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Article

Probability Models of Fire Risk Based on Forest Fire Indices in Contrasting Climates over China

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Abstract: Fire weather indices have been widely applied to predict fire risk in many regions of the world. The objectives of this study were to establish fire risk probability models based on fire indices over different climatic regions in China. We linked the indices adopted in Canadian, US, and Australia with location, time, altitude, vegetation and fire characteristics during 1998-2007 in four regions using semi-parametric logistic (SPL) regression models. Different combinations of fire risk indices were selected as explanatory variables for specific regional probability model. SPL regression models of probability of fire ignition and large fire events were established to describe the non-linear relationship between fire risk indices and fire risk probabilities in the four regions. Graphs of observed versus estimated probabilities, fire risk maps, graphs of numbers of large fire events were produced from the probability models to assess the skill of these models. Fire ignition in all regions showed a significant link with altitude and NDVI. Indices of fuel moisture are important factors influencing fire occurrence in northern China. The fuel indices of organic material are significant indicators of fire risk in southern China. Besides the well skill of predicting fire risk, the probability models are a useful method to assess the utility of the fire risk indices in estimating fire events. The analysis presents some of the dynamics of climate-fire interactions and their value for management systems.

Key words: climate; forest fire; meteorological risk; fire risk indices; semi-parametric logistic regression model

1 Introduction

Forest fires have caused enormous losses in terms of human lives, environmental damage, and economic disruption in China. The average death toll reached two to three thousand persons per year and the average loss directly related to wildland fires reached more than one hundred million US dollars annually during the past decade in China (Guo 2005).

Weather is considered a determinant for forest fires (Brown *et al*. 2008; Carrega 1991; Davis and Michaelsen 1995; Finney 2005; Flannigan and Harrington 1988; Gill and Moore 1996; Gu *et al*. 2008; Jiang *et al*. 2008; Keeley 2004; Moritz 2003; Peters *et al*. 2004; Taylor *et al*. 2008; Zhou *et al*. 2006), and fire regime is very sensitive to climate (Beverly and Martell 2005; Duffy *et al*. 2005; Whitlock *et al*. 2003). Relationships between the temporal and spatial structure of lightning- and human-started fires and meteorological factors have been explored (Bartlein *et al*. 2008) and the impact of weather on forest fire change with location and vegetation types (Viegas and Viegas 1994; Viegas *et al.* 1992; Flannigan and Harrington 1988; Cunningham 1984). Wildfires are both frequent and extensive in Northeast of China during the winter season. In contrast, fires are concentrated during the summer season in South China. The fire regimes in contrasting climates over China reflect weather-related controls.

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Some efforts have been made to develop fire risk indices to assess fire risk and to enhance preparedness. Fuel moisture content is one critical factor influencing fire ignition and distribution (Carlson and Burgan 2003; Chandler *et al*. 1983; Van Wagner 1977). Moisture exchange of vegetation litter is controlled by rapid atmospheric changes (Saglam *et al*. 2006; Viney 1991). In addition, live fuel moisture is dependent on species characteristics, climate and soil water content (Castro *et al*. 2003; Rothermel 1972). However, direct measurements of fuel moisture are slow and time consuming. For practical purposes, it is better to simulate variation in fuel moisture content in relation to meteorological and soil factors such as surface air temperature, soil moisture, humidity, probability of lightning, and atmospheric stability (Gillett *et al.* 2004; Keetch and Byram 1968; Turner and Lawson 1978).

Over the past decades, a variety of fire-risk rating systems based on different meteorological variables have been developed in a variety of locations, such as the McArthur Forest Fire Danger Index (FDI) (McArthur 1967), quantified by Noble *et al*. (1980), the Fire Weather Index (FWI) (Van Wagner 1977), and the National Fire Danger Rating System (NFDRS) (Deeming *et al*. 1977). All integrated rating systems include sub-models for estimating fuel moisture, such as the Keetch-Byram Drought Index (KBDI) of the NFDRS (Deeming *et al*. 1977), the Fine Fuel Moisture Code (FFMC), the Duff Moisture Code (DMC), the Drought Code (DC) of the FWI, and the drought factor (DF and DG) and Forest Fire Danger Index (FFDI) of the FDI (Griffiths 1999; Noble *et al*. 1980).

Efforts have been made to link fire risk indices with fire characteristics (e.g., burnt area). However this deterministic method is deficient in predicting fire from indices due to the complicated multiple factors affecting fire occurrence. These fire risk indices reflect vegetation fuel, water status, and atmospheric dryness. The point-to-point temporal correlation statistics appear to be a poor method to describe the non-linear relationship between fire risk indices and fire counts (Roads *et al*. 2005). Furthermore, the correlation statistics are not adequate to analyze variables with small counts such as the occurrence or absence of forest fire (mostly 0 or 1). Consequently we propose that the probability method may serve as a replacement to predict the likelihood of fire and fire severity. A Poisson model has been used to assess the skill of fire weather indices in estimating numbers of fires (Dayananda 1977; Mandallaz and Ye 1997). Stepwise regression was used to study the relationship of fire weather indices to the logarithm of the number of fires and the area burned (Carvalho *et al*. 2008). The logistic regression was used to evaluate the effects of fire risk indices on probability of fire days (Anderson *et al*. 2000; Catry *et al*. 2009; Cunningham and Martell 1972; Martell *et al*. 1989; Martell *et al*. 1987). A logistic regression with fire risk indices and spatial variables as explanatory variables was used to study spatial autocorrelation between nearby fires (Chou *et al*. 1993; Chou *et al*. 1990). Relationships between temporal variables, fire risk indices and fire occurrences were studied from time-since-last-fire data (Grissino-Mayer 1999; Johnson and Gutsell 1994; Peng and Schoenberg 2001; Reed 1998; Reed *et al*. 1998). Non-parametric or SPL regression with spatially and temporally explanatory variables has been used to study relationship between fire risk indices and probability of fire ignition and large fire events (Brillinger *et al*. 2003; Brillinger *et al*. 2006; Preisler *et al*. 2004; Preisler *et al*. 2008; Preisler and Westerling 2007). The SPL regression model is a logistic regression technique with piece-wise polynomials to estimate the probabilities of interest as functions of explanatory variables. This statistical model is a useful method to estimate the probability of fire risk and to quantify the relationship between fire risk indices and fire risk (Brillinger *et al*. 2003; Brillinger *et al*. 2006; Preisler *et al*. 2004; Preisler *et al*. 2008; Preisler and Westerling 2007).

