	0.15	Elevation (m)	0.34	1,2,3,4,5	Very low, low, moderate, high, very high
		Slope (^{o})	0.33	1,2,3,4,5	Very low, low, moderate, high, very high
		Aspect (^{o})	0.33	1,2,3,4,5	Very low, low, moderate, high, very high
Vegetation condition	0.4	Fraction vegetation cover	0.5	1,2,3,4,5	Very low, low, moderate, high, very high
		Vegetation type	0.5	1,2,3,4,5	Very low, low, moderate, high, very high
Anthropogenic factors	0.3	Distance from settlement (km)	0.6	1,2,3,4,5	Very low, low, moderate, high, very high
		Distance from road (km)	0.4	1,2,3,4,5	Very low, low, moderate, high

For a quantitative measurements, each influencing factor was obtained by a weighted model as follows:

$$Y = \sum_{i=1}^{n} w_i x_i \quad (2)$$

where Y represented the four influence factors, x_i (i=1,2,3,…,n) contained the variables used for the evaluation of each influence factor, and w_i was the weight of each variable.

To measure forest fire probability, the FFPI was calculated as:

$$FFPI = 0.4 \times V + 0.3 \times A + 0.15 \times T + 0.15 \times M \quad (3)$$

where V was the vegetation condition, A was an anthropogenic factor, T was a topographical factor and M was a meteorological factor.

2.3.3 Validation method

A receiver operating characteristics (ROC) curve, which is a frequently used technique for accuracy validation, was employed to validate the accuracy of the proposed model. The area under the ROC Curve (AUC) represented the performance of the model. AUC values usually range from 0.5 to 1, where a value close to one indicates that the performance of the model is excellent, while a value close to 0.5 indicates poor performance.

3. Results

3.1 Results of the distance analysis

The distance of each fire location to the nearest settlement was calculated. The results showed that the minimum distance was 58 m and the maximum distance was 28,750 m. The medium distance was 4,000 m, whereafter the fire numbers declined as the distance increased. As shown in Fig. 4, the number of fires relative to the distance to the nearest settlement presented a trend of first increasing, reaching a peak, and then decreasing.

Within 1 km of settlements, 41 fires occurred, which accounts for 7.72% of the total fires. More fires occurred between 1 and 6 km, where the number of fires exceeded 55 and a percentage of over 10% for each 1 km distance. Most fires occurred between 3 and 4 km, where the number of fires reached 75, and accounted for 14.12% of the total fires. Within a distance of 10 km, 469 fires occurred, which accounted for 88.32% of the total fires.

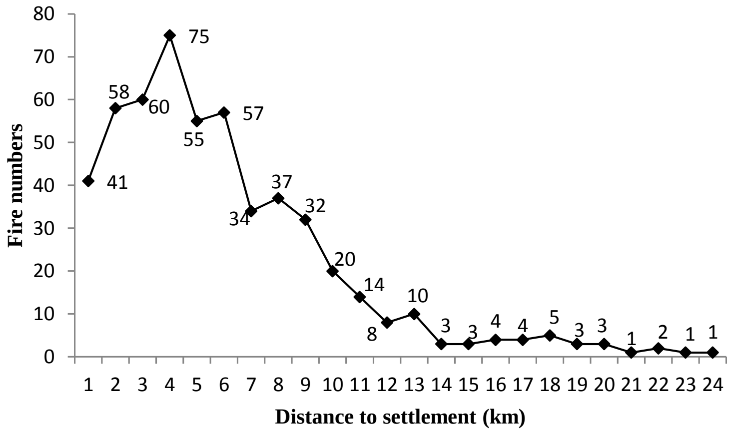

Figure 4: Distance analysis of fire locations to settlements

The distance of each fire location to the nearest road was also calculated. The results showed that the minimum distance was 26 m and the maximum distance was 31,087 m. As shown in Fig. 4, there was an obvious trend of declining fire numbers as the distance increased. Forty-nine fires arose within 1 km from roads, which accounted for 9.23% of the total fires. Most fires (355) occurred within a 10-km distance, which accounted for 66.86%. At distances greater than 10 km, the fire numbers declined dramatically. When the distance increased to 21 km, the number of fires reached 515, which accounted for 96.97% of the total fires. The fire density also did not show a regular trend as the distance increased.

