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Spatial and temporal patterns and driving factors of forest fires based on an optimal parameter-based geographic detector in the Panxi region, Southwest China

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Abstract

Background The Panxi region in China is among the areas that are most severely impacted by forest fires. Despite this, there is currently a lack of comprehensive and systematic research on the spatial and temporal distribution patterns, as well as the drivers, of forest fires in the region. To reveal bio-geo-climatic and anthropogenic influences, this study investigated the temporal and spatial characteristics of forest fires and migration patterns of the center of gravity of forest fires in Panxi. A parametric optimal geographical detection model was utilized to quantify the influence of various individual factors and their combinations on the spatial patterns of forest fire occurrence in the whole Panxi region and sub-region, by analyzing the forest fire dataset from 2004 to 2020.

Results From 2004 to 2020, the Panxi region experienced an upward trend in the number of forest fires and the area burned. However, the trends were not consistent over the entire period. Between 2004 and 2014, both the number of fires and the area burned showed fluctuations and an overall increase. In contrast, between 2015 and 2020, there was a significant decrease in the number of fires, while the area burned showed a continued upward trend. The study identified abrupt changes in the frequency of forest fires and burned areas, primarily in 2007 and 2016. Spatially, forest fires in Panxi exhibited a positive correlation and local clustering. The river valley basin and hilly regions displayed a higher incidence of forest fires, which were concentrated mainly along the hill edges. In the whole area of Panxi, climatic factors have a predominant influence on forest fire occurrences. Specifically, evaporation, maximum temperature, average temperature, number of days without rain, and minimum temperature demonstrated the strongest explanatory power. Furthermore, this relationship was found to be reinforced when combined with topographical, human activities, and vegetation factors. The spatial variation of drought within each sub-district has a stronger explanatory power for the distribution characteristics of forest fires in the region than at the Panxi-wide scale. The factor with the maximum interaction in most regions was the dual factor of rainfall and drought.

Conclusions The study's findings validate the applicability of geographic probes for identifying the drivers of fire occurrence and enhance our understanding of the drivers and their combined effects on the spatial context of the fire-incident study area.

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Resumen

Antecedentes La región de Panxi en China está entre las áreas más severamente impactadas por los incendios forestales. A pesar de ello, hay al día de hoy una falta de investigaciones comprensivas y sistemáticas sobre los patrones espaciales y temporales en su distribución, como así también de los factores conducentes a los incendios forestales en esa región. De manera de revelar las influencias bio-geo-climáticas y antropogénicas, este estudio investigó las características espaciales y temporales y los patrones de migración del centro de gravedad de los incendios forestales en Panxi. Un modelo paramétrico de detección geográfica óptima fue utilizado para cuantificar la influencia de varios factores individuales y sus combinaciones sobre los patrones espaciales de ocurrencia de incendios en la región de Panxi y en una subregión, mediante el análisis de una base de datos de incendios ocurridos entre 2004 y 2020.

Resultados Desde 2004 y hasta 2020, la región de Panxi experimentó una tendencia alcista en el número de incendios y en el área quemada. Desde luego, estas tendencias no fueron consistentes sobre el período total. Entre 2004 y 2014, tanto el número de incendios como el área quemada mostraron fluctuaciones y un incremento en general. En contraste, entre 2015 y 2020, se notó un decremento significativo en el número de incendios mientras que el área quemada mostró una tendencia al aumento. El estudio identificó cambios abruptos en la frecuencia de los incendios y áreas quemadas, fundamentalmente en 2007 y 2016. Espacialmente, los incendios forestales en Panxi exhibieron una correlación positiva y un agrupamiento local. La cuenca del valle que bordea el río y las regiones con colinas mostraron las incidencias más grandes de los incendios, que se concentraron mayoritariamente alrededor de los bordes de las colinas. En la totalidad del área de Panxi, los factores climáticos tienen una influencia predominante en la ocurrencia de los incendios. Específicamente, la evaporación, la temperatura máxima, el número de días sin lluvia, y las temperaturas mínimas demostraron ser las variables explicativas más poderosas. Además, esta relación se ve reforzada si se combinaba con factores topográficos, vegetacionales, e influencia humana. La variación espacial de la sequía dentro de cada sub-distrito tuvo un poder explicativo más fuerte sobre las características de distribución de los incendios que a mayor escala en la región de Panxi. La interacción máxima en la mayoría de las regiones se debió al factor dual entre precipitaciones y sequías.

Conclusiones Los resultados de este estudio validan la aplicabilidad de las pruebas geográficas para identificar los factores conducentes de los incendios forestales y aumenta nuestros conocimientos sobre estos factores conducentes y sus efectos combinados sobre el contexto espacial de los incidentes de incendios en el área de estudios.

Introduction

Forest fires are one of the essential disturbance factors in forest ecosystems (Hu et al. 2012) and one of the natural disasters in the world that affect a large area, are more destructive and difficult to rescue, and cause significant changes in the structure and function of forest landscapes (Hu et al. 2020; Song et al. 2015; Yang et al., 2013; Han et al. 2015). Forest fires are also compound extreme events (Pausas and Keeley, 2021; Zscheischler et al. 2020; Ridder et al., 2020; Richardson et al., 2022). With global warming, increased extreme weather, increased forest combustible material, and increased forest management activities, the frequency of forest fires and burned areas will increase significantly, and the global forest fires will enter a new round of high incidence period (Luo et al. 2016). Meanwhile, fires present severe threats to social systems, causing loss of life and damage to property (Syphard et al. 2007, 2017). Continuous changes in climate regimes around the world have affected the severity and intensity of fire events. Asia has been the region with the highest increases in fire activity (Bowman et al. 2009). As one of the countries with more serious forest fires, China urgently needs to conduct in-depth research on the response characteristics and occurrence trends of forest fires in typical regions in the context of climate change (Sun et al. 2016; Shi and Touge 2023; Su et al. 2015), especially on the spatially and temporally driven influences on forest fire occurrence, as it can help to accurately assess future forest fire risks and effectively carry out forest fire prevention and suppression (Syphard et al. 2017).

It has been shown that the likelihood of fire ignition and spread can be influenced by various factors, usually classified as climate, vegetation, topography, and human activity (infrastructure and socio-economic) (Maingi and Henry 2007). Of these factors associated with fire occurrence, climate effects occur on a regional scale, whereas vegetation, topography, and human

activity occur on a more minor, "local" scale (Ali et al. 2009). Among the factors that may cause a forest fire risk, forest fire weather is one of the most dominant factors. Climate variables are considered determining factors in fire ignition and spread (Turco et al. 2013). The spatial and temporal variability of forest fire and climate has led to a complex fire-climate relationship in China (Guo et al. 2016; Ye et al. 2017; Yao et al. 2017; Du et al. 2021). Long-term fire studies in China are mainly based on temperature and precipitation anomalies, atmospheric circulation, and sea surface temperature anomalies. Meanwhile, other meteorological variables and many drought indices have been found to be closely related to forest fires in different parts of the world (Littell et al. 2016; Shawki et al. 2017).

Forest vegetation can influence fire ignitability through fuel characteristics such as type, load, and moisture content (Minnich and Bahre 1995). Climate seasonality can affect fire dynamics by drying out the biomass available for burning or stimulating the growth of grasses that also become flammable fuels during droughts (Bowman et al. 2009). Topographic factors (e.g., elevation, slope gradient, and aspect) can be used to explain fire incidence. These factors can also affect vegetation's amount and structure and influence the speed and direction of fire spread (Rothermel 1991; Maingi and Henry 2007). Humans influence the spatial pattern and frequency of fire through activities related to building developments, transportation networks, and recreation (Cardille et al. 2001). These regional and local factors can also interact to influence each other in various ways. Investigation of these interactions can provide a more nuanced understanding of forest fire spatial patterns and regimes. Forest fire management requires understanding the spatial characteristics of fire occurrence patterns and a quantification approach for assessing the relative importance of various driving factors at a regional scale.

The Panxi region, encompassing the Liangshan Yi Autonomous Prefecture (referred to as Liangshan Prefecture) and the city of Panzhihua, is situated in the southwest of Sichuan Province. Its high forest coverage, averaging 55.42%, marks it as a crucial area for forest fire prevention and control in the province. Notably, more than 50% of the province's forest fires, burned areas, and forest damage occur in this region (Zhang 2019). Despite extensive research on forest fires in northern China and identifying dominant variables influencing fire distribution and occurrence, more research is needed for the forests in southwestern China (Zhang and Yin 2021). The fire risk classification and estimation in this region rely primarily on a few variables and constrained analysis methods. Consequently, undertaking a comprehensive study on the driving factors of forest fires in the Panxi region can significantly enhance our understanding of forest fire distribution in China.

This study utilizes various data sources, including measurements of temperature, precipitation, relative humidity, wind speed, evaporation, self-calibrating Palmer Drought Severity Index (scPDSI), terrain parameters, population density, road density, and vegetation type. Using the linear trend and bivariate spatial autocorrelation analysis methods, we aim to demonstrate the spatial distribution and barycenter displacement of the Panxi forest fire during different periods. To achieve this, we will utilize Local Indicators of Spatial Autocorrelation (LISA) and standard deviation ellipse techniques. The main objective of this study is to quantitatively investigate the spatial association between fire occurrence and the driving factors in the Panxi region based on historical fire records and multisource bio-geo-climatic and anthropogenic data. To achieve this, we sought to answer the following research questions: (1) What were the primary driving factors, and how important were they in determining the spatial distribution of fire occurrence in Panxi? (2) How did pairs of driving factors interact to influence fire occurrence? The findings of this study will offer valuable insights for enhancing remote fire prediction techniques in the Panxi region.