Although some fire risk indices, such as the FWI, FFWI, DF, DG, and FFDI have been introduced to some areas of China (Tian *et al*. 2009; Yang *et al*. 2010; Zhao *et al*. 2009), no research has been conducted on their relationship to forest fire activity in contrasting climates over China, and a national standard is vitally important (Di *et al*. 1993; Shu *et al*. 2003). The relationship between forest fires and weather indices is still poorly understood over diverse biomes. This study will assess the variation of these weather fire indices and their applications in forest fire risk predictions in four contrasting climates in China. In this study, a SPL regression model was used to assess the utility of the fire risk indices on estimating fire characteristics and produced prediction of large fire events. We will establish SPL regression models with selected fire risk indices as explanatory variables to estimate the probability of fire ignition and large fire events. Although human activities cause many forest fires, this anthropogenic effect becomes most pronounced when weather conditions are conducive to the expansion of forest fires. In this paper we focus on the meteorological component of the changes in potential forest fire risk. The significance of this study is to provide an evaluation of the performance of weather indices over a wide range of climatic and ecological regions.

2 Materials and methods

2.1 Study area

China's landscape can be divided into an eastern monsoonal region, a dry inland in Northwest, and the Tibetan Plateau. This study covers the monsoonal region where plenty of rainfall (with annual rainfall 1200 mm) is received but significant seasonal variation within dry and wet seasons are characterised by air mass transitions between inland air and oceanic air. The study area was divided into four sub-regions according to their distinct biomes. The North China Plain has a dominant vegetation of deciduous broad-leaved trees; the Northeast of China is dominated by cool temperate coniferous forest; the Southeast of China is dominated by mixed evergreen broadleaf and deciduous broad-leaved

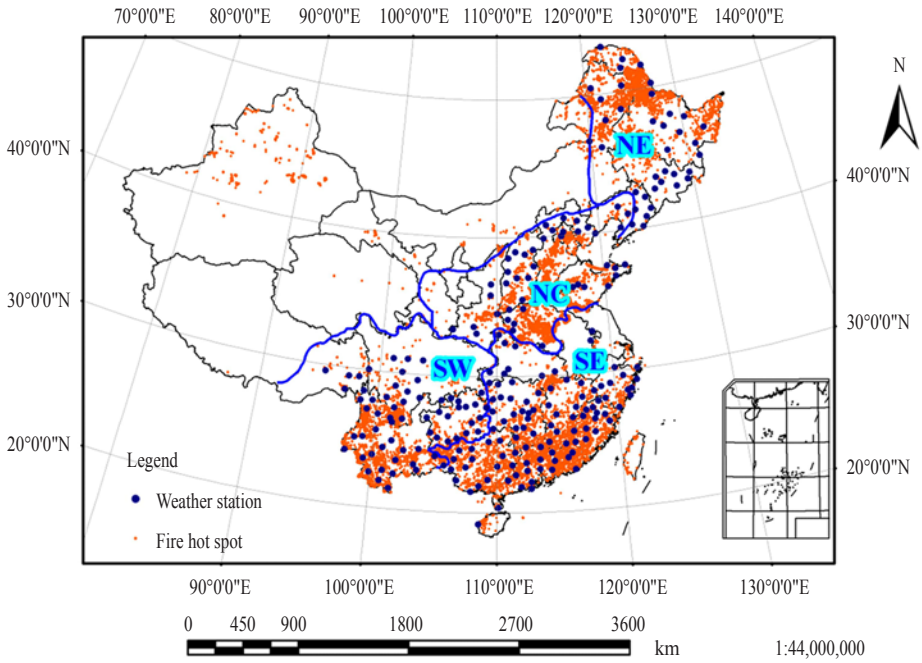

Fig. 1 Distribution of study areas and weather stations used for this study. The blue dots are the locations of the weather stations. The red dots are the locations of firehots in China during 1998–2007.

forest, and the Southwest of China is dominated by tropical rain forest (NC, North China Plain; NE, the Northeast of China; SE, the Southeast of China; SW, the Southwest of China) (Fig. 1). Climate and vegetation properties of the 4 regions are listed in Table 1.

2.2 Meteorological data

Daily values of precipitation, maximum temperature, average temperature, wind speed, relative humidity from 245 stations covering the majority of the four climate regions were obtained from the China Meteorological Administration to calculate fire indices (Fig. 1) (1998–2007). For the purposes of this study, the FWI components were computed using daily maximum temperature, daily mean relative humidity, and daily average wind speed instead of the noon values of these weather inputs.

2.3 NDVI data

The Normalized Difference Vegetation Index (NDVI) was applied as a measure of vegetation status. The NDVI values for this study were extracted from the spot vegetation NDVI data and GIMMS-NDVI-China data (Data source: Environment & Ecology Scientific Data Center of western China, National Natural Science Foundation of China; http://westdc.westgis.ac.cn).

2.4 Fire occurrence data

We used fire count and burnt area data from the European Space Agency (ESA) to identify fire activity in each of the research regions. Fire counts were extracted from the Along Track Scanning Radiometer (ATSR) World Fire Atlas (European Space Agency, ATSR World Fire Atlas, available at http://dup.esrin.esa.int/ionia/wfa/index.asp) and from the Data User Element of the European Space Agency. These data were derived from the optical ATSR sensor on board the European ERS-2 satellite. The ATSR instrument has a spatial resolution of 1 km×1 km. All hot spots (including gas flares) with a high temperature at night are precisely

Table 1 Climate and vegetation conditions in the 4 regions.

	NC	NE	SE	SW
Regional climate	Temperate climate	Cold temperate and frigid climate	Humid subtropical and tropical climate	Tropical and subtropical climate
Dominant monsoon or air mass	Pacific Ocean monsoon	Siberian cold air mass	East Asian Monsoon system	Indian Ocean monsoon, south-east monsoon
Annual mean T (℃)	7/16	–10	16–20	12/16
Summer T (℃)	26	17	35	20
Winter T (℃)	–7	–29	–3	7
Annual precipitation (mm)	400–900	400–650	1300–1900	1100
Rainfall seasons	April–November	June–August	April–September	May–October
Driest seasons	December–March	November–March	December–February	November–March
Vegetation	Deciduous broad-leaved forest	Cool temperate coniferous forest	Evergreen broad-leaved forest, Deciduous broad-leaved forest	Tropical rain forest

located using the 3.7 micron thermal channel. Fire detection algorithm 2 (Hot spot if: 3.7 micrometers > 308 Kelvin) was used for the ATSR data. A detailed description of the fire detection algorithm is available at the ESA website (http://dup.esrin.esa.int/ionia/wfa/index.asp). The data from the website also include fire information concerning spatial coordinates, ignition date, land cover classification and biomass burned. There are several problems that exist in these data, including ATSR frame overlap (some fires can be detected twice) and global underestimation of the hot spot number (only night time fires are detected). We removed the obvious duplicated records and believe that the visualizations of the data presented here reflect real patterns with possible underestimates due to occasional day-only fires. The fire database used for the four regions in this study comprised the period between 1998 and 2007. The monthly numbers of fires were computed from daily reports within 1-degree grid cell for each weather station. Maps of historical probabilities of large fire events for the months of February and November showed the spatial and temporal structure of the fire risk in the study region during 1998–2007 (Fig. 2).