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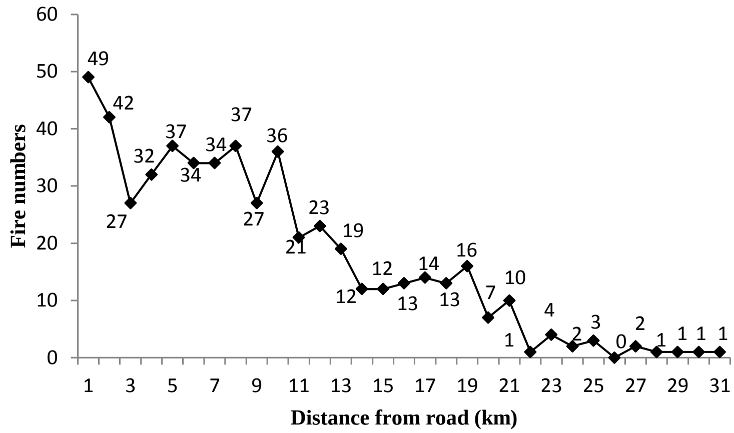

Figure 5: Distance analysis from fire locations to roads

The fire numbers and percentages were considered as the main factors that determine the probability rank of anthropogenic factors. By comprehensively considering the distance analysis result, a rating of fire probability due to anthropogenic factors was set (Table 3).

Table 3. The rating of fire probability of anthropogenic factors

Distance to settlements (km)	<1	1–6	6–9	9–15	15–20	>20
The rating of fire probability	4	5	4	3	2	1
Distance to road (km)	<2	2–6	6–10	10-20	>20	
The rating of fire probability	5	4	3	2	1	

3.2 Forest fire probability evaluation

According to the method mentioned above, the FFPIs of the study area were calculated and split into five probability classes as shown in Fig. 6, including very low, low, moderate, high and very high.

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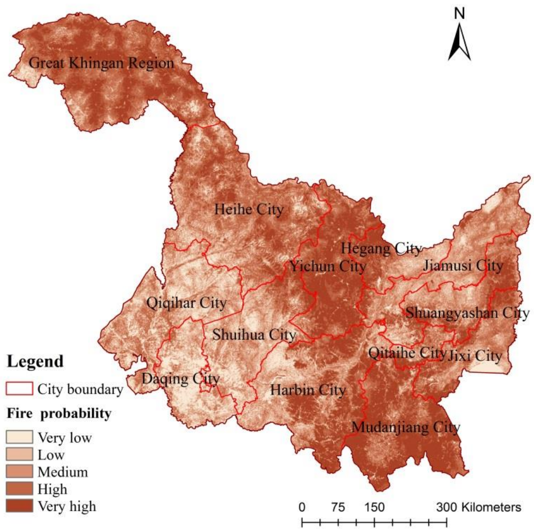

Figure 6: Forest fire probability distribution in Heilongjiang Province

The forest fire probability grade represents the possibility of a fire occurring. The results show that high probability areas cover 13.10×10^6 hectares, or 28.99% of the total area, which is the largest area. Very high probability areas cover 11.00×10^6 hectares, which account for 24.35% of the total area. Medium probability areas cover 9.46×10^6 hectares, or 20.94% of the total area. Low probability areas cover 7.84×10^6 hectares, or 17.45% of the total area. Finally, very low probability areas cover 3.74×10^6 hectares, or 8.28% of the total area.

The high and very high probability areas exceeded 50% of the total area, meaning that Heilongjiang Province is a forest fire-prone area. However, the distribution of fire probability was quite heterogeneous. As shown in Fig. 6 and Table 4, most high and very high probability areas are distributed in the Great Khingan Region, Heihe City, Yichun City, Harbin City and Mudanjiang City, which respectively account for 20.90%, 15.02%,12.17%,11.71% and 14.12% of the total high and very high areas. Other cities, such as Qitaihe City and Daqing City, high and very high areas only account for 1.35% and 0.77%, respectively.

Table 4. Areas of different fire probability in Heilongjiang province (Unit: 10^4 hectares)

City	Very low	Low	Medium	High	Very High
Great Khingan Region	14.61	39.75	86.41	269.60	234.08
Heihe City	29.66	105.27	171.45	266.64	95.46
Yichun City	2.08	8.77	24.02	108.71	184.64
Hegang City	7.89	29.07	31.36	35.80	41.76
Jiamusi City	23.61	82.73	114.68	81.17	24.64

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Shuangyashan City	7.33	37.81	56.08	67.75	51.62
Qiqihar City	85.02	150.83	115.82	67.97	1.85
Shuihua City	58.81	110.83	91.78	60.07	27.58
Qitaihe City	2.80	11.13	16.09	18.92	13.51
Daqing City	79.65	72.28	40.93	17.65	0.83
Jixi City	18.81	31.32	55.54	74.17	43.18
Harbin City	41.27	98.41	108.80	132.68	149.66
Mudanjiang City	2.57	10.22	33.29	108.90	231.38

3.3 Model validation

Two hundred and twenty-seven forest fires that occurred during 2000–2005 in Heilongjiang Province were used as validation data to measure the accuracy of the proposed model. The number of fires occurring at the different levels of forest fire probability were calculated, as shown in Table 5. The results show that most fires happened in high and very high probability zones, with fewer in low probability zones. Indeed, over sixty-eight percent of the fires occurred in high and very high probability zones.