Materials and methods

Study area

The Panxi region, located in the southwestern region of Sichuan province, encompasses an area of around 63,600 km^2 and is situated in the mountains of southwestern Sichuan and the northern part of the western Yunnan-Guizhou plateau. The topography of this region is characterized by high elevations in the west, low elevations in the east, and a dominant mountainous landscape, featuring significant surface undulations and relative heights of 1000–2500 m. The climate in this region is categorized as semi-dry south subtropical and subtropical monsoonal, with an average annual temperature of 21 °C and annual precipitation of 800 mm. The precipitation is mainly concentrated between June to October, reflecting distinct dry and rainy seasons with adequate sunshine and intense evaporation. Additionally, the mountain climate displays vertical zonality (Zhao et al. 2022). The Panxi region can be categorized into four regions. Namely, the high mountain valley warm temperate zone, the mountainous subtropical semi-humid zone, the southern subtropical humid zone, and the mountainous central subtropical humid zone, based on climate and topographic zoning (Fig. 1). The forest stock in the Panxi region is approximately 210 million cubic meters, making it one of China's three major forest areas and a significant Yunnan pine forest

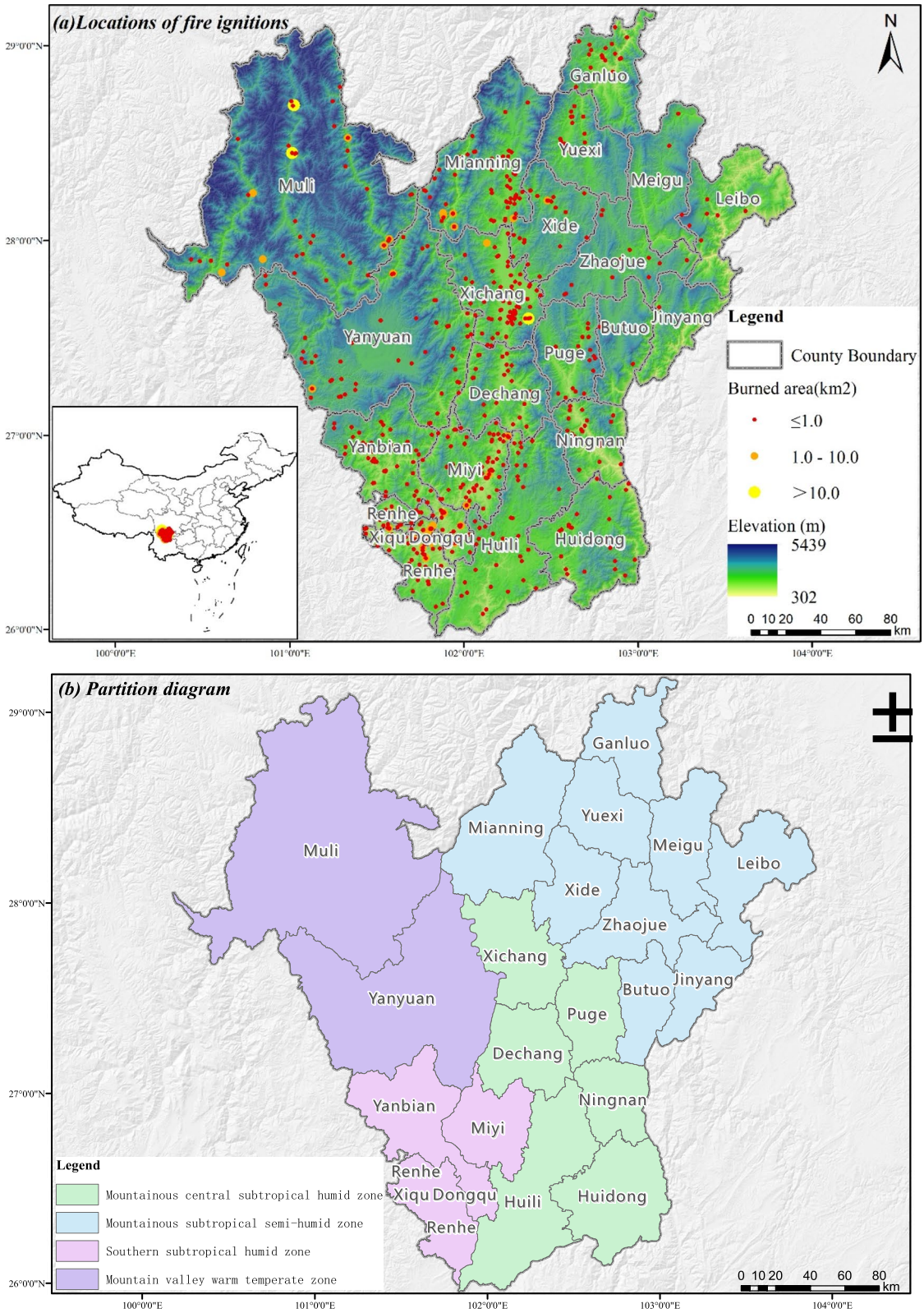


Fig. 1 Map of the study area showing the extent of the Panxi in Southwest China (dark gray area), locations of fire ignitions during 2004–2020 as displayed on top of the DEM image (**a**) and a schematic map of the area (**b**)

area and southern subtropical economic forest area in Sichuan. The vegetation types in the region are mainly divided into two parts, featuring alpine meadows and subalpine green coniferous forests in the northwest and subtropical parched evergreen broad-leaved forests in the remaining region (Zhong 1986). Due to the monsoon circulation, the dry season in the western Panxi region lasts from November to May every year, with frequent forest fires and a fire prevention period from January to May. The complex topography of the region poses challenges for fighting forest fires.

Fire occurrence datasets

The 17-year fire data (2004–2020) in the Panxi region were obtained from the Forest Fire Prevention Command of the Sichuan Provincial People's Government and the Sichuan Forestry and Grassland Bureau. 1643 fires were recorded during the fire season 2004–2020 (January–May). Points of the recorded fires are marked in Fig. 1a. These fire data were real-time observations by field staff at Sichuan Forest Bureau.

Attributes of a fire record include fire location, time, and date of ignition (start date) and extinction (end-date), burned size (burned area of a fire), and cause of ignition. Since 2004, the forest fire database has been collecting fire records, including information about the ignition date, fire size, cause, and approximate starting location. In this study, Kernel Density Estimation (KDE) was utilized to model the distribution of fire occurrences in the Panxi region.

Factors affecting fire occurrence

Based on previously published studies, we collect several variables that are thought to influence fire occurrence (He et al. 2017; Shi and Touge 2023; Syphard et al. 2007; Bowman et al. 2020; Williams et al. 2019; Abram et al. 2021; Sippel et al., 2020; Byrne and O'Gorman 2018; Boer et al., 2020) and group them into four categories of environmental controls (Table 1): climate, topography, human activity, and vegetation.

The daily meteorological data were mainly from the China Integrated Meteorological Information Service System (CIMISS), constructed by the National Meteorological Information Center of the China Meteorological Administration. Meteorological elements include average, maximum, minimum, daily precipitation, evaporation, relative humidity, average wind speed, etc. Self-calibrating palmer drought severity index (scPDSI) data were acquired from the Climatic Research Unit (CRU) at the University of East Anglia, UK. The dataset was obtained monthly, and the spatial resolution was 0.5°×0.5°.

Topographic factors consist of three explanatory variables: elevation, slope, and aspect (Jarvis et al. 2008; Su et al. 2019). Elevation data is obtained from the NASA Shuttle Radar Topography Mission (SRTM) at a resolution of 90 m. The dataset was made available online through the SRTM. The aspect and slope surfaces were generated using the surface toolbox of the ArcGIS 10.6 program based on the DEM dataset.

The vegetation types dataset used in this study was sourced from a digital map published by the Chinese

Table 1 The selection of driving factors for the forest fire

Data category	Parameter	Data source	Format	Variable name (units)
Climate	Annual mean temperature	CIMISS	Continuous	Tave (℃)
	Annual average maximum temperature	CIMISS	Continuous	Tmax (℃)
	Annual average minimum temperature	CIMISS	Continuous	Tmin (℃)
	Annual average relative humidity	CIMISS	Continuous	RH (%)
	Annual total precipitation	CIMISS	Continuous	*P* (mm)
	Mean wind speed	CIMISS	Continuous	Wind (m/s)
	Number of rainless days	CIMISS	Continuous	No_rain_da (day)
	Potential evapotranspiration	CIMISS	Continuous	EVA (mm)
	Drought index	CRU at the University of East Anglia, UK	Continuous	scPDSI (unitless)
Topography	Elevation	SRTM90	Continuous	DEM (m)
	Slope	SRTM90	Continuous	Slope (°)
	Aspect	SRTM90	Continuous	Aspect (unitless)
Human activity	Road density	NGCC	Continuous	Road (km/km^2)
	Population density	Statistical yearbook	Continuous	Population
Vegetation	Vegetation type	Vegetation Map of the People's Republic of China	Categorical	Vegetation (unitless)

Academy of Sciences in 1982. The dataset served as a surrogate for the surface fuel map.

The population density data were obtained based on county-level population data from the 2020 statistical yearbook and rasterized by GIS software. Provincial-level and township-level road data were obtained from the National Geomatics Center of China at a 1:1,000,000 scale.

Kernel density estimation (KDE)

The location of fire ignition is frequently recorded retrospectively and may not be precisely defined. To minimize the associated uncertainty, a continuous surface can be employed (Amatulli et al. 2013). In this study, we utilized the kernel density estimation (KDE) method to model the distribution of fire occurrences in the Panxi region. The KDE approach incorporates a symmetric probability density function for each point location, generating a smooth cumulative density function. This method has improved the accuracy and reliability of fire ignition mapping, particularly in areas where the ignition point is difficult to determine due to complex terrain or other environmental factors (Zuo et al. 2019).To account for the sensitivity of the bandwidth parameter to the geographic detector, a bandwidth of 30 km was used to analyze the fire density surface (Guo et al. 2020). The resulting KDE fire occurrence surface was generated with a spatial resolution of 5 km × 5 km.