2.5 Fire weather indices

Fire weather indices were calculated using observed data from the weather stations. Both means and maximums of the indices for monthly periods were calculated because much of the large fires occur during extreme fire weather conditions.

2.5.1 The FWI System

The FWI System (Van Wagner 1987) is a weather-based system including three moisture codes that represent the moisture content of fine fuels (fine fuel moisture code, FFMC), loosely compacted organic material (duff moisture code, DMC), and a deep layer of compact organic material (drought code, DC). These moisture indices are combined to create fire behavior indices: Initial Spread Index (ISI): a combination of wind and FFMC that estimates the potential spread rate of a fire. Buildup Index (BUI): a combination of the DMC and DC that represents the availability of fuel for consumption. Fire Weather Index (FWI): a combination of the ISI and BUI that estimates the potential intensity of a spreading fire. By considering the nonlinearity with respect to control effort, the daily severity rating (DSR) – a power function of the FWI to increase the weight of higher values of FWI — was added in FWI (Van Wagner 1970; Williams 1959).

2.5.2 The Fosberg (1978) Fire Weather Index

FFWI was designed as a supplement to the once-daily fire risk calculations provided by the 1972 NFDRS (Deeming *et al*. 1977). For the purposes of the present study, the FFWI components were computed once per day using daily mean temperature, daily mean relative humidity, and daily average wind speed.

The FFWI is given by:

$$\mathrm{FFWI} = \eta\sqrt{1+U^2}\,/0.3002 \tag{1}$$

η is given by

$$\eta = 1 - 2(m/30) + 1.5(m/30)^2 - 0.5(m/30)^3 \tag{2}$$

m is given by:

$$m = \begin{cases} 0.03229 + 0.281073h - 0.000578hT \\ \qquad for\ h < 10\% \\ 2.22749 + 0.160107h - 0.01478T \\ \qquad for\ 10\% < h \le 50\% \\ 21.0606 + 0.005565h^2 - 0.00035hT - 0.483199h \\ \qquad for\ h > 50\% \end{cases} \tag{3}$$

where U is the daily average wind speed (mile h^{-1}), T is daily mean temperature (°F), h is daily mean relative humidity (%).

2.5.3 The Keetch-Byram Drought Index

The KBDI, which conceptually describes the soil moisture deficit, is used to assess wildfire potential as part of the revised 1988 U.S. National Fire Danger Rating System (NFDRS) (Richard and Heim 2002).

The equation for computing the incremental rate of

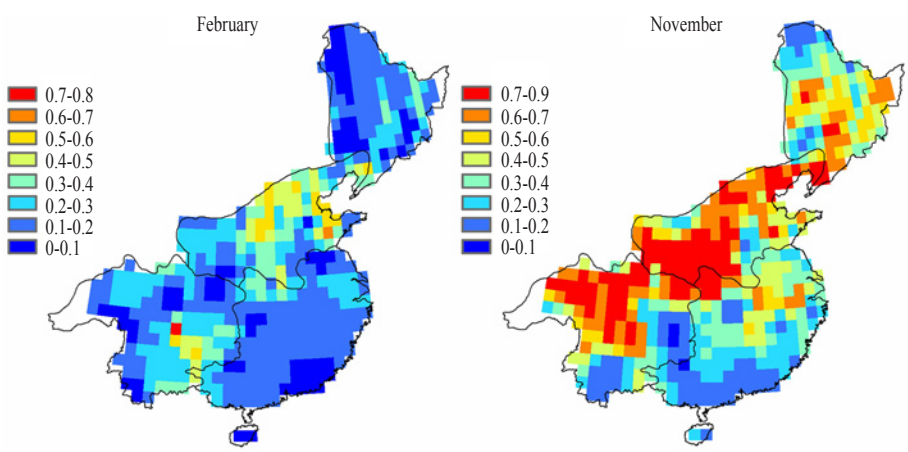

Fig. 2 Historical probabilities of large fire events for the months of February and November calculated from the observed fire data for the period of 1998–2007 showing the spatial and temporal structure of the fire risk in the study region.

change of the index, ΔQ is

$$\Delta Q = [203.2 - Q][0.968\exp(0.0875T + 1.5552) - 8.30]\Delta t \times \frac{0.001}{1 + 10.88\exp(-0.00173R)} \quad (4)$$

The new value for KBDI on the current day is calculated as

$$K = Q + \Delta Q \quad (5)$$

where K is the new value for KBDI on the current day, T is the daily maximum temperature (ºC), R is the mean annual rainfall (mm), Q is a value for the soil water depletion (mm), ΔQ is the incremental depletion of soil moisture in the time increment Δt (mm), and Δt is a time increment set equal to 1 day. This equation (4) describes the drying rate of the soil. Note that the temperature factor has no effect unless the day's maximum temperature is above 10.8 ℃. If $T < 10$ ℃ then, by default, $\Delta Q = 0$. The equation is converted from the original by Keetch and Byram (1968), which had inputs of temperature in ℉ and rainfall in inches to temperature in ℃ and rainfall in mm. Further explanation of the calculations for the index can be found in Keetch and Byram (1968).