Table 5. Number of fires in each probability zone

Level of fire probability:	Very low	Low	Moderate	High	Very high
Number of fires	6	19	46	82	74
Percentage	2.63%	8.33%	20.18%	35.96%	32.46%

In this study, we found an AUC value of 0.790, at the 95% confidence level (Fig. 7), meaning that the model showed good performance.

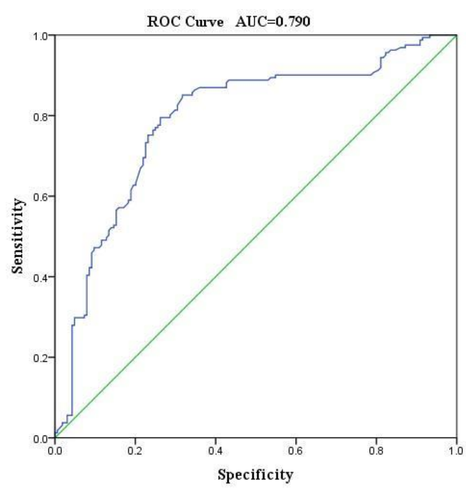

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Figure 7: ROC curve and AUC value of the forest fire probability model

4. Discussion and conclusions

4.1 Influence of human activities on fire probability

The influence of human activities on fire probability, which were represented by the distances from roads and settlements, was estimated by a distance analysis. Fire numbers, percentages and densities were calculated in each 1 km range. The results show that fire risk declined as the distance to roads increased, where those within 2 km were faced with the highest risk. In terms of the distance to settlements, the highest fire numbers and percentages occurred from 1 to 6 km, but not within 1 km. This suggests a lower fire probability within 1 km, and a higher fire probability from 1 to 6 km. This result is different to previous studies (Hong et al., 2017; Matin et al., 2017) that considered that the nearer one is to a settlement, the greater the fire probability becomes.

4.2 Different fire risk distributions at the city scale

At the city scale, according to the percentage of high and very high probability areas in the city, the fire risk could be divided into three grades (Fig.8). The high risk cities include Yichun City, Great Khingan Region and Mudanjiang City, where the high and very high areas account for 89.38%, 78.16% and 88.07% of the total city area, respectively. The medium risk cities include Heihe City, Hegang city, Shuangyashan City, Qitaihe City, Jixi City and Harbin City, where the high and very high area percentages are between 50% and 55% of the total city area. Other cities, including Jiamusi City, Qiqihar City, Shuihua City and Daqing City, are faced with low fire risk, where the percentage is 32.38%, 16.57%, 25.11% and 8.74%, respectively.

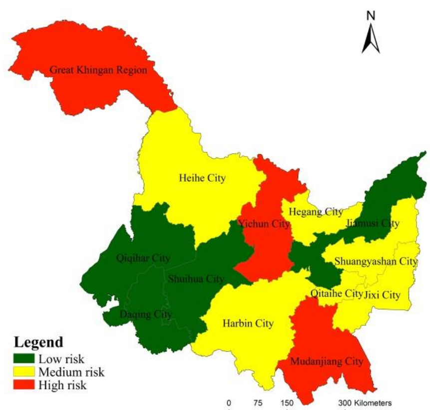

Figure 8: Forest fire risk at the city scale in Heilongjiang Province

In this study we proposed a synthetic method for evaluating forest fire probability based on assessing the influence of human activities. The variables used in the study were relatively fewer and easily obtained from existing datasets, which makes the method easily repeatable for other years in the study area. The main conclusions are as follows:

(1) The influencing distance to settlements and roads is mainly within 10 km. The most influential distance to roads is within 2 km, and the most influential distance to settlement is from 1 to 6 km. Areas within these distances face more risk of fire and should been defined as vigilance priority areas. We consider that the influencing distance should increase as traffic conditions improve, especially for the distance to settlements.

2) The distribution of fire probability in Heilongjiang province is heterogeneous. Yichun City, Great Khingan Region and Mudanjiang City are faced with high fire risks, which should been given priority for surveillance.

Our results can help governments and forest managers to readily identify high forest fire probability locations easily, and to take actions or form policies to avoid future loss of resources, properties and human life.

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Author contribution: Wei Yang and Xiaoli Jiang designed the model, Xiaoli Jiang processed the data, Wei Yang prepared the manuscript with contributions from all co-authors.

Competing interests:

The authors declare no conflicts of interest.

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