Spatial autocorrelation

Spatial autocorrelation refers to the consistency between the similarity of attribute values of the research object and the similarity of their locations. Spatial autocorrelation is an important form of spatial dependence, which indicates the correlation between the research object and its spatial location. Spatial autocorrelation is an important indicator for testing whether the attribute values of a certain element are significantly related to the attribute values of adjacent spatial points. It can be divided into two categories: positive autocorrelation and negative autocorrelation. Positive autocorrelation indicates that the attribute values of a unit change in the same direction as those of its neighboring spatial units, while negative autocorrelation indicates the opposite (Ord et al., 1995; Getis and Ord, 2010).

Global spatial autocorrelation

Global spatial autocorrelation is a description of the spatial characteristics of attribute values across the entire region. Moran's I is used to measure the spatial relationships of spatial features, like correlation coefficients in general statistics. Its values range between −1 and 1. A value greater than zero indicates positive spatial correlation, while a value less than zero indicates negative correlation, and a value equal to zero suggests no spatial correlation. Its calculation formula is as follows.

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} W(i,j)(X_i - \overline{X})(X_j - \overline{X})}{\sum_{i=1}^{N} (X_i - \overline{X})_i^2} \tag{1}$$

In the formula, N represents the number of research objects, X_i represents the observed values, $\overline{X}$ represents the mean of X_i, and $W(i, j)$ represents the spatial connectivity matrix between research objects i and j.

Local spatial autocorrelation

Global spatial autocorrelation assumes that space is homogeneous, meaning there is only one trend that extends across the entire area. However, spatial heterogeneity of regional features is not uncommon. Therefore, it is necessary to develop local statistical methods to measure the correlation properties of each spatial feature at a "local" level, typically in its neighboring context. The results are often visualized on maps. By defining different types of "local" ranges (using different spatial connectivity matrices), local spatial autocorrelation analysis can help us better understand the heterogeneity characteristics of spatial features. In this paper, local Moran's I is used to measure local spatial autocorrelation. Local Moran I decomposes Moran I into individual spatial units. Anselin (1995) refers to it as stands for Local Indicators of Spatial Association (LISA). For a given spatial unit i.

$$I_i = \frac{X_i - \overline{X}}{S_3} \sum_{j=1}^{N} W(i,j)(X_j - \overline{X}) \tag{2}$$

$$S_3 = \left(\sum_{j=1, j \neq i}^{N} X_j^2 \right) / (N-1) - \overline{X}^2 \tag{3}$$

In the equation, N, X_i, $\overline{X}$, and $W(i, j)$ have the same meanings as in formula (1).

Bivariate global spatial autocorrelation is useful for describing the correlation between forest fires in Panxi and assessing their spatial distribution pattern, whether it is dispersed, random, or clustered. Meanwhile, local autocorrelation is employed to evaluate the degree of correlation between neighboring forest fires. Specifically, we adopted the indicators of High–Low (H–L),

Low–High (L–H), and Low–Low (L–L) types of spatial agglomeration to measure the level of clustering of forest fires in the study area.

Standard deviation ellipse (SDE)

SDE method is a geostatistics method that can accurately reveal the spatial distribution characteristics of various types of geographical features (Wong 1999; Li et al. 2016). This method was first proposed by the sociologist Lefever. It was mainly used to reveal the spatial relationship of geographical factors (Zhang et al., 2022). This method is employed to quantify the directional distribution of forest fires, which captures essential spatial features such as the degree of dispersion and directional trend. Specifically, an ellipse's long and short axes are computed based on the standard deviation of the mean center of gravity in the X and Y coordinates. The long half-axis corresponds to the direction of the forest fire distribution, while the short half-axis represents the extent of the distribution. Importantly, the flatness value increases with the prominence of directionality. Additionally, the size of the ellipse reflects the concentration degree of the historical spatial patterns of forest fires. This method provides a comprehensive and quantitative approach to analyzing forest fire spatial patterns, which can inform effective forest management and wildfire prevention. It can be implemented in ArcGIS (Wang 2014). The calculation method is as follows.

Weighted average center:

$$\overline{X}_{\omega} = \frac{\sum_{i=1}^{n} \omega_i x_i}{\sum_{i=1}^{n} \omega_i} \tag{4}$$

$$\overline{Y}_{\omega} = \frac{\sum_{i=1}^{n} \omega_i y_i}{\sum_{i=1}^{n} \omega_i} \tag{5}$$

Ellipse direction:

$$\tan\theta = \frac{A+B}{C}$$

$$A = \left(\sum_{i=1}^{n} \omega_i^2 \tilde{x}_i^2 - \sum_{i=1}^{n} \omega_i^2 \tilde{y}_i^2\right)$$

$$B = \sqrt{\left(\sum_{i=1}^{n} \omega_i^2 \tilde{x}_i^2 - \sum_{i=1}^{n} \tilde{y}_i^2\right) + 4\sum_{i=1}^{n} \omega_i^2 \tilde{x}_i^2 \tilde{y}_i^2}$$

$$C = 2\sum_{i=1}^{2} \omega_i^2 \tilde{x}_i \tilde{y}_i$$

X-axis standard deviation:

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (\omega_i \tilde{x}_i \cos\theta - \omega_i \tilde{y}_i \sin\theta)^2}{\sum_{i=1}^{n} \omega_i^2}}$$

Y-axis standard deviation:

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} (\omega_i \tilde{x}_i \sin\theta - \omega_i \tilde{y}_i \cos\theta)^2}{\sum_{i=1}^{n} \omega_i^2}}$$

In the formula, (x_i, y_i) is the spatial coordinate of the study object. ω_i represents the weight at spatial element i. θ is the azimuth of the ellipse. $\tilde{x}_i$ and $\tilde{y}_i$ represent the deviation of the study object's spatial coordinates from the average center. σ_x and σ_y represent the standard deviations (Zhang et al., 2022).

Optimal parameters-based geographical detector (OPGD) model

Geodetectors are a powerful tool for detecting and analyzing the density of forest fire occurrences by filtering climatic, topographic, human activity, and vegetation factors (Song et al. 2020). This approach can reveal the spatial differentiation of forest fires and identify their main driving forces. In this study, we employed the Optimal Parameters-based Geographical Detector (OPGD) to investigate the drivers of forest fires in Panxi, as it is a more objective and finely discretized method. The OPGD model includes five parts:

(1) *Factor detector*. As the core part of geographical detector, the factor detector reveals the relative importance of explanatory variables with a q-statistic. The q-statistic compares the dispersion variances between observations in fire occurrence density and driving factors (Wang et al. 2010, 2016; Guo et al., 2020). The q value of a potential variable v is computed by:

$$q_v = 1 - \frac{\sum_{j=1}^{M} (N_{v,j} - 1)\sigma_{v,j}^2}{(N_v - 1)\sigma_v^2} \tag{6}$$

where N_v and σ_v^2 are the number and variance of observations within the fire occurrence density, and $N_{v,j}$ and $\sigma_{v,j}^2$ are the number and variance of observations within the jth (j=1; …; M) sub-region of driving factors v. A large q value means the relatively high importance of the explanatory variable, due to a small variance within sub-regions and a large variance between sub-regions (Song et al. 2020).

(2) *Parameters optimization*. The parameters optimization consists of the optimization of spatial discretization and optimization of spatial scale (Song et al. 2020). The OPGD model's role is to optimize the discretization process for each continuous geographical variable by selecting the best method and the most suitable number of breaks. The q values for all explanatory variables are compared at different spatial scales to investigate their relationships. The optimal spatial scale is determined by selecting the one where the 90% quantile of q values for all explanatory variables reaches the highest value. This optimization is crucial for accurate spatial analysis.

(3) *Interaction detector*. The interaction detector is a tool used to evaluate and quantify the impact of spatial interactions between two overlapping variables. It does so by comparing the q values of the interaction with the q values of the individual variables. This analysis aims to understand the relative importance and influence of these interactions in the context of the spatial analysis being conducted. The interaction detector was used to identify whether any two driving factors impart synergistic effects on the spatial pattern of fire occurrence density (Guo et al. 2020).

(4) *Risk detector*. The risk detector is used to test if spatial patterns represented by mean values of fire occurrence density are significantly different among sub-regions classified by a certain driving factor. The difference between any two categories (η and κ) for each factor based on a t-test (Wang et al. 2010).

$$t_{\overline{Y_\eta}-\overline{Y_\kappa}} = \frac{(\overline{Y_\eta} - \overline{Y_\kappa})}{\sqrt{\frac{\sigma_\eta^2}{N_\eta} + \frac{\sigma_\kappa^2}{N_\kappa}}} \tag{7}$$

where N is the number of observations, $\overline{Y}$ and σ^2 are the mean value and the variance of observations within sub-regions η and κ.

(5) *Ecological detector*. The ecological detector is a method used to compare and determine the relative impacts of different explanatory variables, and it employs the F-statistic to test the significance of these differences. This analysis helps in understanding which driving factors have a stronger influence on the outcomes under investigation.

$$F = \frac{N_\eta (N_\kappa - 1) \sum_{j=1}^{M_\eta} N_{\eta,j} \sigma_{\eta,j}^2}{N_\kappa (N_\eta - 1) \sum_{j=1}^{M_\kappa} N_{\kappa,j} \sigma_{\kappa,j}^2} \tag{8}$$

where M is the number of sub-regions and $\sum_{j=1}^{M} N_j \sigma_j^2$ is the sum of variance within sub-regions of variables η and κ. The density values of all cells and their attributes of all driving factors were inputted into the OPGD model which was obtained from an open-source software package "GD" in R. Firstly, we calculated the q-values of each continuous factor for various grading methods and interruptions. The q-values range from 0 to 1, where larger values indicate more vital spatial differentiation of forest fires and weaker explanatory power of the influencing factors on the spatial differentiation of forest fires. The OPGD model detects the spatial stratification heterogeneity of forest fires and identifies the combination of parameters with the highest q-values (grading method and the number of interruptions) for spatial discretization. Then we used interaction detection to analyze the joint effect of two factors on forest fires. By calculating the q-values of individual factors and their superimposed factors, we can determine whether and to what extent meteorological elements interact with the terrain. Overall, the OPGD approach can provide insights into the complex relationships among various factors affecting forest fires, supporting evidence-based decision-making in forest management and wildfire prevention.

