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A Time-dependent Stochastic Grassland Fire Ignition Probability Model for Hulun Buir Grassland of China

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Abstract: Grassland fire is one of the most important disturbance factors in the natural ecosystems. This paper focuses on the spatial distribution of long-term grassland fire patterns in the Hulun Buir Grassland located in the northeast of Inner Mongolia Autonomous Region in China. The density or ratio of ignition can reflect the relationship between grassland fire and different ignition factors. Based on the relationship between the density or ratio of ignition in different range of each ignition factor and grassland fire events, an ignition probability model was developed by using binary logistic regression function and its overall accuracy averaged up to 81.7%. Meanwhile it was found that daily relative humidity, daily temperature, elevation, vegetation type, distance to county-level road, distance to town are more important determinants of spatial distribution of fire ignitions. Using Monte Carlo method, we developed a time-dependent stochastic ignition probability model based on the distribution of inter-annual daily relative humidity and daily temperature. Through this model, it is possible to estimate the spatial patterns of ignition probability for grassland fire, which will be helpful to the quantitative evaluation of grassland fire risk and its management in the future.
Keywords: grassland fire; binary logistic regression; GIS spatial analysis; ignition probability; Monte Carlo method

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1 Introduction

Grassland fire is one of the most important disturbance factors to the natural ecosystems, which has been becoming a very critical problem at present due to global warming and human activities (Veblen *et al.*, 1999; Flannigan *et al.*, 2009; Finch and Marchant, 2011). According to the statistics, there are 5417 grassland fires in China during 1991 and 2003, and the fire-affected areas was up to 60 042 km^2 (Zhou and Lu, 2009). Fire disaster has not only caused heavy losses of life and property, but has also directly affected the pastoral production, and brought instability to ecological security in the grassland regions (Liu *et al.*, 2010).

Ignition probability means the probability of fire occurred in certain area due to natural or human-caused factors, which is necessary to analyze the risk of grassland fire. Grassland fire ignition probability at multiple spatial and temporal scales based on historical fire records is important to fire managers and scientists, which is also an essential element in analyzing and assessing fire danger (Koutsias *et al.*, 2004; Filipe *et al.*, 2009). Modeling wildfire ignition probability was carried out in different countries with different methods. The main wildfire ignition probability assessment methods used in existing research include kernel density estimation

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method (de la Riva *et al*., 2004; Giuseppe *et al*., 2007), and multiple regression method (Pew and Larsen, 2001; Vasconcelos *et al*., 2001; Kalabokidis *et al*., 2007; Martinez *et al*., 2009; Zhang *et al*., 2010).

Kernel density estimation method, using implicit density interpolation techniques to interpolate or diffuse spatial information, based on the spatial distribution of historical fire point, is not able to reflect the relation of fire and the factors associated with ignition (de la Riva *et al*., 2004; Koutsias *et al*., 2004). The key of this method is the selection of bandwidth that directly impacts the results of kernel density estimation method. Koutsias *et al*. (2004), who analyzed the bandwidth selection, argued that the estimate result would be more accurate when bandwidth was close to the mean nearest neighbor distance of historic ignition points. Meanwhile, it was very essential to analyze the uncertainty of spatial influencing areas of historic ignition point to achieve more accurate estimate result (de la Riva *et al*., 2004; Giuseppe *et al*., 2007).

In multiple regression method, binary logistic regression model and artificial neural network model are often utilized to develop ignition probability based on historic fire data as response variables, and other factors that impact on the ignitions as independent variables. For example, many scholars assessed ignition probability in the forest region or grassland of different countries using binary logistic regression and analyzed the contribution of different impact factors on ignition probability (Chou *et al*., 1993; Kalabokidis *et al*., 2007). With the increasing impact of human activities, some scholars analyzed the relationship between human-caused ignition probability and other influence factors (Pew and Larsen, 2001; Martinez *et al*., 2009; Zhang *et al*., 2010). Some scholars assessed ignition probability using artificial neural network model (Vasconcelos *et al*., 2001; Vasilakos *et al*., 2007). Through comparative analyses on binary logistic regression model and artificial neural network model, it was found that artificial neural network model demonstrated slightly better accuracy and robustness, however it is not able to identify the importance of each variable, since the weights of independent variables after training can not be easily interpreted. For the logistic regression model, it allows more interpretation capacity than the artificial neural network model (Vasconcelos *et al*., 2001; Kalabokidis *et al*., 2007).

The study on fire ignition probability mentioned above focused on the assessment of the average annual wildfire ignition probability and the relationship between wildfire ignition probability and influence factors. However, using the average annual or seasonal meteorological factors (temperature, precipitation, relative humidity) to assess wildfire ignition probability, the influence of daily meteorological factors on wildfire ignition probability was ignored. In all these researches, only Zhang *et al*. (2010) assessed grassland fire ignition probability using daily meteorological factors. Meanwhile, few studies focused on the time-dependent stochastic grassland fire ignition model.

Grassland fire prone areas account for about 1/3 of the total grassland area of 4×10^6 km^2 in China, and the Hulun Buir Grassland is one of highly occurred grassland fires regions (Liu *et al*., 2008). There were about 700 grassland fires occurred in this region, which burned about 47 100 km^2 from 1986 to 2008, causing great damage in the grassland husbandry, ecological environment, social economic development and so on. In this paper, the Hulun Buir Grassland fire ignition points data and 12 ignition factors, including natural conditions, human activity, vegetation type was analyzed to discuss the relationships between the ignition density or ignition ratio in different range of each ignition factor and grassland fire events from 1986 to 2008. Based on the relationships, a grassland fire ignition probability model was developed. Then, a time-dependent stochastic ignition probability model reflecting the contribution of meteorological factors and its seasonal change was developed by using Monte Carlo method, that will be helpful to the quantitative evaluation of grassland fire risk and the management of grassland fire in the future.

2 Data and Method

2.1 Study area

The Hulun Buir Grassland (47.33°–50.25°N, 115.50°–121.17°E) is located in the northeast of the Inner Mongolia Autonomous Region of China with an area of approximately 83 000 km^2, consisting of four banners (i.e. counties) and two county-level cities (Fig. 1). Hulun Buir Grassland is a typical temperate semi-arid and semi-humid area. Because of its high latitude, mean annual temperature ranges from –2.5℃ to 0℃ and absolute minimum temperature can be low as –49℃, while annual precipitation varies from 280 mm to 400 mm. In winter, the grassland is strongly impacted by the Mongolian high-pressure while the summer monsoon was weak, so the study area is dry and cold in winter, and rainless and windy in spring. The region is rich in grassland vegetation covered with meadow steppe, typical steppe and desert steppe from east to west. The meadow steppe is located in the Yimin River Basin of the eastern of Hulun Buir Grassland, and *Carex pediformis*, *Filifolium sibiricum*, *Stipa baicalensis* are its typical vegetation type. The typical steppe located in the Orxon Gol River Basin of the middle part of the Hulun Buir Grassland with *Stipa grandis*, *Aneurolepidium chinense* widely distributed. For desert steppe in westernmost of Hulun Buir Grassland, the dominant vegetation is *Stipa krylovii*.