2.5.4 The McArthur Forest Fire Danger Meter

$$FFDI = 2exp(-0.450+0.987\ln(D)-0.0345H+0.0338T+0.0234V) \quad (6)$$

The equation used to calculate the drought factor (D) in the FFWI proposed by Noble *et al*. (1980). D_N is given by

$$D_N = \frac{0.191A_P(K+104)}{3.52A_P + P - 1} \quad (7)$$

The variable A_P is calculated as

$$A_P = (N+1)^{1.5} \quad (8)$$

The equation used to calculate the drought factor (D) proposed by Griffiths (1999). D_G is given by

$$D_G = \min\left\{10.5\left[1 - \exp\frac{-(K+30)}{40}\right]\frac{y+42}{y^2+3y+42}, 10\right\} \quad (9)$$

where y is defined by

$$y = \begin{cases} (p-2)/N^{1.3}, \text{if } N \geq 1 \,\&\, P > 2 \\ (p-2)/0.8^{1.3}, \text{if } N = 0 \,\&\, P > 2 \\ 0, \text{if } P \leq 2 \end{cases} \quad (10)$$

In the above equations, K is soil dryness KBDI (mm) (Keetch and Byram 1968), T is the daily maximum temperature (℃), H is the daily minimum relative humidity (%), V is the daily-mean wind speed (km h^{-1}), R (mm) is the total rain in the most recent 24 hours with rain, N is the number of days since the last rainfall event, P is the amount of rainfall (mm) in the last event.

2.6 Probability models for fire risk

As measures for fire risk, three probabilities were used in our study: probability of ignition (p_1), conditional probability of a large fire event (p_2) and unconditional probability of a large fire event (p_3). Specifically, probability of ignition was the probability of at least one fire occurring in a given 1-degree grid cell with the weather station as the center during a given month. Conditional probability of a large fire event was the probability of an ignition becoming a large fire (> 400 ha) in a given 1-degree grid cell with the weather station as the center in a given month. Unconditional probability of a large fire event was the probability that an area of size greater than 400 ha will burn in a 1-degree grid cell with the weather station as the center in a given month and year.

We used a semi-parametric logistic regression model (Brillinger *et al*. 2006; Hastie *et al*. 2001) to estimate the first two fire risk probabilities for each study region:

$$logit(p_k) = \beta_o + g_1(lon_k, lat_k) + g_2(month_k) + g_3(elev_k) + \sum_{n=1} h_n(X_{nk}) \quad (11)$$

where the subscript k indicates the 1×1-degree×month grid cell with each weather station as the center; p is either the probability of ignition or conditional probability of a large fire event; (*lon, lat*) are the latitude and longitude of the weather station of the 1×1-degree grid cell; *month* is the month in year; *elev* is the elevation (in meters) at location; X_n are explanatory variables (e.g., the fire weather indices mentioned above). The functions $g_i(\ldots)$ and $h_n(\ldots)$ are non-parametric smoothing functions (e.g., thin plate spline function and basis spline), which would characterize the non-linear relationships between the explanatory variables and the logit of fire probability better than parametric functions.

For studying the usefulness of the various fire weather indices on estimating the probability of fire, we used the Akaike information criterion (AIC) (Sakamoto *et al*. 1986) statistics to choose between indices. Historical model (B) with location and month as the explanatory variables only and fire weather index model (named after the index) with location, month and one fire weather index as the explanatory variables were compared by the AIC statistics. The regression model with the "best" selection of indices was used to estimate the first two fire probabilities described above using cross validation. The unconditional probability of a large fire event was estimated by multiplying the first two estimated probabilities. Statistical analyses were conducted with the R statistical package (R Development Core Team 2010).

Model appraisal for the final selected model was done by producing graphs of observed versus estimated probabilities (Hosmer and Lemeshow 1989). Based on some criteria, all grid cells were grouped and the observed fraction of responses in each group was compared with the average estimated probability for that group. We used a grouping method to assess the goodness-of-fit of the model at different scales. The grouping was done

according to similar estimated probabilities (within 1% of each other). We grouped together cells with the similar estimated probabilities (within 1% of each other, e.g. Cells with the estimated probabilities between 2.5% and 3.4% were grouped together in one group), and compared the mean estimated probabilities with the observed fraction of responses in each group. The observed fraction is the percentage of the number of observed large fire events in the number of all cells in each group.

One set of fire risk maps (Preisler *et al*. 2004) used in this study was based on estimated probabilities of a large fire event in a given grid cell. An inverse-distance weighted (IDW) method was used to interpolate these fire risk probabilities to the 1-degree grid cell level. Rules for defining levels of fire risk are as follows:

$$\begin{array}{lll} \text{Low} & \text{if} & \hat{p} + 2\text{s.e.} \le a_1 \\ \text{Moderate} & \text{if} & a_1 \le \hat{p} + 2\text{s.e.} < a_2 \\ \text{High} & \text{if} & a_2 \le \hat{p} + 2\text{s.e.} < a_3 \\ \text{Extreme} & \text{if} & \hat{p} + 2\text{s.e.} \ge a_3 \end{array} \quad (12)$$

where $\hat{p}$ are the estimated probabilities of area burned being greater than 400 ha; s.e. are jackknife standard error estimates of $\hat{p}$; α_i (i = 1, 2, 3) are probability cutoff points with values 0.1, 0.3 and 0.5 in our study.

Another set of fire risk maps (Preisler *et al*. 2008) was produced using the odds ratio statistic to estimate departure from the normal conditions. $\hat{\theta} = \log(\hat{\gamma})$ is the logarithm of the estimated odds relative to historical values,

$$\hat{\gamma} = \frac{\pi(1-\pi_H)}{\pi_H(1-\pi)} \quad (13)$$

where π is the selected model estimate probability and π_H is the probability based on model with location and month as the explanatory variables only (historical model). Criteria for defining levels of fire risk are as follows:

$$\begin{array}{lll} \text{Lower than historical} & \text{if} & \hat{\theta} + 2\hat{\sigma} < 0 \\ \text{Normal} & \text{if} & -2\hat{\sigma} \le \hat{\theta} \le 2\hat{\sigma} \\ \text{Higher than historical} & \text{if} & \hat{\theta} - 2\hat{\sigma} > 0 \end{array} \quad (14)$$

where $\hat{\sigma}$ is the one standard deviation from the historical odds for the given month.

Table 2 the selected indices in the final regression model for the probabilities of fire occurrence in the 4 regions (index followed with -X indicates the maximum values of that index).

Study region	Selected indices in the regression model
NC	Altitude, FFMC, DMC, DC-X, FWI, FFWI, FFDI, NDVIGimms
NE	Altitude, FFMC-X, DMC-X, DC-X, BUI-X, KBDI-X, FFDI-X, NDVIspot-X
SE	Altitude, DC-X, ISI, BUI, FFWI, DG, NDVIGimms
SW	Altitude, DMC-X, DC-X, ISI, BUI-X, FWI, DSR-X, KBDI-X, FFDI, DG,NDVIspot-X

One of the basic interests in fire management is the expected fire count for a given region and time period. In our study, we summed the estimated probabilities over individual weather station grid cells of the selected region and months of the year, and then calculated the approximate confidence intervals.