The Mann Kendall Trend Test (M-K test)

The Mann-Kendall Trend Test is a method recommended by the World Meteorological Organization for meteorological research. It is a non-parametric test which considers outliers and accepts independent data, and is widely used on hydro-meteorological data analysis (Hamed and Rao 1998; Suryanto and Krisbiyantoro 2018). One of the advantages of this method is that it does not require sample data to follow a specific pattern, and the presence of some outliers will not significantly interfere with the overall analysis results (Kendall, 1975). Because the Mann-Kendall method can be used to analyze time series data with continuous increasing or decreasing trends (monotonic trends) and is applicable to most distributions, it can be applied to the study of time series issues related to forest fires.

If time series data of length n is known ($x_1, x_2, x_3, ...x_n$), then the steps of the Mann-Kendall test on the data can be described as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \tag{9}$$

$$\mathrm{sgn}(x_j - x_i) = \begin{cases} 1, x_j - x_i > 0 \\ 0, x_j - x_i > 0 \\ -1, x_j - x_i < 0 \end{cases} \tag{10}$$

The Mann-Kendall test statistic z is calculated using the equation:

$$z = \begin{cases} \frac{S-1}{\sqrt{V(S)}}, S > 0 \\ 0, S = 0 \\ \frac{S+1}{\sqrt{V(S)}}, S < 0 \end{cases} \tag{11}$$

$$E(S) = 0 \tag{12}$$

$$V(S) = \frac{n(n-1)(2n+S)}{18} \tag{13}$$

The hypotheses used in the Mann-Kendall test are as follows: one is null hypothesis (H_0), which specify existence of no trend and other is Alternative hypothesis (H_1), which expresses significant increasing or decreasing trend in data over a time period. H_0 is rejected if $|z| \geq z_{1-\alpha/2}$, with the conclusion that there is a trend in the time series data used. The critical value $z_{\alpha/2}$ is obtained from the standard normal table as 1.96 at $\alpha = 0.05$.

Results

Temporal distribution characteristics of forest fires

From 2004 to 2020, 1643 forest fires occurred in the Panxi region, with an average of 96.6 fires per year. Figure 2 shows that the forest fires in the region exhibited an overall increasing trend, reaching a peak in 2014 and then decreasing. From 2004 to 2014, the number of forest fires fluctuated, with an average increase of 2.3 fires per year. From 2015 to 2020, the number of fires decreased significantly, with an average decrease of 1.7 fires per year. According to the standard of China Forest Fire Prevention Office, the forest fires in Panxi area are divided into four grades: forest fire alarm ($\leq 0.01\,km^2$), general fire ($\leq 1\,km^2$), serious fire ($\leq 10\,km^2$) and super fire ($> 10\,km^2$) fire spread speed (FSS) according to the burned area (Qian et al., 2017). Analyzing the forest fire data classified into different levels according to the Chinese Forest Fire Prevention Regulations, it was found that forest fires in the Panxi region were primarily at the levels of forest fire warning and general fire. Overall, the forest fires at the levels of forest fire warning and super large fires showed an upward trend, while those at the general fire and serious fire showed a downward trend. From 2004 to 2020, the accumulated area burned in the Panxi region was $350.79\,km^2$, with an average of $20.63\,km^2$ per year, showing a fluctuating upward trend overall.

Using the Mann-Kendall (MK) test to analyze the change points of forest fire occurrence, the intersection of the statistical values of the number of fires and burned area (UF and UB) were found to be concentrated around 2007 and 2016, suggesting a sudden change in the frequency and extent of forest fires during this period (Fig. 3). Based on this observation, forest fires in the Panxi region were categorized into two stages.

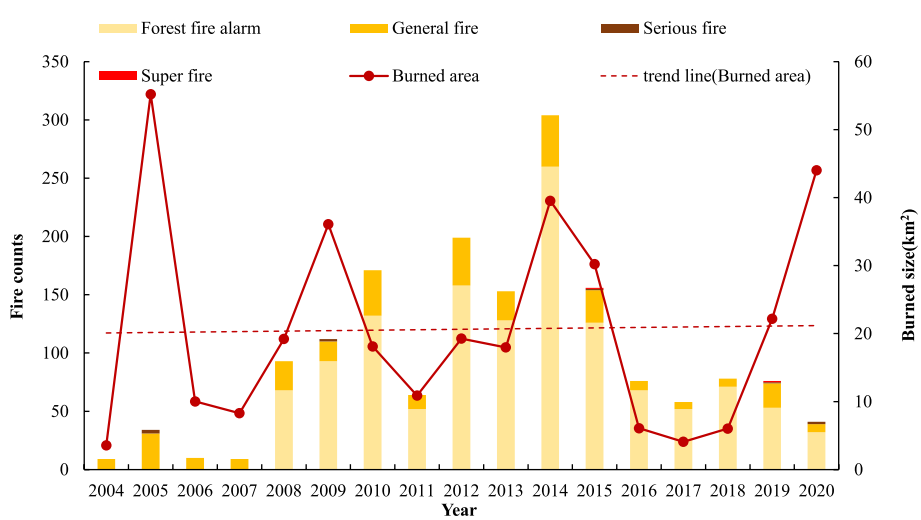


Fig. 2 Inter-annual dynamics of fire counts and burned areas of forest fires in different grades

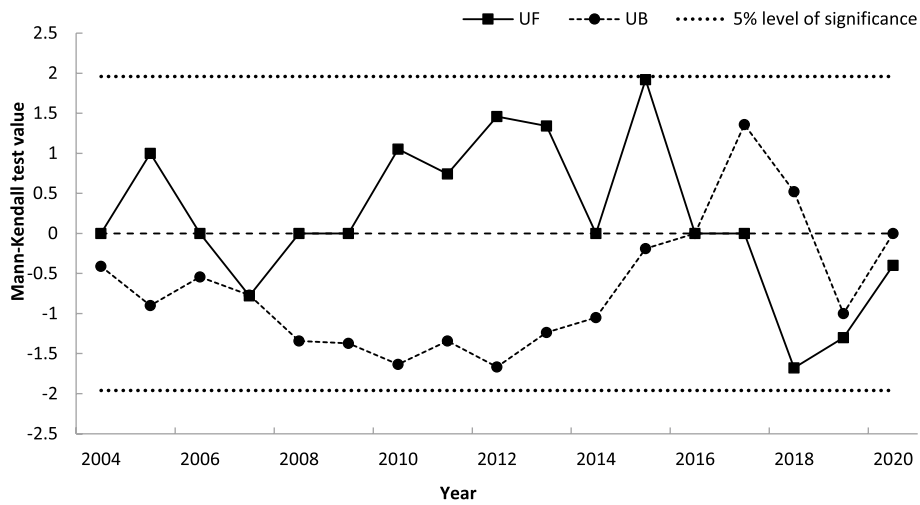


Fig. 3 Mann-Kendall mutation sites for forest fires in the Panxi region from 2004 to 2020

From 2004 to 2007, the number of fires was relatively low, and the burned area decreased, but the level of fires was more serious. In contrast, from 2008 to 2016, the number of fires increased significantly, and the burned area expanded. Nevertheless, there were fewer major fire outbreaks. From 2017 to 2020, the number of fires decreased. However, major fires still occurred occasionally. These findings provide insights into the temporal dynamics of forest fires in the region, which can inform strategies for fire prevention and management.

To determine the length of the annual fire season, it is common practice to calculate the duration between the start date of the first fire and the end date of the last fire. As shown in Fig. 4, the first fire date exhibits a significant downward trend, with most fire outbreaks occurring in late April. In contrast, the last fire date demonstrates an upward trend, indicating a prolonged fire season in recent decades. Notably, between 2004 and 2014, there has been a significant shift in the start and end dates of the fire danger period in the Panxi region. Specifically, the fire danger period tends to commence earlier, while its conclusion tends to be later. These findings offer valuable insights into the temporal patterns of fire activity in the region, which can guide fire management strategies and enhance fire prevention efforts.

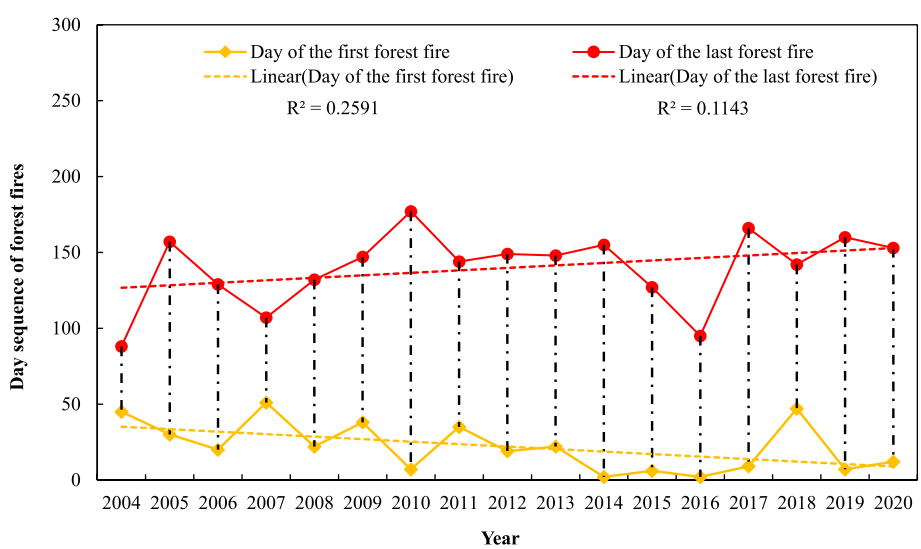


Fig. 4 Trends in daily values of forest fire initiation and termination during the fire risk period in the Panxi region from 2004 to 2020

Spatial distribution characteristics of forest fires

Based on the distribution of forest fires in county units, the regions with high forest fire incidence are Yanbian County, Panzhihua City, and Miyi County in the southwest of Panxi, as well as Xichang County and Mianning County in the central and northern regions (see Fig. 5a). The global Moran's I value for forest fires is 0.054 with a ρ-value of 0.001. The grid units in Yanbian County, Panzhihua City, Miyi County, Xichang County, and Mianning County with high forest fire occurrence frequency exhibit significant high-high clustering. The surrounding areas of high-incidence forest fire areas are characterized by low-high clustering. At the same time, the western and eastern regions have a low incidence of forest fires and display high-low clustering (Fig. 5b).