2.2 Ignition and non-ignition points selection

The official wildfire database in the Forestry Bureau of Hulun Buir City (i.e., prefecture) from 1986 to 2008 was obtained, including location (latitude and longitude), date of ignition, total area burned, ignition cause, fire levels, *etc*. Because of the ignition location reporting uncertainties, this database is corrected to avoid duplications and all inconsistent records are removed. Based on the locations of the ignition points and using the National 1∶250 000 Topographic Database, its completeness and accuracy are ensured by GIS spatial analysis. After this, 548 points were chosen from a total number of 677 ignition points in the database and the spatial distribution of these selected ignition points is shown in Fig. 2a.

The amount and spatial distribution of non-ignition points are critical to ignition probability assessment. In order to make spatial characteristics of ignition and non-ignition points fit for random distribution without overlaying or being nearby, in the past studies various methods have been developed on generating non-ignition points, including the amount and locations. For instance, using Mean-Nearest-Neighbor-Distance method (Koutsias *et al*., 2004; Kalabokidis *et al*., 2007), the amount of non-ignition points greater or equal to the ignition points are randomly generated. In this paper, the amount and locations of non-ignition points are also determined with similar method following the past studies. The mean nearest neighbor distance of the 548 ignition points in the study area is 4890.54 m, which is used to determine the amount of non-ignition points. Thus, the sum of ignition/non-ignition points is 1043 and the number of non-ignition points is 495. The spatial distribution of non-ignition points is shown in Fig. 2b.

2.3 Influence of independent factors

The probability of wildfire ignition is determined by both natural conditions and human activities, such as weather, topography, fuel type and distance to road, *etc*. Human-caused fires rank the first in both total amount and the burned area, accounting for 56.28% and 57.47% of total, respectively in Hulun Buir Grassland (Table 1). Twelve factors of four groups were selected to analyze

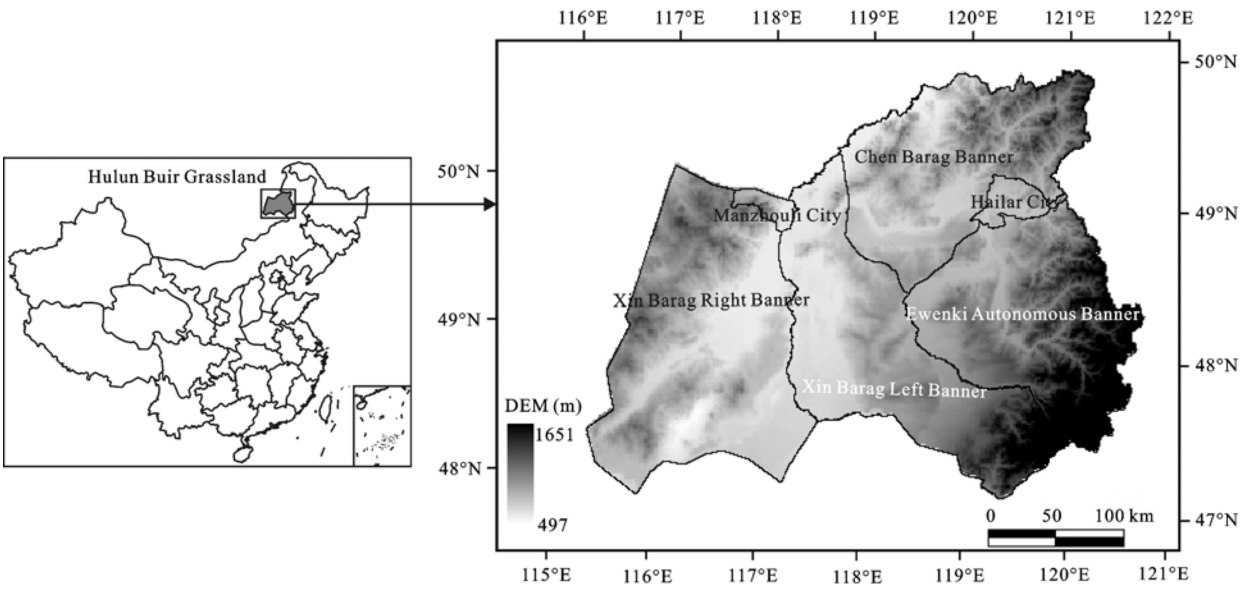

Fig. 1 Location of Hulun Buir Grassland in China

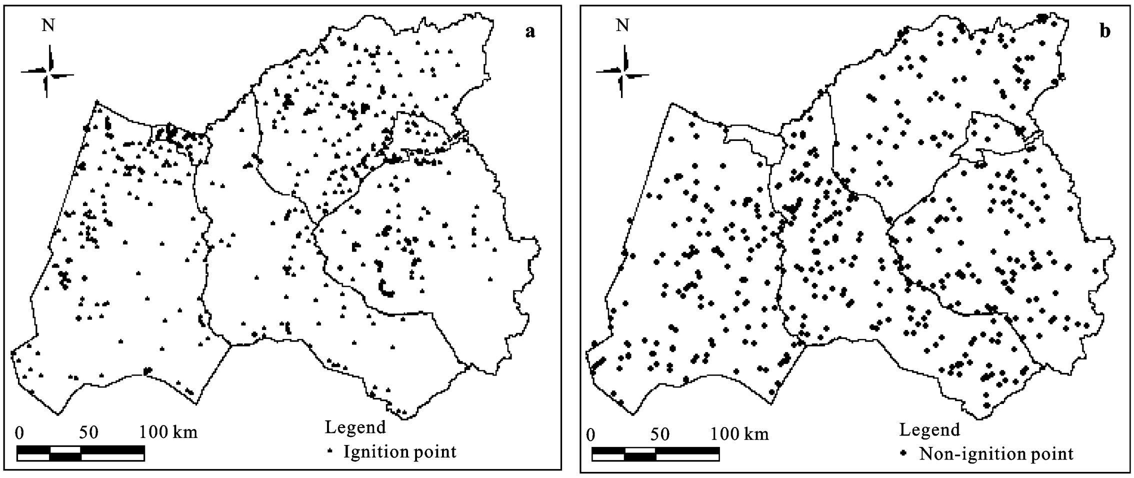

Fig. 2 Distribution of ignition points (a) and non-ignition points (b) in Hulun Buir Grassland from 1986 to 2008

Table 1 Number and percentage of each type of grassland fire in Hulun Buir Grassland (1986–2008)

Grassland fire cause	Burned area (km^2)	Burned area percentage (%)	Number of grassland fire	Percentage of grassland fire (%)
Human-caused	27058.18	57.47	381	56.28
Fire from Mongolia	8213.40	17.45	40	5.91
Lightning	2975.50	6.32	28	4.13
Others	8831.81	18.76	228	33.68

fire ignition probability, including factors of human activities (distance to national/provincial road, distance to county-level road, distance to town and distance to village), natural factors of meteorology (daily temperature, daily relative humidity and daily precipitation), topography (elevation, slope and aspect), vegetation (grassland type) and biomass distribution (annual Net Primary Productivity (NPP)). Spatial distribution of all factors was developed in Geographic Information System (GIS) to set up a raster database of explanatory variables of wildfire ignition probability in the Hulun Buir Grassland (Table 2), with spatial resolution of 500 m × 500 m in Albers projection.