3 Results

3.1 Regional-significant fire weather indices

The forest fires in the 4 regions have different times of year for peak fire risk. This is due to spatial variation in the occurrence of drought, wind speed, precipitation patterns, temperature, and accumulated snow, all of which lead to different fire-danger patterns. This seasonality of forest fire risk among the various forest regions is different. Because of the gentle topography, the presence of ecotones between grassland and forest and the influence of the monsoon in spring and autumn, forest fires in NE spread quickly and over large areas. In contrast, the number of forest fires is large but the burnt area is small over southern forests, while the area extent of forest fire is largest in NE, but with low numbers.

In NC, the present land cover and vegetation types include cropland, shrub, forest and rangeland. In this area, locust trees (*Robinia pseudoacacia* L.) and littleleaf peashrub (*Caragana microphylla* Lam.) are the most common species. The NE is characterized by a temperate climate, with long, cold, dry winters and short, warm, humid summers affected by the Siberian cold air mass (Zhou *et al*. 1991). Snow covers the forest floor for around six months between November and late April. The precipitation in this region is lower than in the southern parts of China. The vegetation of this area includes the southern extension of eastern Siberian boreal forests (Zhou *et al*. 1991). Birch (*Betula platyphylla* Sukaczev) and pine (*Pinus sylvestris* L. var. *mongolica* Litv.) are mixed with larch (*Larix gmelini* Rupr.) in most areas owing to fire disturbance and forest harvesting (Xu 1998). The area is an important forestry region of China. The main timber bases are located in Greater Xingan forest district, Greater Xingan forest district, and Changbai Mountains forest district. In SE, the East Asian Monsoon system brings warm and wet humid weather in summer and cooler drier weather in winter. Mean monthly temperatures are above 15 ℃ from April to October (Domos and Gongbing 1988; Sweeting 1999). The

Table 3 the selected indices in the final regression model for the conditional probabilities of a large fire event in the 4 regions (index followed with -X indicates the maximum values of that index).

Study region	Selected indices in the regression model
NC	Altitude, FFMC, DMC, DC-X, DSR-X, KBDI-X, FFDI-X, NDVIspot-X
NE	DG, NDVIGimms
SE	DMC, DC, KBDI
SW	DMC-X, ISI, FFWI, FFDI, NDVIGimms

region falls within a transitional subtropical vegetation zone (Box 1995; Ren 1985). There are many pine and *Eucalyptus* plantations in the region. Some remnant forests have almost disappeared due to deforestation and land-use conversion to agricultural production. Land cover types include conifer and broadleaf forests, orchard, cropland, scrub, and other secondary vegetation. Fires occurred almost every month, although the peak number of fires occurred mainly in January to March. SW has a marked dry season from November to April with high fire risk and a wet season from May to October. Vegetation of this area is mainly composed of mixed rain forest which has a high biodiversity and dipterocarp rain forest, with the former widely distributed in this area (Cao and Zhang 1997; Pu *et al*. 2001).

To study the effects of fire risk indices on the probabilities of fire occurrence and the conditional probabilities of a large fire event in contrasting climates, we plotted the AIC statistics for historical model (B) and fire weather index models for the 4 regions. After comparing models with mean and maximum values of the same fire weather index as the explanatory variable respectively, we plotted the better model which had lower AIC value for each index. All AIC values in the plots are relative to the AIC values of B models which were set to zero in each region. Fig. 3a demonstrates the relative importance of each index on the probabilities of fire occurrence in the 4 regions. Indices which were most strongly associated with the fire occurrence were different in the 4 regions. Altitude and FFMC in NC, FFMC and NDVI spot in NE, FWI and FFMC in SE, KBDI and FFDI in SW indicated the highest relative decrease in AIC values for probability of fire occurrence. The indices that were most strongly associated with the large fire events were altitude and DMC in NC, FFMC and DG in NE, DMC and BUI in SE, DMC and FFDI in SW (Fig. 3b).

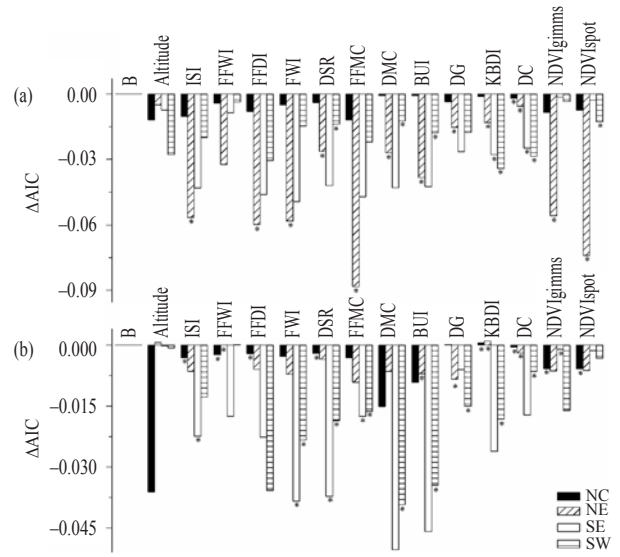

Fig. 3 The relative importance of each fire risk index on the probabilities of fire occurrence described by the Akaike information criterion (AIC) statistics (a) and the conditional probabilities of a large fire event (b) for historical model (B) and fire risk index models in NC, NE, SE and SW. Fire risk index models calculated by the maximum values of the index were marked by asterisk. All AIC values in the plots are relative to the AIC values of B models which were set to zero in each region, i.e. $(AIC_{index}-AIC_B)/AIC_B$.

According to the AIC statistics for each index, we developed the final regression model base on the historical model by adding selected indices with low AIC and only if they met the 0.05 significance level tested by the null hypothesis. Tables 2 and 3 present the selected indices in the final regression models of the probabilities of fire occurrence and the conditional probabilities of a large fire event in the 4 regions. Except for the location and month, variables selected in the fire occurrence model, were different from those in the large fire events model in each region. For fire occurrence models, altitude, DC and NDVI were selected by all regions, FFDI and DMC were selected by all except SE, and most indices selected in NE and SW were maximum values. For the large fire events models, NDVI was selected by all regions except SE, DMC was selected by all except NE, and most indices selected in NC were maximum values.