Forest fires in the Panxi region are mainly concentrated in valley basins and hilly areas. The number of forest fires above 1500 m was 825, while below 1500 m was 818, representing 49.8% of the total forest fires. Forest fires in valley basins and hilly areas tend to be concentrated along the hills' edges. Specifically, 13 fires occurred in valley basins below 1000 m, while the remaining forest fires occurred between 1000 and 1500 m, totaling 805 times. The number of forest fires occurring in the mountain areas above 1500 m but below 2500 m was 673, accounting for 40.9% of the total forest fires. Forest fires in mountainous areas above 2500 m were 152 times (Fig. 6).

Forest fire gravity center migration

Calculate the standard deviation ellipse parameters (Table 2) and the movement trajectory of the forest fire centroid (Fig. 7) from 2004 to 2007, 2008 to 2016, and 2017 to 2020. Forest fires were predominantly observed in the northwest and south of the Panxi region during 2004–2007, characterized by the lowest flattening rate and least directional orientation of the standard deviation ellipse and relatively discrete fire occurrence. From 2008 to 2016, forest fires were mainly concentrated in the central and southern regions of Panxi, with the center of gravity shifting towards the southeast. During 2017–2020, forest fires occurred more frequently in the region's southwest, with the center of gravity shifting towards the northwest. This period was characterized by the largest flattening rate and the most obvious directional orientation of the standard deviation ellipse. Changes in fire frequency and center of gravity suggest a more significant impact of latitude than longitude on forest fires in Panxi. In addition, compared with the period of forest fire concentrated in northwest Panxi in 2004–2007, the elliptical trend of 2008–2016 and 2017–2020 is consistent with the strike line of dry and hot valley in Anning River Basin. This indicates that there is a strong relationship between forest fire frequency and dry-hot valley during these periods.

Detection of driving force of forest fire disaster

Previous studies have shown that temperature and precipitation are the main factors affecting the frequency of forest fires. Additionally, elevation, slope, aspect, vegetation index, road density, and population density were important driving factors (Guo et al., 2020). In this study, we used the density of fire occurrence as the dependent variable for an optimized geographic detector parameter. We detected nine climatic factors, three terrain factors, two human activity factors, and one vegetation factor that explain forest fires in Panxi. The geographic probe model was further used to measure the degree of influence of each driving factor on the spatial distribution of forest fire frequency, explore potential factors from a spatial perspective, and explore geographic variables' interaction effects.

For each continuous type factor, the q-values are calculated under different grading methods (equal spacing grading, natural spacing grading, quantile spacing grading, geometric spacing grading, and standard deviation spacing grading) and a different number of interruptions, and the parameter combination with the highest q-value (grading method and the number of interruptions) is selected. Since the number of classes is preferable within seven categories, the initial intermittent interval is set from 3 to 7 categories. As an example, EVA and the number of rain-free days are discretized. For EVA, when the classification method is standard deviation spacing, and the number of categories is 7, the q-value is the largest (Fig. 8a). Therefore, the standard deviation spacing method was chosen to classify EVA into seven categories (Fig. 8b). Similarly, the natural spacing grading was chosen to classify the number of rain-free days into six categories (Fig. 8c and d). The same principle is used for the discretization of other continuous-type factors.

The factor detector was used to determine the relative influence of single driving factors on fire incidence (Guo et al., 2020). Use the factor detection function of the parameter-optimal geodetector to identify the ability of a single factor to explain the Panxi forest fire (Fig. 9a). Except for slope and slope direction, the explanatory power of all the factors was less than 0.01, and the detection results were significant. Notably, all major determinants are climate factors. In descending order, the average q-values of climate, vegetation, topography, and human activity factors are 0.1470, 0.1400, 0.0169, and 0.0070, respectively. EVA shows the biggest q-value (0.504) among all factors, indicating that it is the most influential factor on fire occurrence density over the period 2004–2020. In descending order, the q-values of

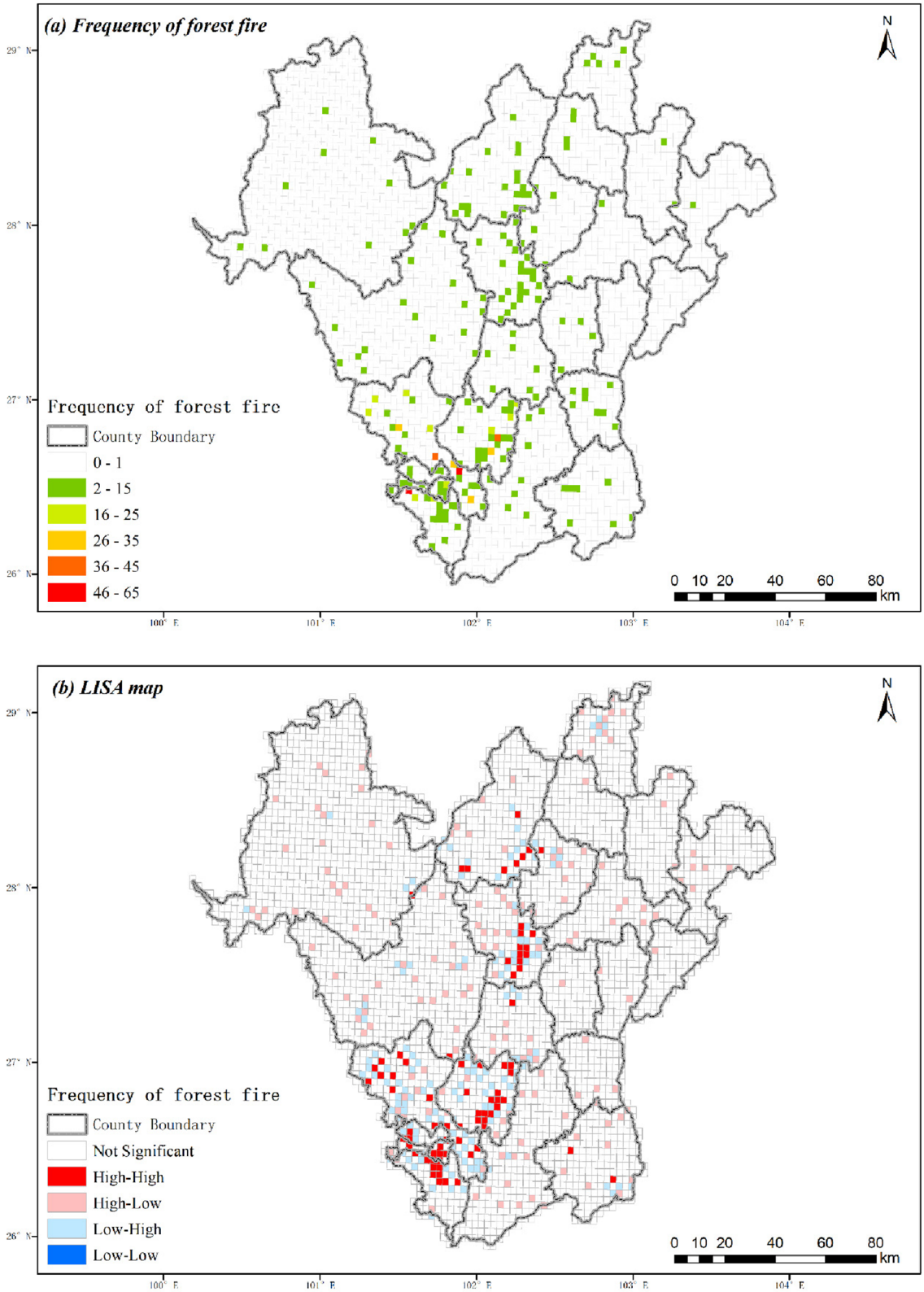


Fig. 5 Frequency (**a**) and LISA map (**b**) of forest fire in grid cells of Panxi region