The number, density or ratio of ignition as the evaluation indicators were selected to analyze the impact of different independent factors on the distribution of

Table 2 Ignition factors and their sources in Hulun Buir Grassland

Ignition factor	Code	Source
Distance to village (km)	DIS_rural	Land Use Database in Hulun Buir City
Distance to town (km)	DIS_urban	Land Use Database in Hulun Buir City
Distance to county-level road (km)	DIS_roadc	National 1∶250 000 Topographic Database
Distance to provincial/national road (km)	DIS_roadp	National 1∶250 000 Topographic Database
Elevation (m)	DEM	SRTM DEM dataset (90 m × 90 m)
Slope (°)	Slope	SRTM DEM dataset (90 m × 90 m)
Aspect (°)	Aspect	SRTM DEM dataset (90 m × 90 m)
Vegetation type	VEG	Vegetation Map of China
Annual NPP (g C/m^2)	NPP	NASA/MODIS MOD17A3 data
Daily temperature (℃)	TEM	Daily ground observation meteorological dataset of CMDSSS
Daily relative humidity (%)	RH	Daily ground observation meteorological dataset of CMDSSS
Daily precipitation (mm)	PRE	Daily ground observation meteorological dataset of CMDSSS

Notes: NPP is Net Primary Productivity; CMDSSS is China Meteorological Data Sharing Service System grassland ignition points. The number of ignition was the number of fire points in the different range value of each independent factor. The density of ignition is a ratio of independent number to area in the different range value of each ignition factor except for meteorological factors, calculated as follows:

$$D(i)_{\mathrm{ig}} = \frac{N(i)_{\mathrm{ig}}}{A(i)_{\mathrm{ig}}} \tag{1}$$

where $D(i)_{\mathrm{ig}}$ is the density of ignition in the ith range; $N(i)_{\mathrm{ig}}$ is the number of ignition in the ith range; $A(i)_{\mathrm{ig}}$ is the area of ignition in the ith range.

The ratio of ignition is an evaluation indicator for meteorological factors (temperature, relative humidity and precipitation) and has the following form:

$$R(i)_{\mathrm{ig}} = \frac{N(i)_{\mathrm{ig}}}{N_{\mathrm{ig}}} \bigg/ \frac{N(i)_{\mathrm{fa}}}{N_{\mathrm{fa}}} \tag{2}$$

where $R(i)_{\mathrm{ig}}$ is the ratio of ignition in the ith range; N_{ig} is the total of ignition points; $N(i)_{\mathrm{fa}}$ is the number of each meteorological factor value in the ith range, and N_{fa} is the total number of each meteorological factor value. The quantitative relationships between influencing factors and fire ignition are analyzed respectively as follows.

(1) Roads. The distribution of ignition points in the vicinity of different level roads was analyzed by using the number and density of ignition located in different road buffers. It is found that the number of ignition decreased as the distance to roads increased, regardless of national, provincial or county-level road. Inside the distance of 48 km from national or provincial roads, the number of ignition accounted for 86.68% of total ignition points, and the ignition density decreased with the increase of distance. When distance is larger than 48 km, however, ignition at first increased and then decreased (Fig. 3a). Inside the distance of 12.5 km from county-level roads, the number of ignition accounted for 77.01% of total ignition points, and the ignition density decreased with the increase of distance, but its trend was not obvious at the distance exceeding 12.5 km (Fig. 3b). Therefore, ignition density is higher near road, and different levels of roads have different degree of influence on the distribution of ignition points in general.

(2) Residential areas. The distribution of ignition points in different level residential areas was analyzed by using the number and density of ignition located in different buffers of residential areas. The distribution trends of the number of ignition in different distances from the resident areas (town and village) were not significant. At a distance of 40 km away from town, the number of ignition accounted for 52.01% of total ignition points, ignition density tends to decrease with the increase of distance, but its trend was not obvious at the distance exceeding 40 km (Fig. 3c). At a distance of 21 km away from village, the number of ignition accounted for 57.30% of total ignition points, the ignition density decreases with the increase of distance, but there is no obvious trend at the distance exceeding 21 km (Fig. 3d). The result demonstrated that the different level residential areas influence the distribution of ignition points differently. Also, the nearer to the residential areas and the higher the ignition density, the greater the influence of resident areas on ignition.

(3) Topographic factors. The distribution of ignition points was analyzed in different topographic factors like elevation, slope and aspect. The ignition points were mainly distributed in the range elevation of 600–800 m, accounting for 82.85% of total ignition points. The number and density of ignition firstly increased and then decreased with the increase of elevation (Fig. 4a). For slope, the number of ignition dropped with the increase of slope, but the trend of density ignition firstly increased and then decreased (Fig. 4b). For aspect, no obvious trend of ignition number and density was found (Fig. 4c).

(4) Meteorological factors. For temperature, the trends of the number and ratio of ignition in different temperature ranges were similar, firstly increased and then decreased, and their maximum values appeared in the range of 2.5℃–3.5℃ (Fig. 4d). Regarding relative humidity, the number of ignition firstly increased and then decreased with relative humidity increasing, so the total trend of ignition ratio decreases with relative humidity increases (Fig. 4e). As to precipitation, there were 350 ignition points at the period without precipitation, accounting for 63.87% of total ignition points, which shows that ratio of ignition is higher during dry season. It displays that the ignition ratio decreases with the precipitation increases in the range less than 3.5 mm of precipitation. The trend of ignition ratio is stochastic with no significant trend (Fig. 4f).

(5) Vegetation type. The vegetation in Hulun Buir Grassland was divided into nine types by sub-vegetation