3.2 Selection of model skills

Fig. 4 shows the graphs of observed versus estimated probabilities grouping by similar estimated probabilities (within 1% of each other) for the final models (top panels) and the historical models (bottom panels) in NC (a, e), NE (b, f), SE (c, g) and SW (d, h). The grouping was done by grouping together cells with the similar estimated probabilities (within 1% of each other, e.g. cells with the estimated probabilities between 2.5% and 3.4% were grouped together in one group), and compared the mean estimated probabilities with the observed fraction of responses in each group. The observed fraction is the percentage of the number of observed large fire events in the number of all cells in each group. The dashed lines are the approximate point-wise 95% confidence bounds. Most of the observed points fall inside the estimated point-wise 95% confidence bounds from the final model in NC, NE and SW. The range of estimated probabilities from the final model is 0 to 0.96 in NC, 0 to 0.99 in NE, 0 to 0.83 in SE and 0 to 0.97 in SW. For a model with perfect estimate skill, the estimated probabilities span a range from 0 to 1. For a model with no skill, the estimated probabilities have no range. The better the skill of a probability model, the wider range of estimated probabilities. There are fewer observed points falling outside confidence bounds from the final model than those from historical model in NC, NE and SW. The estimated probabilities from the final model spanned a wider range of value than those from historical model in all the 4 regions. The final model improved on the historical model in NC, NE and SW in these two ways. The larger confidence bounds for the middle part of probabilities for these models may be related to fewer observations in these

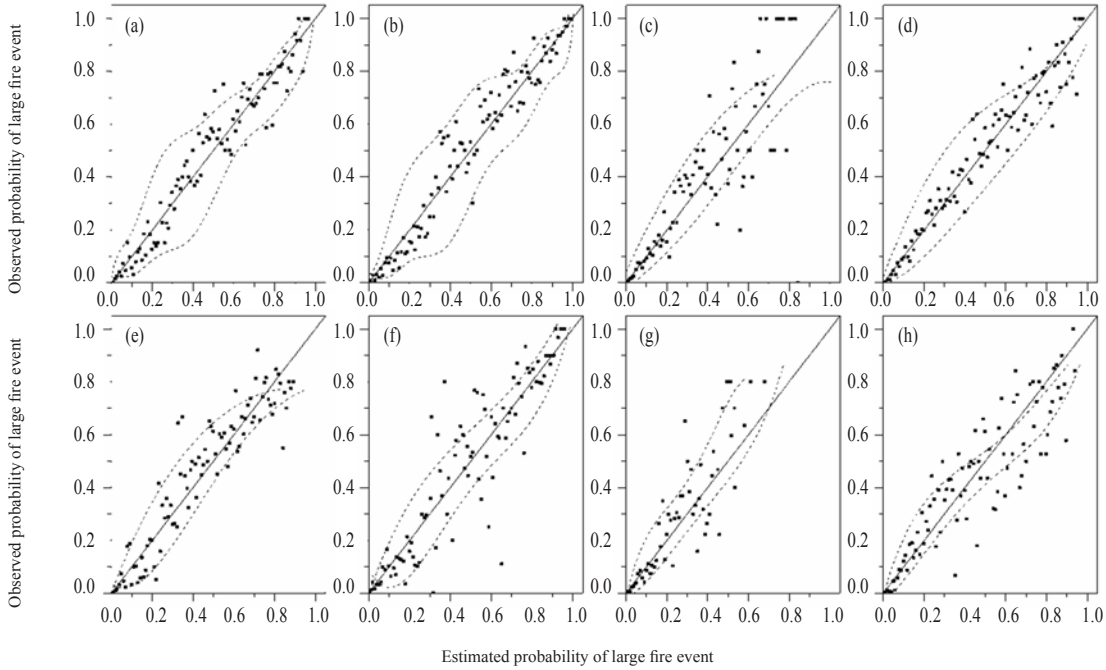

Fig. 4 Observed versus estimated probabilities grouping by similar estimated probabilities (within 1% of each other) for the final models (top panels) and the historical models (bottom panels) in NC (a, e), NE (b, f), SE (c, g) and SW (d, h). The grouping was done by grouping together cells with the similar estimated probabilities (within 1% of each other, e.g. Cells with the estimated probabilities between 2.5% and 3.4% were grouped together in one group), and compared the mean estimated probabilities with the observed fraction of responses in each group. The observed fraction is the percentage of the number of observed large fire events in the number of all cells in each group. The dashed lines are the approximate point-wise 95% confidence bounds.

groupings.

3.3 Fire risk maps

Fire risk maps with estimated fire risk levels and observed large fire events were plotted for February 2001 and November 2005 (Fig. 5), showing outputs from the final models in the 4 regions. The fire risk levels used in the maps were the following: low (estimated probability < 10%), moderate (10%–30%), high (30%–50%), extreme (> 50%). In these maps, most points of large fire events matched with extreme and high risk level grid cells. The maps show good predictive capability of the models in the four regions.

To further assess the spatial and temporal fire risk, we produced another set of maps using the odds ratio statistic to estimate departure from the normal conditions. The odds ratio maps need to be accompanied by maps of estimated probabilities. Examples are presented here for February 2003 and February 2004 (Fig. 6). For the period of February 2003, because odds ratio maps imply different fire risk from normal, not real fire risk, many points for large fires fall inside the grid cells of normal. Compared with the map of probabilities in that month, many grid cells marked as high in east SW in the odds ratio maps predict large fire events when the same grid cells have moderate or low probability (<

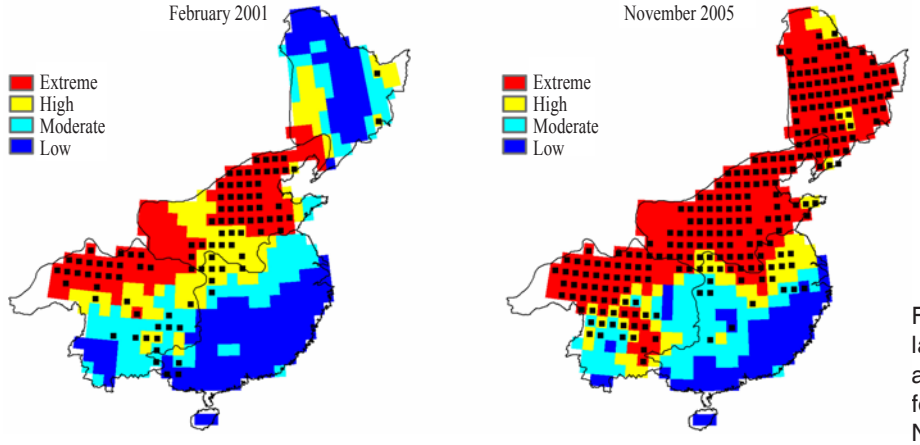

Fig. 5 Fire risk maps with estimated large fire events probability levels and observed large fire events (dots) for the months of February 2001 and November 2005.