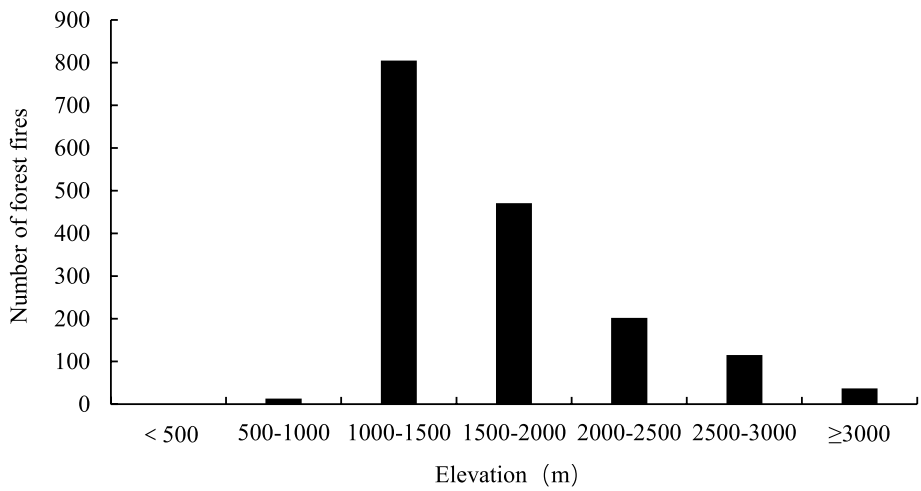


Fig. 6 Frequency of forest fires in different altitude

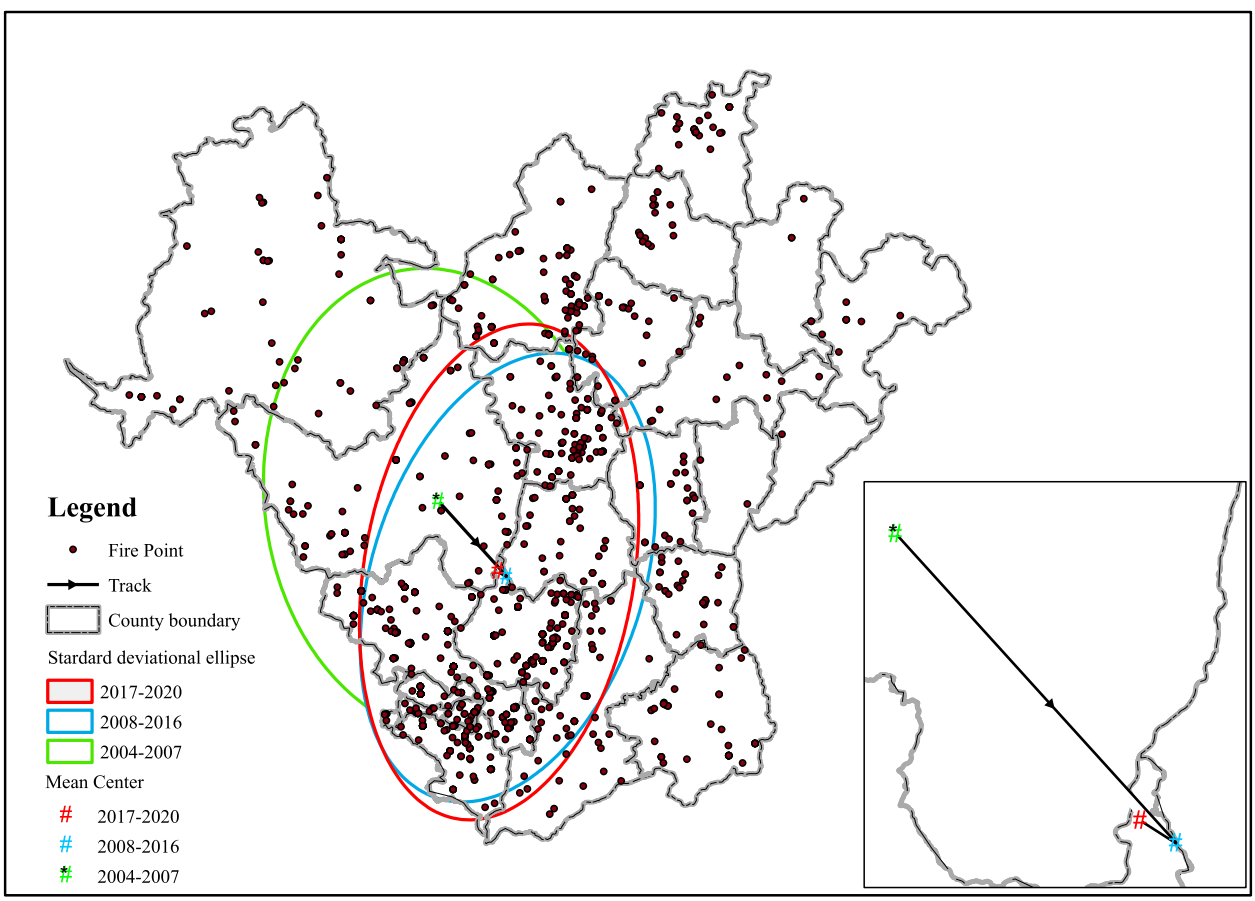
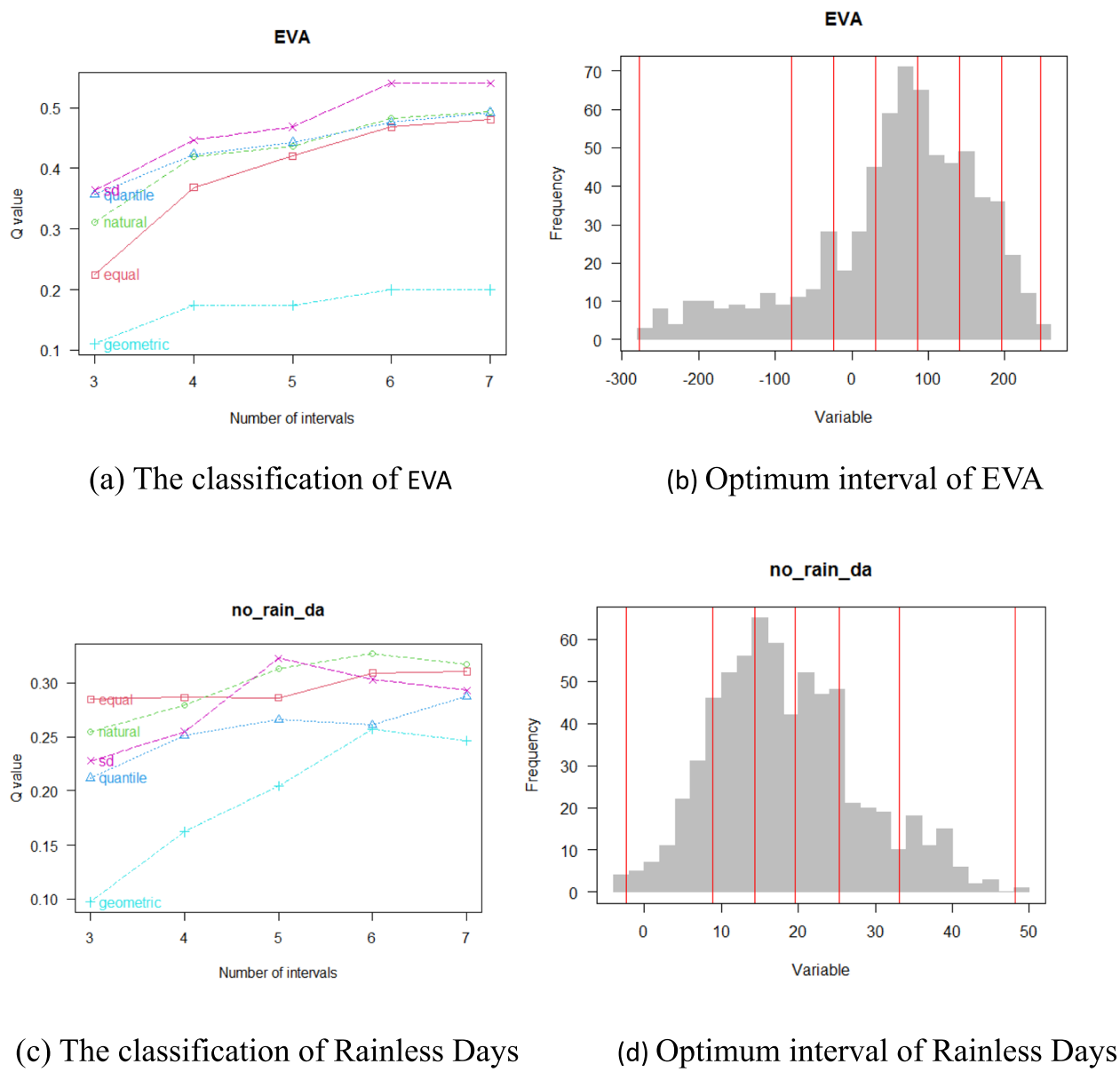


Fig. 7 Standard deviation ellipse of historical forest fire points in Panxi

other climate factors (maximum temperature, average temperature, number of days without rain, minimum temperature, precipitation, altitude, relative humidity, drought index, and wind speed) ranged from 0.109 to 0.462. Factor detection shows that climatic factors play a dominant role in the Panxi forest fire. We consider

Table 2 Standard deviation ellipse parameters of historical forest fire points in Panxi

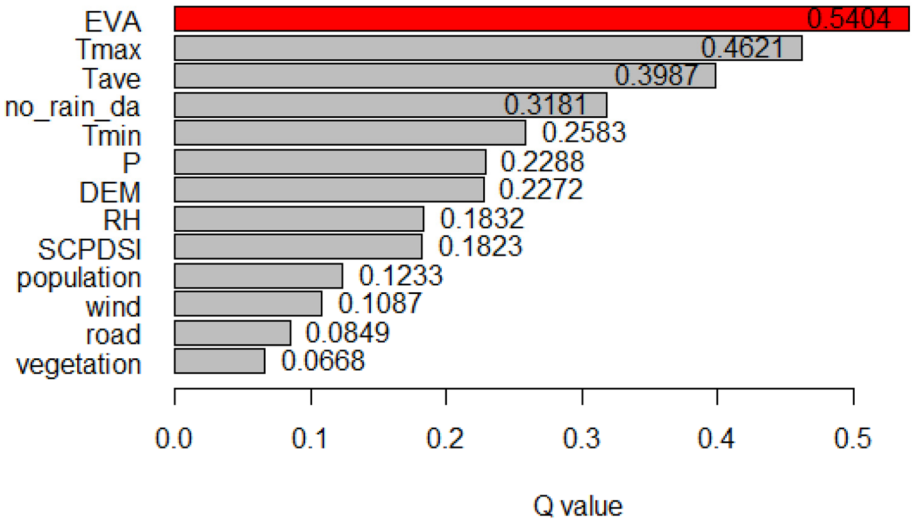
Time period	Longitude of center of gravity (°E)	latitude of center of gravity (°N)	Short half axis (km)	Semimajor axis (km)	Oblateness	Direction angle (°)
2004–2007	101.638	27.489	0.737	0.990	0.253	172.032
2008–2016	101.926	27.172	0.574	0.977	0.403	17.742
2017–2020	101.889	27.200	0.570	1.056	0.486	9.634