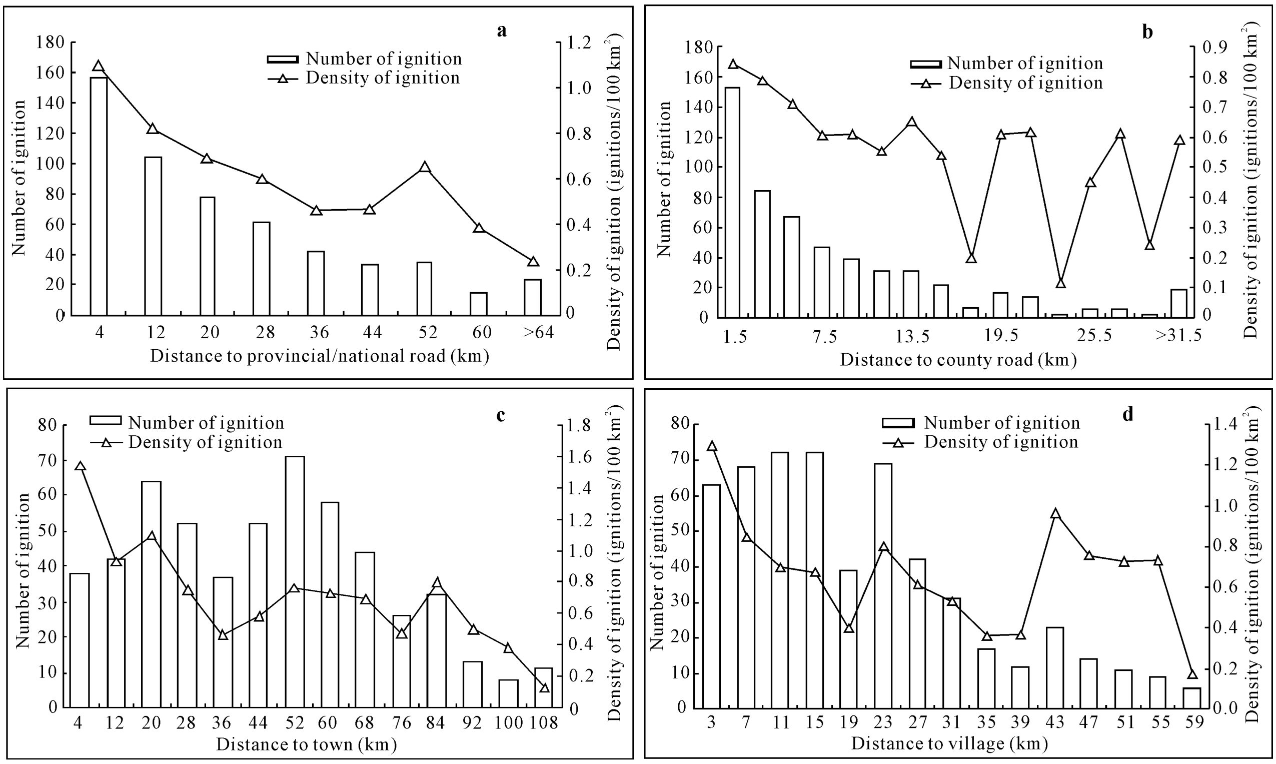

Fig. 3 Distribution of number and density of ignition at different distances to provincial/national road (a), county-level road (b), town (c) and village (d)

(Editorial Board of Vegetation Map of China, Chinese Academy of Sciences, 2007). Temperate grass-forb meadow steppe, temperate needle arid steppe and temperate grass, *carex* and forb swamp meadow were mainly distributed in this region, accounting for 76.24% of the total area. The number and density of ignition in different vegetation type areas are illustrated in Table 3. The areas of higher ignition density were mainly located in temperate broadleaf deciduous shrub areas of ecotone among forest and grassland and farmland area of the farming-pastoral ecotone. These two regions were also areas of frequent human activities.

(6) Annual NPP. The data of NPP were derived from NASA EOS/MODIS MOD17A3 dataset from 2000 to 2006, which was produced by using BIOME-BGC model. The dataset has been widely used for global and regional vegetation biomass estimation, carbon cycle and global change (e.g., Zhao *et al.*, 2005; Rasmus *et al.*, 2006; Guo *et al.*, 2008). NPP distribution is used in this paper to represent the spatial distribution of biomass. The number and ratio of ignition in the NPP range of 120–240 g C/m^2 is higher than those in others and it accounts for 93.61% of total ignition points (Fig. 5).

2.4 Ignition probability model

2.4.1 Relationship of fire ignition and independent factors

The probability of grassland fire ignition, in the form of a binary distribution, is mainly determined by natural and human factors. In this paper, the binary logistic regression model, as a probabilistic non-linear and multivariate analysis model, has been applied for analyzing the relationship between the binary classification results and independent factors. The prediction result of grassland fire state is ignition or non-ignition. In previous researches, wildfire ignition probability was assessed directly with the ignition factors by binary logistic regression model (Chou *et al.*, 1993; Pew and Larsen, 2001; Kalabokidis *et al.*, 2007; Martinez *et al.*, 2009; Zhang *et al.*, 2010). But the binary logistic regression model is a monotonic increasing function of independent variable and dependent variable. When the influence of ignition factors on ignition probability is not monotonic in some study areas, the influencing analysis may become unreasonable. There is a strong monotonic increasing exponential relationship between the ignition probability and the density of ignition (Filipe *et al.*, 2009). In this