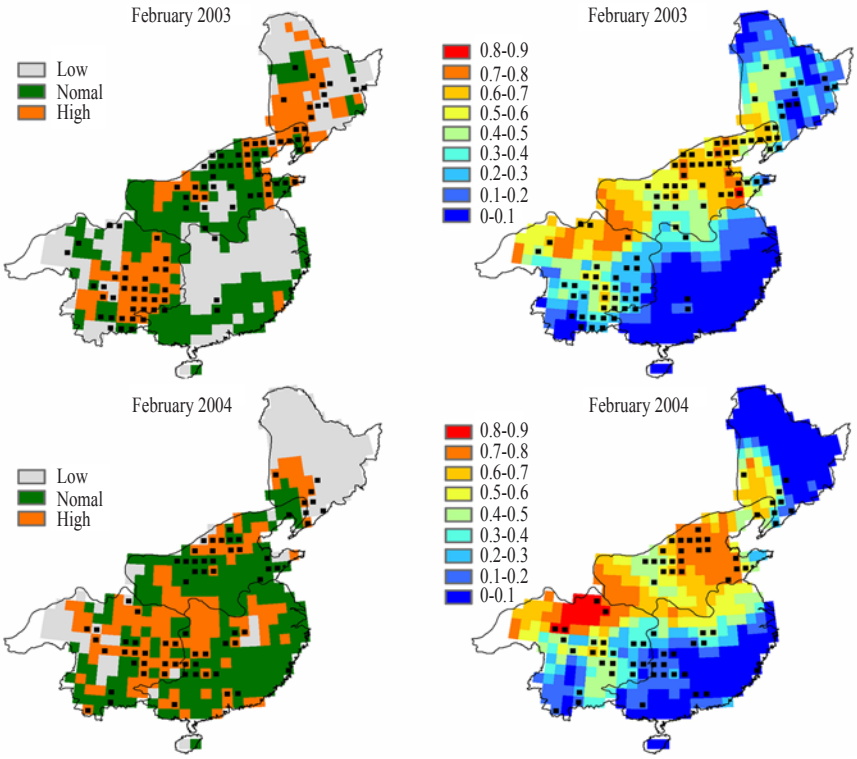

Fig. 6 Odds ratio maps (left panels) using the odds ratio statistic to estimate departure from the normal conditions and maps (right panels) of estimated probabilities for February 2003 and February 2004.

30%). A similar example can be found in east SW and west SE for February 2004. When the probability of large fire is < 30% and the odds ratio is high, the fire risk is higher than normal. Using the odds ratio maps compared with probability maps, managers could minimize the number of times that large fire events are missed.

3.4 Expectation of total number of fires

We also plotted the estimated total number of large fire events for the monthly period within each region. The estimated total number of large fire events was calculated by adding all the probabilities in every weather station grid cells in the region in that month. The years of 2000, 2002, 2006 were used for examples of our outputs (Fig. 7). In Fig. 7, observed numbers of large fire events (dots) and estimated 95% confidence limits (shaded regions) are also plotted. The final models gave better results for estimating numbers of large fire events on monthly basis in SE and SW than those in NC and NE. Overall, 17%, 8%, 4%, and 2% of the dots of observed large fire numbers fall outside the estimated 95% confidence bounds in NC, NE, SE, SW respectively. In the NC and NE, the observed numbers of large fire events were greater than the upper estimated 95% confidence bound in month of October and November.

4 Discussion

Results of our study show that the significant indices explaining the variance of fire occurrence probabilities in the 4 regions differ. SE used the fewest indices in the fire occurrence probability model. Altitude was selected as the major explanatory variable in all regions, which showed the strong influence of altitude on fire ignition. This result is consistent with previous studies (Moreira *et al*. 2010; Badia-Perpinyã and Pallares-Barbera 2006; Vazquez and Moreno 1998; Kilinc and Beringer 2007). This influence of altitude on fire ignition may be due to the fact that lightning strikes are more likely to occur at higher altitude, and this correlation between altitude and lightning strikes causes higher frequent lightning-caused ignitions at higher altitude which confirms previous studies (Vazquez and Moreno 1998; Kilinc and Beringer 2007). For all the four regions, NDVI values showed an influence on fire ignition similar to previous studies (Gianelle *et al*. 2009; Huesca *et al*. 2009). NDVI in this study is a variable reflecting the seasonal and inter-annual variations of vegetation cover which cannot be captured by the fire weather indices very well. The SW model selected the greatest number of FWI indices in the four regions. FFMC, DMC and DC were explanatory variables in the models in NC and NE where fuel moisture is an important factor influencing fire occurrence. FFMC, DMC and DC represent the moisture contents of different fuel layers. Selections of FFMC, DMC and DC in SE and SW indicated that fuel moisture plays a different role according to the fuel layers in the two regions. In several other studies, fuel moisture content was found to positively related to fire ignitions (Viegas *et al*. 1992; Renkin and Despain 1992; Nash and Johnson 1996; Ray *et al*. 2005; Chuvieco *et al*. 2009).

The numbers of explanatory variables selected in the probability models of conditional large fire event were fewer than the probability models of fire ignition in the four regions. Altitude influenced large fire events only