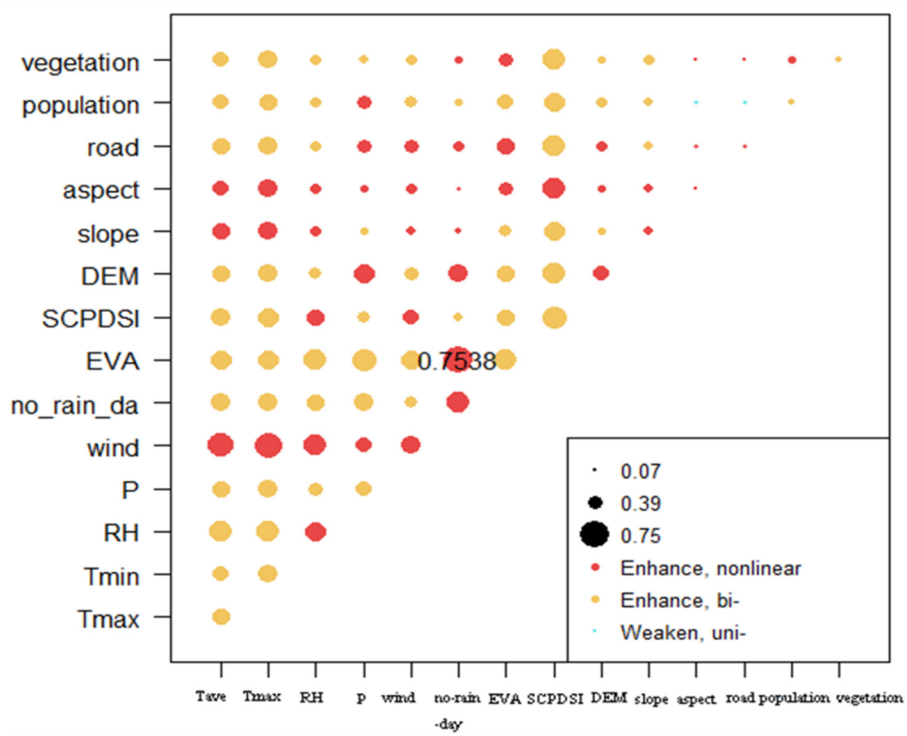
(a) The classification of EVA (b) Optimum interval of EVA

(c) The classification of Rainless Days (d) Optimum interval of Rainless Days

Fig. 8 Discretization for continuous variables. **a** The classification of EVA. **b** Optimum interval of EVA. **c** The classification of Rainless Days. **d** Optimum interval of Rainless Days



(a) Result of factor detection



(b) The result of interaction detection

Fig. 9 Results of factor detection and interaction detection for climate, topography and human activity in Panxi. **a** Result of factor detection. **b** The result of interaction detection

these five variables (EVA, maximum temperature, average temperature, number of days without rain, minimum temperature) with *q*-values greater than 0.3 as the major driving factors determining the spatial patterns of fire occurrence in the study area. The explanatory power of topography, vegetation type, and human factors alone is relatively weak.

The interaction detector was used to examine the combined effects of two factors on the density of fire occurrence in Panxi (Fig. 9b). In total, 105 pairs of interactions

existed between any two factors in this study. All interactions showed bivariate or nonlinear enhancement, except for the population with slope and slope direction as insignificant. Among them, 50.5% of factor interactions showed nonlinear enhancement. For instance, the *q*-value of EVA was 0.5404, and the wind speed was 0.1087. The sum of the individual *q*-values of EVA and wind speed (0.6491) was lower than the *q*-value of their interaction (0.7538). Meanwhile, 47.6% of factor interactions showed bivariate enhancement. For example, the *q*-value of relative humidity was 0.1871, and the *q*-value of maximum temperature was 0.4621. The *q*-value of the interaction between relative humidity and maximum temperature was 0.6492, higher than any single factor (relative humidity or maximum temperature) but lower than the sum of their individual *q*-values (0.6492).

The interaction detection between climate factors and terrain, human activities, and vegetation factors (Fig. 9b) revealed significant interactions between climate factors. The interaction between EVA and wind speed had the strongest explanatory power, with a *q*-value of 0.7538, indicating that together they could explain 75.4% of the Panxi forest fire. The interaction between EVA and other factors showed bivariate growth, except for the nonlinear enhancement with the drought index and slope direction, with *q*-values ranging from 0.4 to 0.8. The interactions between different terrain factors were insignificant except for the interaction between altitude and relative humidity factors, which showed nonlinear enhancement with a *q*-value of 0.5. Moreover, among the interactions between the EVA factor and terrain factors, the interactions between altitude, slope, and EVA were the most significant, all of which were greater than the individual effects of each terrain factor. Interaction detection showed that although individual terrain factors had no significant impact on the Panxi forest fire, their explanatory power was enhanced when interacting with the EVA factor, indicating that specific terrain conditions would significantly exacerbate the occurrence of the Panxi forest fire when encountering high evapotranspiration.

According to climate and terrain zoning, Panxi is subdivided into four regions (Fig. 1b): high mountain and canyon warm temperate, mountainous subtropical semi-humid, southern tropical humid, and mountainous central subtropical humid. We conducted factor detection and interaction analysis on these regions (Table 3). Results indicate that, except for the EVA factor in the high mountain and canyon warm temperate region, the explanatory power of the other regions was dominated by the drought factor (scPDSI). Compared to the single-factor detection results of Panxi as a whole, the q-value of the drought factor was higher in the four regions, indicating that the spatial differentiation of drought within each region had a stronger explanatory power for the distribution characteristics of forest fire disasters within the region.

According to the interaction detection results in Table 3 for each climate region, rainfall and drought are the two factors with the largest interaction in the southern tropical humid region and the mountainous subtropical semi-humid region. In the high mountain and canyon warm temperate region, the two factors with the largest interaction are scPDSI and EVA. In the mountainous central subtropical humid region, the two factors with the largest interaction are wind speed and precipitation factors. Except for the nonlinear interaction enhancement in the mountainous central subtropical humid region, the other three regions showed enhancement in two factors. The q value of the maximum factor interaction in the southern tropical humid region and the mountainous subtropical semi-humid region is higher than that of Panxi as a whole, indicating that the interaction between rainfall and drought factors has a stronger explanatory power for the differentiation characteristics of forest fires in these two regions.

Discussion

Fire regime

Previous studies have mainly focused on the spatiotemporal distribution of forest fires in the southwestern region, but there has been limited research on the clustering characteristics of forest fires (Qiao et al. 2020; Tian et al. 2017; He et al. 2017; Zheng et al. 2020). In this study, the temporal clustering and spatial heterogeneity

Table 3 Results with the most explanatory power of the factor and intersection detectors of each region of Panxi

Regions	Factor detection		Interactive detection		
	The most explanatory power of the factor	*q*-value	The most explanatory power of interaction factors	*q*-value	Type of interaction
The high mountain valley warm temperate zone	EVA	0.6222	scPDSI and EVA	0.7101	Bivariate enhancement
The southern subtropical humid zone	scPDSI	0.6495	P and scPDSI	0.8026	Bivariate enhancement
The mountainous subtropical semi-humid zone	scPDSI	0.7231	P and scPDSI	0.8546	Bivariate enhancement
The mountainous central subtropical humid zone	scPDSI	0.4084	P and wind	0.6729	Nonlinear enhancement

of forest fire dynamics in Panxi area were analyzed. The results indicated that the number of forest fires and the burned area in the Panxi region increased over time. However, the number of forest fires has decreased since 2015. This could be attributed to reducing human-induced fires due to the implementation of effective community education programs and stringent fire management policies. Another potential factor was the decrease of aboveground biomass resulting from high temperatures and dry conditions in the preceding period, which reduced the burning rate in the Panxi region (Bai et al. 2020; Wang 2014).

Although the general forest fires and major fires showed a downward trend from 2004 to 2020, the forest fire alarms and extra-large fire level forest fires showed an upward trend. Previous studies have shown that average temperature and wind speed influenced fire occurrence by altering the moisture content of the combustibles (Zhang and Su 2017; Wang 2014). These fires could escalate to larger scales under certain conditions, such as high wind speed or inadequate firefighting.

The burning area has increased since 2015, influenced by the warming and drying trend in the Panxi region, and so has the number of forest fires in its northern mountainous region. We observed spatial clustering of forest fire frequency in some local areas, especially during 2008–2016 and 2017–2020, with valley basins and hilly areas being the most affected regions. Forest fires were predominantly located at the edge of the hills, reflecting the spatial variation of climatic factors in the dry and hot valleys. Our findings are consistent with previous research that showed a dense distribution of forest fires along the dry and hot valley areas in Panxi, decreasing northward (Xiong et al. 2020; Xie et al. 2022). This conclusion supports the hypothesis that higher temperature, longer drought periods, lower relative humidity, and precipitation contribute to the aggregation of forest fires in this area.

Climate affects the number of forest fires and burned areas by influencing the accumulation and dryness of combustible materials (Liu et al. 2019; Su et al. 2021). This study also found a correlation between the extension of the fire prevention season and climate change. Under the IPCC's A2 and B2 climate change scenarios, some studies predict an extension of the fire season in Southwestern China (Wu et al. 2022).