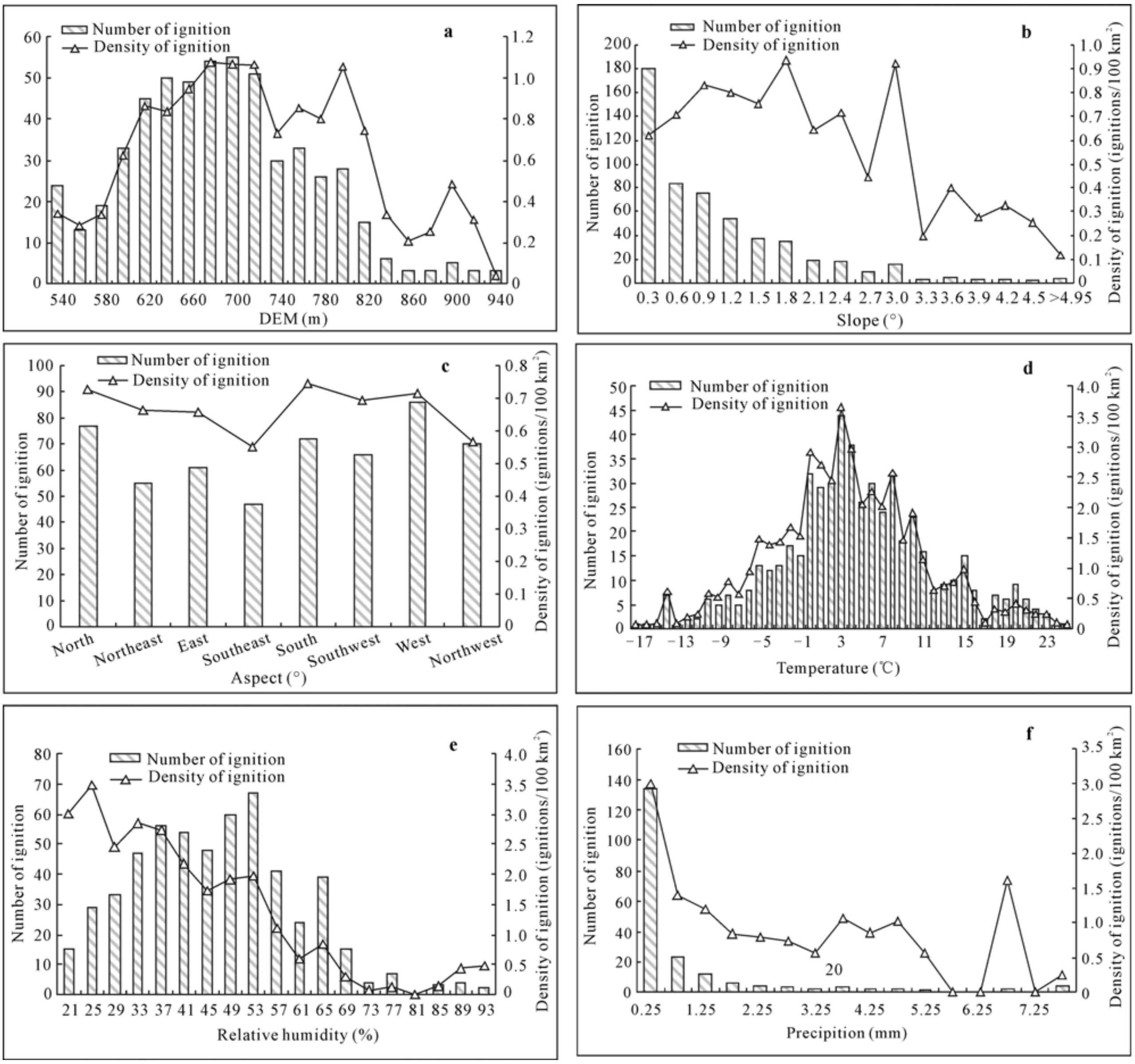

Fig. 4 Distribution of ignition number and density at different elevation (a), slope (b), aspect (c), temperature (d), relative humidity (e) and precipitation (f) grades

Table 3 Ignition number and density under different vegetation type areas

Vegetation type	Ignition number	Ignition density (ignitions/100 km^2)
Temperate broadleaf deciduous scrub	8	0.97
Farmland	10	0.91
Temperate needle arid steppe	341	0.77
Temperate grass-forb meadow steppe	101	0.75
Temperate grass, *carex* and forb swamp meadow	37	0.63
Temperate grass and forb holophytic meadow	13	0.46
Temperate grass and forb meadow	13	0.40
Cold-temperate and temperate swamp	5	0.31
Others	18	0.18

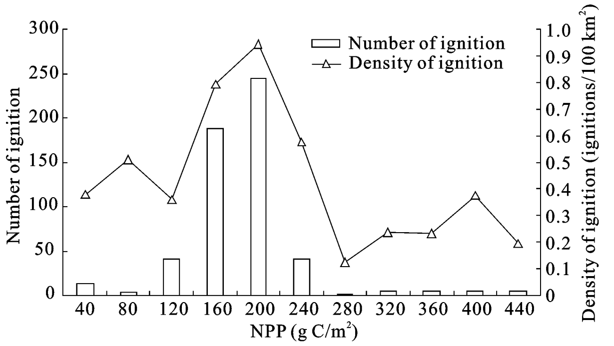

Fig. 5 Distribution of ignition number and density under different NPP

paper, the density or ratio of ignition can interpret the relationship between grassland fire ignition distribution and ignition factors more explicitly and clearly. A grassland fire ignition probability model was developed based on historic ignition data and the density or ratio of ignition under different independent factors, and the influence of independent factors on ignition probability was also analyzed with the density or ratio of ignition. The regression models of ignition density or ratio and the different independent factors were developed, and their forms, parameters, R^2 are listed in Fig. 6.

2.4.2 Grassland fire ignition probability model

Binary logistic regression model is chosen to combine the influences of all ignition factors with the following form:

$$P_{ig} = \frac{1}{1+\exp[-(b_0 + b_1 x_1 + b_2 x_2 + \cdots + b_i x_i)]} \tag{3}$$

where P_{ig} is the probability of ignition; x_i is the value of the ith ignition factor; b_0 is the constant of model; b_i is the regression coefficients of ignition factor x_i. In this equation, ignition points (P_{ig} = 1) and non-ignition point (P_{ig} = 0) are considered as dependent variables and the density or ratio of ignition of different ignition factors as independent variables. The grassland fire ignition probability function is therefore given as below:

$$P_{ig} = \frac{1}{1+\exp\left[-(b_0 + b_1 f(x_1) + b_2 f(x_2) + \cdots + b_i f(x_i))\right]} \tag{4}$$

where $f(x_i)$ is the mathematic model of ignition density or ratio for the ith ignition factor.

Based on the binary logistic regression model (Equation (4)), the grassland fire ignition probability model had been developed (Equation (5)) , distance to town (*DIS_urban*), distance to county-level road (*DIS_roadc*), elevation (*DEM*), vegetation type (*VEG*), daily temperature (*TEM*), daily relative humidity (*RH*) are the major variables impacting ignition probability and the regression coefficients of each ignition factors in the model were determined by using a stepwise logistic regression procedure with SPSS. The form of logistic regression is given by:

$$\begin{aligned} P_{ig} = 1/(1+\exp(-(1.1772\times f(RH) + 0.8868\times \\ f(TEM) + 2.3348\times f(DEM) + 2.0102\times \\ f(VEG) + 1.1932\times f(DIS\_roadc) + 0.6897\times \\ f(DIS\_urban) - 7.0520))) \end{aligned} \tag{5}$$

2.5 Time-dependent stochastic ignition probability mode

According to the ignition probability model, the ratio of ignition for daily temperature and relative humidity had significant positive relationships with the ignition probability, and their influences were the greatest (Table 4). With Monte Carlo method, according to the distribution of annual mean daily relative humidity and daily temperature from 1986 to 2008, the simulated daily relative humidity and daily temperature data with similar probability distribution characteristics were randomly generated. On the basis of the ignition probability model, a time-dependent stochastic ignition probability model can be described as Equation (6):

$$\begin{aligned} P_{ig}(RH(t),\ TEM(t)) = 1/(1+\exp(-(1.1772\times f(RH(t)) + \\ 0.8868\times f(TEM(t)) + 2.3348\times \\ f(DEM) + 2.0102\times f(VEG) + \\ 1.1932\times f(DIS\_roadc) + 0.6897\times \\ f(DIS\_urban) - 7.0520))) \end{aligned} \tag{6}$$

3 Results and Analyses

3.1 Ignition probability simulation and ignition factors analyses

The overall classification accuracy of the logistic regression model averaged up to 81.7%, identifying that the majority predictions of model are correct for both ignition points (i.e. 84.9% of the ignition points were correctly classified) and non-ignition points observations (i.e. 78.2% of the non-ignition points were correctly classified) (Table 5). Receiver Operating Characteristics (ROC) curve is a statistical method widely used