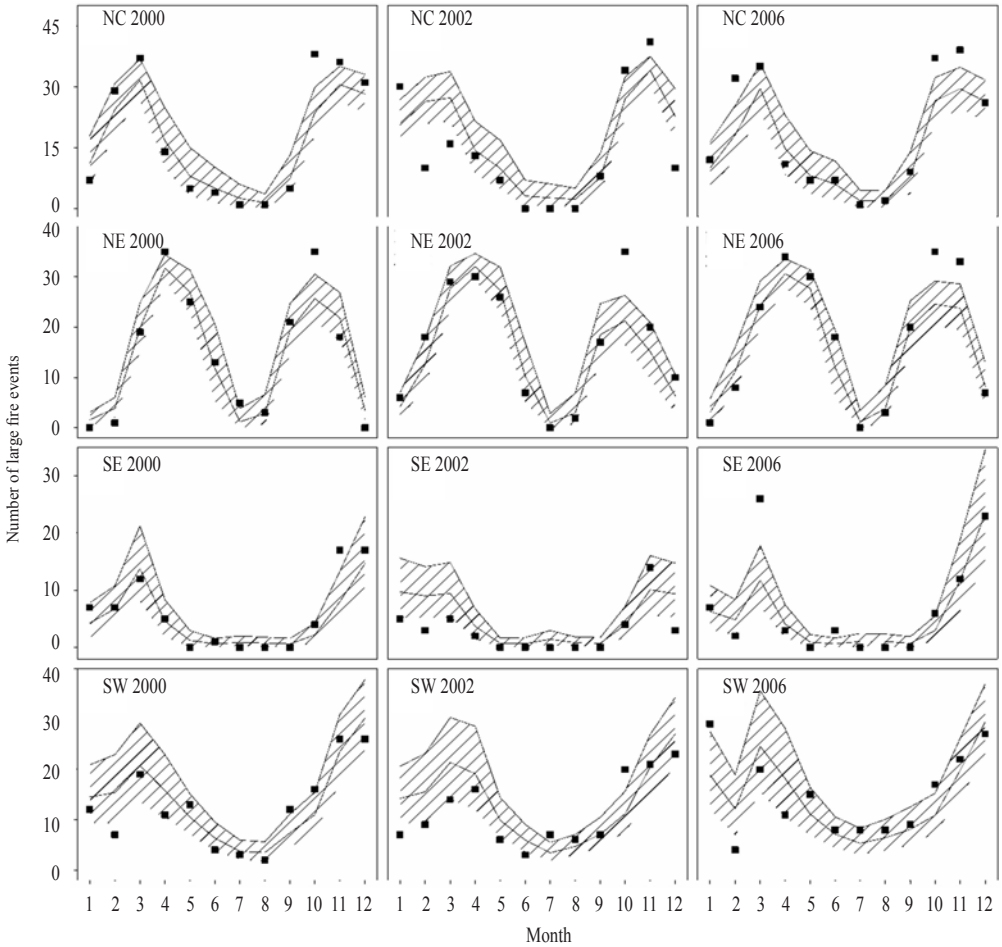

Fig. 7 Estimated monthly total numbers of large fire events for the years of 2000, 2002 and 2006 in NC, NE, SE and SW. Observed numbers of large fire events (dots) and estimated 95% confidence limits (shaded regions) are also plotted.

in NC. The inter-annual changes of vegetation do not show an influence on large fire in SE according to the low significance of NDVI in this region. The selection of the indices in the two kinds of probability models in the 4 regions can be partly supported by specific local weather and vegetation conditions.

The final models with the addition of fire risk indices to the historical models showed improvement on skill of predicting the probability of large fire events in the 4 regions. The addition of fire weather indices to the historical models indicated the influence of weather of fire occurrence and large fire events.

The results of the final models used in NC, NE and SW appeared better than those used in SE when comparing the estimated and observed probabilities of large fire events for similar probability levels. Partly the reason for these is likely to be the fewer occurrences of fire ignition and large fire events in SE. The estimated number of large fire events calculated from the final models in NC and NE appeared to underestimate the large fire events in the months of October and November. This underestimation may be due to factors other than the fire weather indices and vegetation index (NDVI) selected in the final models. The fire risk maps produced in this study appeared useful for managers to predict the probabilities of fire occurrence and large fire events. The odds ratio maps provide a useful reference method for the fire risk maps to minimize the number of times that large fire events are missed. Maps of probabilities of specific fire events provide consistent and comprehensive digital risk maps and can be integrated into a cohesive risk assessment process (Keane *et al*. 2010; Fairbrother and Turnley 2005; Preisler *et al*. 2004; Preisler *et al*. 2008; Preisler and Westerling 2007).

In the study of fire risk, correlation analysis between fire weather index and fire occurrence or burnt area in point-to-point way may not be adequate to indicate the non-linear relationship between these variables. The SPL regression model used in this study is an alternative way to describe the non-linear relationships between fire risk indices and fire risk probabilities as also found by other authors in other regions (Brillinger *et al*. 2003; Brillinger *et al*. 2006; Preisler *et al*. 2004; Preisler *et al*. 2008; Preisler and Westerling 2007).

Similar work is needed in regions with specific climate and vegetation types over different temporal and spatial scales. Other variables influencing fire characteristics

(population density, distance to the nearest road and weather station) may be added in the probability models to improve their skill of prediction. Predictions from climate simulation models will be incorporated to analyze the accuracy of the forecasted indices.

5 Conclusions

Results suggest that the fire weather indices in this study explain the probability of fire occurrence and large fire events well in the 4 study regions. In each region with the same biome, weather is a determinant for fire risk, and different indices were selected as the significant variables for specific regions. As fire risk is sensitive to weather and vegetation conditions, we found that fire ignition in all regions showed a significant link with altitude and NDVI. Indices of fuel moisture are also important factors reflecting seasonality of vegetation which influence fire occurrence in northern China, where there are high seasonal variations of weather and vegetation. The fuel indices of organic material are significant indicators of fire risk in southern China with abundant forest biomass and composition. SPL regression model was a reasonable method to predict the probability of large fire events and the number of large fire events. Besides the skill of predicting fire risk, the probability models are a useful method to assess the utility of the fire risk indices in estimating fire events.

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中国不同气候区基于火险气象指数的火险概率模型

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摘 要：目前，森林火险气象指数被广泛用于世界多个国家和地区。本研究目的为，基于火险气象指数，在中国不同气候区建立火险概率模型。本文在中国4个气候区，使用1998–2007年的气象及火灾数据，以位置变量、月份、海拔、加拿大、美国及澳大利亚的气象火险指数、植被指数为自变量，建立了半参数化Logistic回归模型，分析各自变量与着火概率及大火发生概率之间的非线性关系。在不同区域，模型所选自变量组合不同，这与各气候区不同气象及植被状况有关。通过模型模拟数据和实际观测数据散点图、火险概率图、大面积火灾数量预报曲线图，分析了模型的预测能力。研究结果表明，在4个气候区，海拔和NDVI 指数对着火概率影响显著。模拟可燃物含水量的气象火险指数由于反映出了植被的季节变化特征，在中国北部成为火险概率模型中的重要因子。模拟土壤有机层可燃物状况的火险气象指数在中国南部（东南、西南）成为火险概率模型的重要因子。在中国4个气候区，应用半参数化Logistic回归模型，可以有效模拟月时间尺度着火概率及大火发生概率，并为分析火险气象指数的预报能力提供了有效途径。本研究为进一步分析气候与火险之间的动态关系提供了理论基础。

关键词：气候；森林火灾；气象风险；火险指数；半参数化Logistic回归模型