Determinants of fire occurrence

The factor detector shows that climate variables contribute the most to the spatial pattern of fire occurrence, followed by terrain and human factors, and vegetation factors contribute the least. These results confirm the results of climate fire studies in the region, where climate influences fire mechanisms by regulating fuel abundance, fuel flammability, or both (Westerling et al. 2006; Morgan et al. 1999; Abatzoglou and Williams 2016; Littell et al. 2016). In the study area, the main driving factors are evaporation, maximum temperature, average temperature, no-rain days, and minimum temperature. In the range of different regions, the climatic factors are different. Except for the evaporation factor in the warm temperate zone of high mountains and canyons, the drought factor (scPDSI) has the strongest explanatory power in other regions. These results, on the one hand, confirm that climate has strong flammability limits on forest fire activity, and the drought that occurs simultaneously with the fire season is very important. These results corroborate the results of climate–fire studies in the region (Westerling et al. 2006; Morgan et al. 1999) that show strong flammability-limited climatic controls on forest fire activity, where drought concurrent with the fire season is important. On the other hand, it is proved that the spatial pattern of fire occurrence and the driving factors are heterogeneous (Wu et al. 2022; Guo et al. 2020; Liu et al., 2023). Thus, using the useful information provided by risk detectors to identify high-density areas of fire occurrence can provide effective benefits for optimizing the allocation of fire management resources.

The interaction of pairs of factors on fire occurrence

Usually, complex interactions among the driving factors affect the fire occurrence pattern (Schoennagel et al. 2004). Therefore, it is important to use the geographic detector model to determine how climate, terrain, vegetation, and human activity factors interact (Guo et al. 2020). Our study reveals that the spatial pattern of fire occurrence in Panxi is influenced by the synergistic effects of paired driving factors rather than the individual effects of each factor. We did not observe any cases of additive or antagonistic effects. This finding indicates that the interactions between driving factors are crucial for shaping the spatial pattern of fire occurrence. The interaction detector results show that the explanatory power of terrain, vegetation type, and human factors alone is relatively low. However, it is significantly improved when they interact with climate factors. This work corroborates previous findings that the spatial pattern of fire occurrence is jointly determined by the interactions among climate, vegetation, terrain, and human factors (Rollins 2009). Therefore, we recommend that forest managers pay more attention to the combined effects of various factors, rather than any single factor, when formulating fire management policies.

It has been demonstrated that the interaction between top-down and bottom-up controls can lead to a nonlinear relationship between fire activity and the

ecological consequences caused by fire (Peters et al. 2012). In the Panxi region, more than 50% of the pairwise driving factors showed nonlinear enhancement, mainly related to slope aspect and road density factors. The Xichang River valley experiences more intense fires in the middle of the study area. This is because it serves as the administrative center of Liangshan Prefecture in Panxi, with the highest population and road densities. Fire ignition records indicate that human activities are the main cause of fire in this area.

Meanwhile, the high evaporation and temperature in this area facilitate the ignition of combustible materials. Previous studies have shown that strict forest fire management policies have restricted human activities in forest land. However, with economic development, human activities are associated with infrastructure. Moreover, the expansion of built-up land alters local climate patterns and increases the interaction with fire activity (Abatzoglou and Williams 2016).

The spatial pattern of fire occurrence trend is influenced by topographic factors, which vary depending on the climatic background of the dry-hot valley. The slope aspect affects the distribution of surface heat and water by evaporation and precipitation. However, a single topographic factor has a limited role in the whole study area. Our findings suggest that the study area has a fire-prone climate, and the topographic pattern of fire occurrence is weaker than in a fireless environment because climate affects how single topographic variables influence the spatial pattern of fire occurrence at a regional scale. However, topography can also be a local and micro-scale driver of fire occurrence.

The nonlinear weakening relationship between slope and aspect and population density also indicates that the complex topography and the human ignition potential in the dry-hot valley are the main factors for the high fire occurrence in the Panxi area. Therefore, the spatial pattern of the Panxi fire is better explained by incorporating climatic factors with topography and human activities.

The study area shows a bivariate enhancement of the interaction between population density factors and the paired climate and vegetation types, which is weaker than nonlinear enhancement. Long-term climate influences the spatial patterns of major vegetation types (Liu and Wimberly 2016) and population density, driving the distribution of fires, climate, and vegetation. The population factors also reinforce each other appropriately. Therefore, the interaction between climate, vegetation, and population factors only enhances the impact of each factor on fire occurrence density.

Limitations and future work

This study still has some limitations. This study shows that more fires will occur with the extension of the fire season. When there are longer data series in the future, we can have a more comprehensive understanding of the fire system and its long-term evolution. The data source of this study is field verification data, and the available fire records only have a relatively short time (26 years). However, due to the lack of satellite data, the research results must be more precise. To further study the distribution of forest fire in Panxi and establish a forest fire prediction model based on multi-factor types, further analysis is also needed in the future with multi-source data.

This study has some limitations. It suggests that fire frequency increases with fire season length, but the available fire records are only for a relatively short period (26 years) and lack satellite data. Therefore, the results could be more refined. Future studies with longer data series and multi-source data can provide a more comprehensive understanding of fire regimes and their long-term evolution and establish a forest fire forecast model with multiple factors.

Forest fire is a complex system influenced by multiple factors, and the effects of climate factors on forest fire vary by vegetation type, landform, and other conditions (Ali et al. 2009; Turco et al. 2013; Sanderson and Fisher 2020). In this study, when selecting potential drivers of wildfire occurrence, we primarily considered the impact of the warming and drying trend in the Panxi Mountain area under the background of climate change on wildfires. Therefore, in the selection of climate variables, we considered nine different variables. In contrast, human factors add uncertainty and randomness to forest fires. However, for factors related to human activities, we only considered road infrastructure and population density. On one hand, human infrastructure, such as roads and settlements, influences fire occurrence probability by determining accessibility of human ignition sources to forests and amount of human presence. On the other hand, in this study, comprehensive data on wildfire suppression policies in the Panxi region were not collected, and quantifying these policies presented a challenge. Therefore, this variable was not considered in the existing research.This study did not explore the human impact on forest fires in Panxi but only used road density and population density as proxies for human activity. However, human activities in Panxi have been accelerating in the past few decades, and more forest resources have been converted to agricultural land, leading to more severe fire accumulation. Therefore, future studies should better consider the consequences of these human activities and policies to understand their impacts on the forest fire

in Panxi. In our next research phase, we will further collect relevant data through field surveys and questionnaire interviews. We will use both qualitative and quantitative methods to delve deeper into the impact of human activities on wildfires.

In conclusion, our list of criteria to identify potential forest fires could be expanded for biophysical and social parameters beyond fire size, fire duration, high burn severity, and distance to Wildland-Urban-Interface (WUI) (Lannom et al., 2014). The study of forest fire aggregation characteristics and mechanisms requires further consideration of the spatial variation of each factor and identification of other relevant indicators over time, especially studies that work across many fires and through time to identify alternative meaning metrics. Try to expand it to a more refined space-time scale for analysis. Research is warranted to explore fires' economic and property effects at the community level. And then provide a scientific basis and targeted decision-making for community-level forest fire prevention and control in Sichuan Province.

To study the characteristics and mechanisms of forest fire aggregation, it is necessary to consider the spatial variation of each factor and identify other relevant indicators over time, as well as to conduct cross-fire and temporal analyses with meaningful alternative metrics and to extend the analysis to a finer spatial and temporal scale. Research is warranted to explore the economic and property effect of fires at the community level and then provide a scientific basis and targeted decision-making for the community-level forest fire prevention and control work in Sichuan Province.

Conclusions

This paper analyzes the spatiotemporal characteristics of forest fire in the Panxi region from 2004 to 2020. The OPGD model is employed to investigate the driver factor of forest fires and interactions in Panxi region. The main conclusions are as follows:

From 2004 to 2020, the Panxi region experienced an upward trend in the number of forest fires and the area burned. However, the trends were only consistent over part of the period. Between 2004 and 2014, the number of fires and the area burned showed fluctuations and an overall increase. In contrast, between 2015 and 2020, there was a significant decrease in the number of fires, while the area burned showed a continued upward trend. The dates of the first fire in a year were significantly advanced, but those of the last were significantly delayed. The study identified abrupt changes in the frequency of forest fires and burned areas, primarily in 2007 and 2016. Spatially, forest fires in Panxi exhibited a positive correlation and local clustering. The river valley basin and hilly regions displayed a higher incidence of forest fires, mainly along the hill edges. Combined with the classification of the three periods based on the abrupt change year, the comparative analysis of the standard deviation ellipse in each period shows that the Panxi forest fires are more affected by latitudinal than longitudinal factors. The frequency of forest fires was more concentrated during 2008–2016 and 2017–2020, and their relationship with the Hot Valley was closer.

The explanatory power of climatic factors for spatial variation of forest fires is stronger than other factors for the whole area of the Panxi region. Among them, the main drivers that determine the spatial pattern of fire occurrence in the study area are the five factors, EVA, maximum temperature, mean temperature, number of days without rain, and minimum temperature. The explanatory power of topography, vegetation type, and anthropogenic factors alone is relatively weak. The interaction between climate factors, topography, human activities, and vegetation factors results in a nonlinear or Bivariate enhancement in explanatory power. This finding indicates that the joint driving force of climate, topography, human activities, and vegetation is likely to intensify the occurrence of forest fires.

In the four regions of Panxi, the climate was identified as the dominant driver of forest fire occurrence, but the dominant climate factors varied significantly among the regions. Except for the EVA factor in the warm-temperate zone of high mountain gorges, the explanatory power of drought (scPDSI) was the strongest in the other regions. Compared to the Panxi-wide scale, the spatial variation of drought within each subregion had a stronger explanatory power for the distribution characteristics of forest fires within the region. The factor with the maximum interaction in most regions was the dual factor of rainfall and drought. The study's findings validate the applicability of geographic probes for identifying the drivers of fire occurrence and enhance our understanding of the drivers and their combined effects on the spatial context of the fire-incident study area.

Authors' contributions

JL, YW, HG and YL contributed to the conception and design of the study. JL, YX, YS and RS collected and organized the original data. JL, YX, WG and ZL performed the statistical analysis. JL wrote the first draft of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Availability of data and materials
The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Declarations

Competing interests
The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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