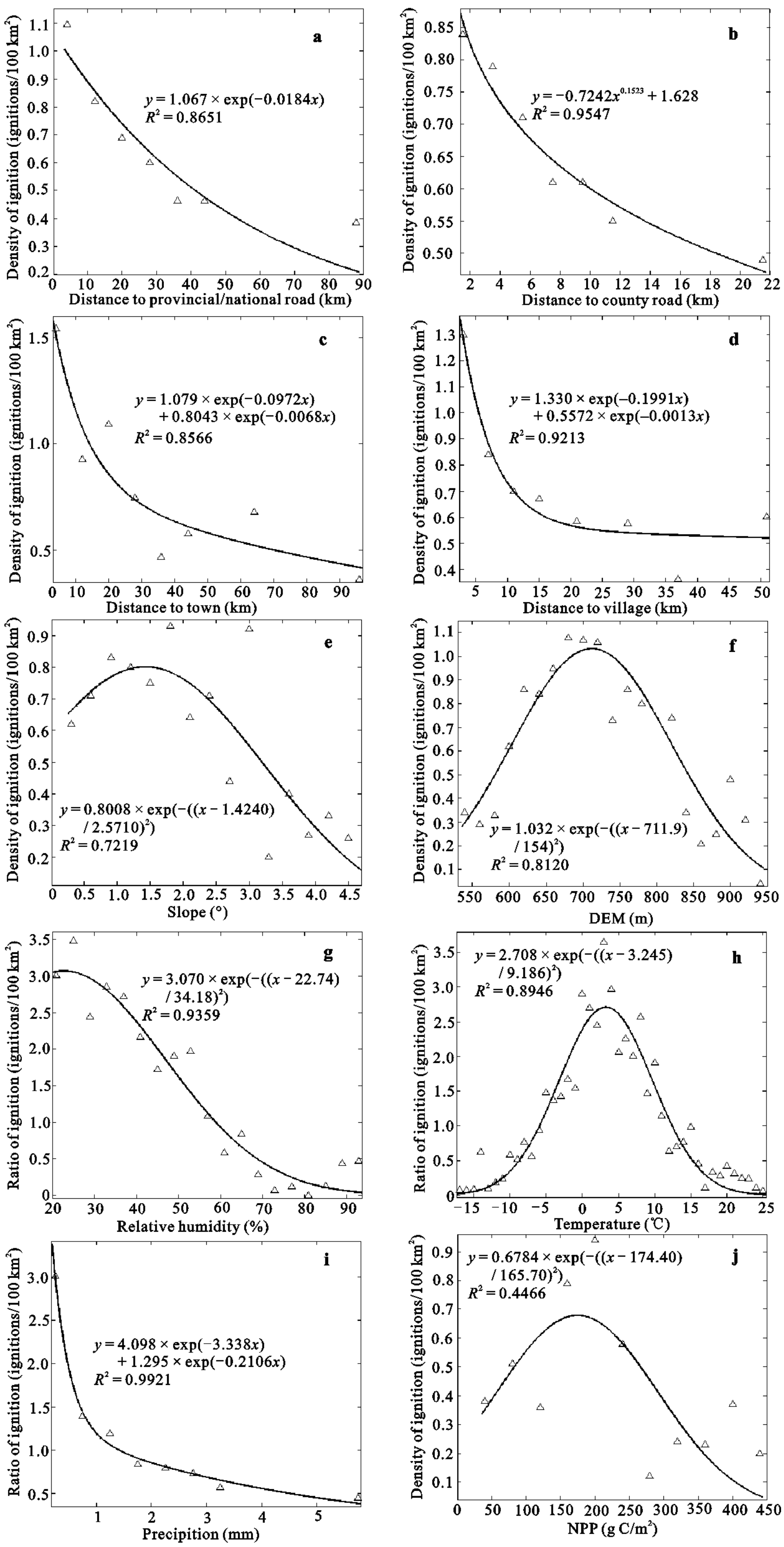

Fig. 6 Regression models of ignition density or ratio for different independent factors

to comprehensively assess the performance of classifier (Zhang and Dong, 2004; Zou *et al.*, 2009). The area under ROC curve for the ignition probability indicated the model prediction accuracy is 91.1% ($p < 0.01$), proving the reliability of model for ignition probability simulation.

Table 4 Parameters for fitted logistic regression model

Ignition factor	Code	*b*	SE	Wald	Sig.
Daily relative humidity	RH	1.1772	0.1030	130.5906	0.0000
Daily temperature	TEM	0.8868	0.0865	104.9758	0.0000
Elevation	DEM	2.3348	0.3462	45.4764	0.0000
Vegetation type	VEG	2.0102	0.5178	15.0725	0.0001
Distance to county-level road	DIS_roadc	1.1932	0.5559	4.6075	0.0318
Distance to town	DIS_urban	0.6897	0.3540	3.7968	0.0514

Notes: *b* is regression coefficient of each ignition factor; SE is standard deviation of regression coefficient; Wald is significance of each single variable on condition that other variables exist

Table 5 Classification table and statistical performance of logistic regression model

Observation		Prediction		Correct prediction (%)
		Non-ignition point	Ignition point	
		0	1	
Non-ignition point	0	387	108	78.2
Ignition point	1	83	465	84.9
Overall precision				81.7

The ignition probability model′s regression coefficients (*b*) of each ignition factor are positive (Equation (5)), which indicates that ignition probability has positive correlations with the density or ratio of the ignition. Daily relative humidity and daily temperature had significant influence on the ignition probability ($p < 0.01$), and their Wald values are 130.591 and 104.976 respectively. Elevation and vegetation type have significant effect on ignition probability ($p < 0.01$) with Wald values of 45.476 and 15.073, respectively. For distance, to county-level road and distance to town, the impact to ignition probability is not significant with Wald values of 4.608 and 3.797 (Table 4). The contribution of other factors to ignition probability, such as daily precipitation, slope, aspect, distance to village, distance to provincial/national road and annual NPP is less significant than those mentioned above.

The temporal distribution of grassland fires is analyzed as shown in Fig. 7a. Grassland fires mostly occurred in spring and autumn, especially in April. For example, 41.22% in number and 60.67% in burned area of the fires occurred in April, closely related to the climatic characteristics of this region.

During 1986 to 2008, annual mean daily relative humidity, as shown in Fig. 7b, has minimum values around the end of April and mid October. Compared to Fig. 7a, clearly these two minimums exactly correspond to two peaks of grassland fire, which also appeared in spring and autumn. In Fig. 7c, the annual mean daily temperature increases at first and reach to the highest in summer, then drop to the lowest in winter. In spring and autumn, the two peak periods of grassland fire occurred, the daily temperature was about 5℃ rather than its highest or lowest temperature.

3.2 Time-dependent stochastic ignition simulation

In this study, the stochastic ignition probability of the study area on April 15 (spring), July 15 (summer), October 15 (autumn) and January 15 (winter) were calculated as examples to display time-dependent simulation of the proposed model. The probability distribution of annual mean daily relative humidity and daily temperature were assumed to be normal distribution. Figure 8 and Fig. 9 showed that the probability density distribution of seasonal mean daily relative humidity and daily temperature obeyed normal distribution in a spatial cell. The Kolmogorov-Smimov test accepts the null hypothesis at the 5% significance level.

The stochastic ignition probability spatial distribution on different dates was analyzed based on GIS (Fig. 10). The area percentage of different ignition probability on different dates is shown in Table 6. The area of high ignition probability on April 15 is largest, then that on October 15, while those in summer and winter are small. The results show that the stochastic ignition probability distribution has he seasonal variation characteristics and

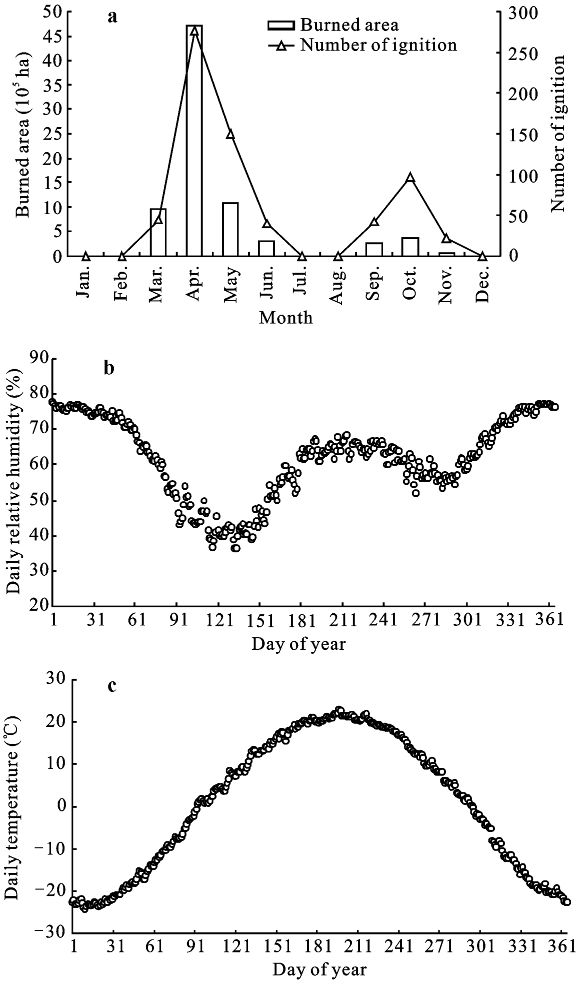

Fig. 7 Monthly numbers and burned area of grassland fire (a), annual mean daily relative humidity (b) and temperature (c) in Hulun Buir Grassland during 1986 and 2008

are consistent to the occurrence of historical grassland fire in the study area.

The area of high ignition probability on April 15 is widely distributed in the eastern and western Hulun Buir Grassland (Fig. 10b), that on October 15 is mainly in the northeast and northwest (Fig. 10d) and the area of high fire probability in summer and winter is only distributed around county-level road (Fig. 10a, c). The results show that the spatial pattern of stochastic ignition probability is obvious on different dates.

The time-dependent stochastic ignition probability model can be used to estimate ignition probability of any day in the future. But the stochastic ignition probability model had uncertainty because of the differences between the fitted and observed values of daily relative humidity, daily temperature. The differences need to be reduced by increasing the number of samples in the future researches.

4 Discussion

For meteorological factors, daily relative humidity has the greatest influence on ignition probability. The spring and autumn are peak periods for fire occurrences because they are the dry seasons. Temperature has greater influence on ignition probability. Precipitation does not have direct influence on ignition probability. In winter, the temperature is lower leading to snow always covers which not only increases water content of dead fuels but also separates combustibles from fire sources, so it is difficult to ignite. In spring, snow melts and evaporates with the increase of temperature, this is the reason for easier ignition. In hot summer, there are only few fire events, because at that time it is rainy, which means that the vegetation grows vigorously and there is much moisture, so it is difficult to fire. In autumn, although the daily temperature decreases gradually with time, the vegetation are withered when their moisture content decrease, so it is easy to ignition.

Among the topographic factors, slope and aspect do not have obvious influence on ignition probability, and only elevation has significant influence on it. Because the higher ignition density area was that with the elevation ranging from 600 m to 800 m, which is a high human activity region with 80.51% residential land located.

Among the human-caused factors, the distance to county-level road and distance to town have the greater influence on ignition probability, with the distance increase, the ignition probability is lower. This result agrees with that from other researchers on ignition probability, such as Vasconcelos *et al*. (2001), Filipe *et al.* (2009), Martinez *et al*. (2009), and Zhang *et al*. (2010).

Based on the daily ignition probability, a lot of ignition points randomly generated, and then the wildfires were assessed by using the spreading model. This method can accomplish the quantitative evaluation of wildfire risk (Mbow *et al*., 2004; Carmel *et al*., 2009). In this paper, with Monte Carlo method, the distribution of seasonal daily relative humidity and daily temperature were calculated, and then the time-dependent stochastic ignition probability model was developed. The

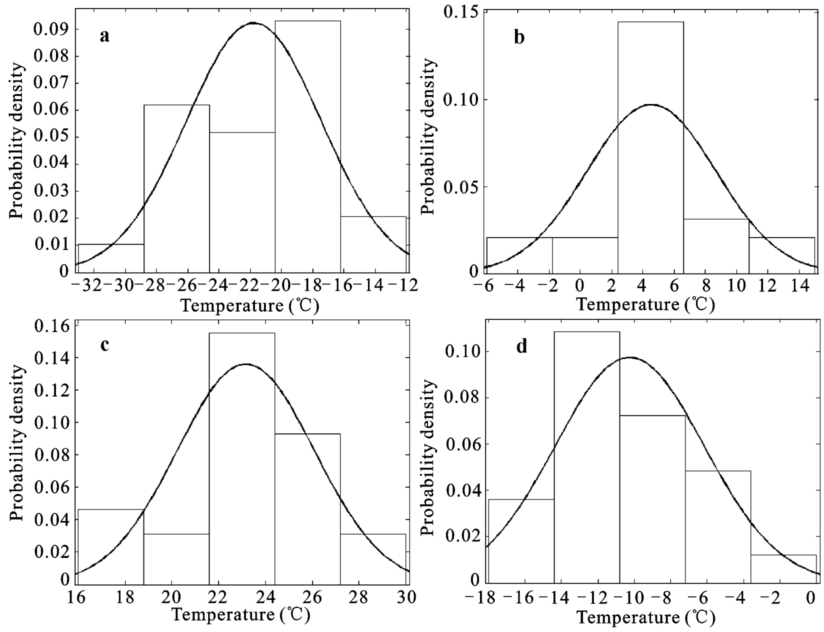

Fig. 8 Probability density distribution of seasonal daily temperature in a spatial cell on Jan. 15 (a), Apr. 15 (b), Jul. 15 (c), October 15 (d) from 1986 to 2008

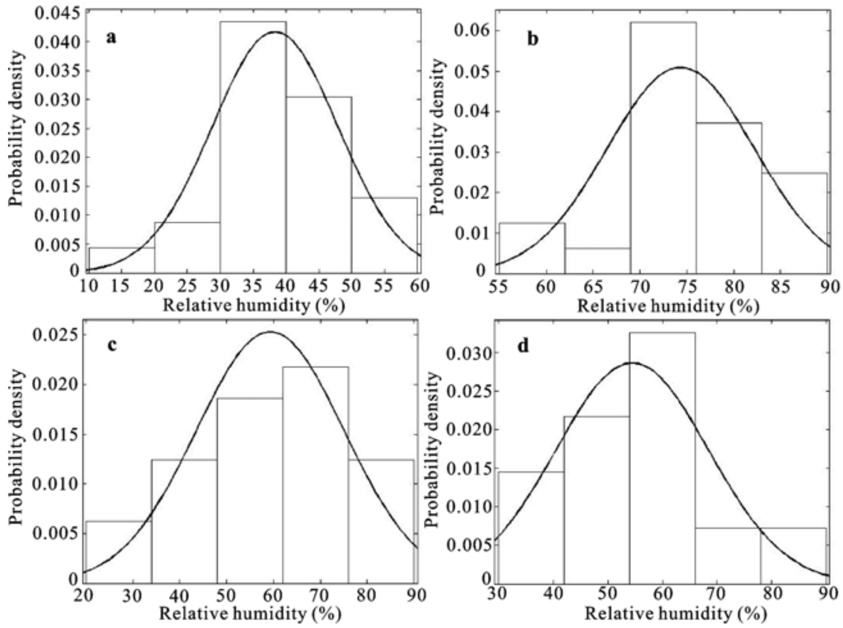

Fig. 9 Probability density distribution of seasonal daily relative humidity in a spatial cell on Jan. 15 (a), Apr. 15 (b), Jul. 15 (c), Oct. 15 (d) from 1986 to 2008

model may provide support for the quantitative evaluation of grassland fire risk in the future.

5 Conclusions

In this study, the temporal and spatial distribution of Hulun Buir Grassland fire during 1986 and 2008 was analyzed, in which 12 ignition factors were selected covering both natural and human-induced effects. Based on the number and density or ratio of ignition of different ignition factors, a time-dependent stochastic ignition probability model was developed. Main conclusions were drawn as follows through this study. 1) The density or ratio of ignition is able to reflect the relationships between grassland fire and different ignition factors. And the ignition probability model, which is

Table 6 Area percentage of different ignition probability on different dates

Ignition probability	Area percentage (%)			
	January 15	April 15	July 15	October 15
0.0–0.1	54.10	0.79	49.07	7.71
0.1–0.2	24.88	2.03	25.13	7.36
0.2–0.3	10.82	1.97	12.48	7.46
0.3–0.4	5.20	2.90	6.25	7.95
0.4–0.5	2.84	4.44	3.53	11.26
0.5–0.6	1.67	5.30	2.37	13.37
0.6–0.7	0.48	6.53	1.11	13.50
0.7–0.8	0.00	11.38	0.06	13.57
0.8–0.9	0.00	20.98	0.00	11.90
0.9–1.0	0.00	43.69	0.00	5.93

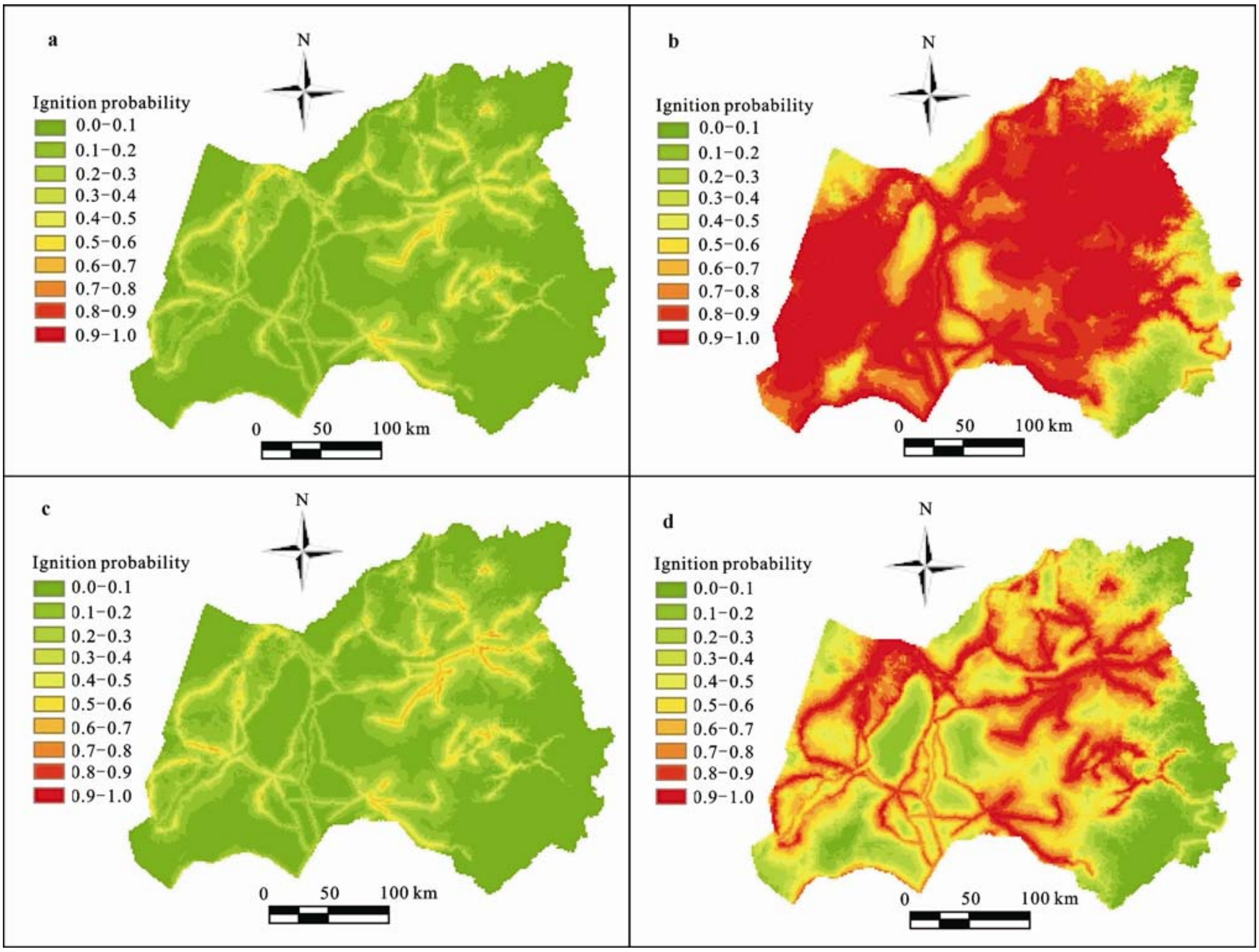

Fig. 10 Distribution of ignition probability on Jan. 15 (a), Apr. 15 (b), Jul. 15 (c), Oct. 15 (d)

based on the density or ratio of ignition of different ignition factors, can better describe the ignition mechanism in the study area. 2) The overall classification accuracy of the proposed ignition probability model is up to 81.7%. Daily relative humidity, daily temperature, elevation, vegetation type and distance to county-level road have significant influences on the ignition probability ($p < 0.05$), and their contribution to the ignition probability decrease in turn. 3) With the Monte Carlo method, the grassland stochastic ignition probability model is built based on the distribution of seasonal daily relative humidity and daily temperature. This model can reflect future daily spatial pattern of grassland ignition probability in the study area. Consequently, it can provide support for the quantitative evaluation of grassland fire risk.

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