Spatiotemporal Distribution and Dynamics of Forest Fires

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Abstract

Based on nearly 20 years of forest fire data, this study investigates the influencing factors and spatiotemporal variations of forest fires in China, conducting data mining and quantitative analysis with multi-source data including meteorological, topographic, and socio-humanistic data. Through methods such as trend testing, kernel density analysis, standard deviation ellipse, and centroid shift analysis, the changing trends of forest fires in China from 2001 to 2019 were analyzed. The results indicate that forest fires in China exhibited an overall fluctuating downward trend from 2001 to 2019, with an upward trend from 2001 to 2014 and a downward trend from 2015 to 2019. Forest fire hotspots in China are predominantly distributed within the following ranges: elevation 200-500 m, slope 5-15°, aspect of south and southeast slopes, temperature 10-15°C, average humidity 60-70%, precipitation less than 5 mm, distance from roads 500-1500 m, and distance from residential areas 4000-7000 m. The majority of forest fires in China occur in the southwestern, southern, northeastern, and eastern regions of the country. From 2001 to 2019, forest fires across the nation displayed an intermittent contraction trend in the north-south direction and remained relatively stable in the east-west direction.

Full Text

Preamble

Study on Temporal and Spatial Distribution and Variation of Forest Fires

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Abstract

Based on forest fire data spanning nearly two decades, this study investigates the influencing factors and spatio-temporal dynamics of forest fires in China through data mining and quantitative analysis of multi-source datasets, including meteorological, topographic, and socio-cultural data. Employing trend tests, kernel density analysis, standard deviation ellipse, and barycentric shift methods, we analyzed the changing patterns of forest fires in China from 2001 to 2019. The results indicate that forest fires in China exhibited an overall fluctuating downward trend during 2001–2019, with an upward trend from 2001–2014 and a downward trend from 2015–2019. Forest fire points were predominantly distributed within specific ranges: elevation 200–500 m, slope 5–15°, south to southeast aspects, temperature 10–15°C, average humidity 60–70%, precipitation less than 5 mm, distance from roads 500–1500 m, and distance from settlements 4000–7000 m. The majority of forest fires occurred in Southwest China, South China, Northeast China, and East China. Between 2001 and 2019, the occurrence of forest fires showed an intermittent contraction trend in the north-south direction while remaining relatively stable in the east-west direction.

Keywords: Forest fires, Multi-source data, Influencing factors, Spatio-temporal variation

Introduction

Forests play a crucial role in maintaining global ecological balance, providing services such as windbreak and sand fixation, environmental beautification, carbon sequestration and oxygen release, and supplying forest products and recreational tourism opportunities [1]. However, forest ecosystems worldwide have increasingly faced threats from forest fires in recent years, causing substantial losses to global ecosystems and human societies [2]. In China, a country characterized by significant environmental, socioeconomic, and forest resource distribution disparities, the interplay between natural and anthropogenic factors and their impacts on forest fire risk has remained a persistent challenge for forest fire prevention and control, forest resource management, and ecological conservation [3]. Understanding the occurrence characteristics and key driving factors of forest fires is essential for forest ecology and management, as well as for predicting and mitigating fire disasters.

This research focuses on the influencing factors and spatio-temporal variations of forest fires in China. Based on nearly 20 years of forest fire data, we conducted data mining and quantitative analysis by integrating fire observation data with multi-source datasets including meteorological, topographic, and socio-cultural data. Through trend tests, kernel density analysis, standard deviation ellipse, and barycentric shift methods, we analyzed the changing trends, spatio-temporal distribution patterns, and evolution of forest fires in China from 2001 to 2019, aiming to uncover underlying essential characteristics and knowledge to provide robust support for forest fire prediction and prevention.

1.1 Study Area Overview

The majority of China's forests are distributed in the northeastern, southern, southeastern, and southwestern regions of the country, with limited quantity and low coverage in the northwest. Although the forest area in Northeast China is relatively large, the forest coverage rate is lower than that in southern regions. Overall, China's forest resources are characterized by low total volume, uneven regional distribution, low quality, unreasonable age-group structure, low forest land output quality, and limited annual growth. Compared with developed forestry countries, China remains a nation with forest shortages and relatively fragile ecosystems [4]. The climate exhibits significant regional characteristics and complexity, spanning multiple climate zones including tropical, subtropical, temperate, and cold temperate zones, with diverse climate types and pronounced north-south differences. Population density is relatively high in eastern and southern coastal areas, while western regions have lower density. China's population is primarily concentrated in eastern, southern, and central regions, with relatively sparse distribution in northwestern and northeastern areas, presenting an unbalanced spatial distribution pattern known as the "Hu Huanyong Line" [5].

[Figure 1: see original paper] Forest resource distribution in the study area (no data for Hong Kong, Macau, and Taiwan)

1.2 Data Sources

This study utilized fire point data, meteorological data, and socioeconomic data as the primary sources (Table 1). Specifically, the Moderate Resolution Imaging Spectroradiometer (MODIS) active fire vector product provided by NASA's Fire Information for Resource Management System (https://earthdata.nasa.gov) was used to record the spatial distribution of fire pixels from 2001 to 2019. Daily meteorological data from 2001 to 2019 were obtained from the China Meteorological Administration's National Meteorological Information Center (http://data.cma.cn) through the China Surface Climate Data (V3.0) daily dataset. The raw data underwent preprocessing, including range checks, value type verification, and logical relationship examination to remove outliers and erroneous values. Population and GDP data were sourced from the Resource and Environmental Data Center of the Chinese Academy of Sciences (https://www.resdc.cn), while road and settlement datasets were obtained from the National Geographic Information Resources Catalog System (http://www.webmap.cn).

Primary data list

2.1.1 Monthly and Daily Distribution Patterns

The monthly and daily variations of forest fires in China reveal distinct patterns. At the monthly scale, the highest number of fire points occurred in March, February, and April, accounting for 45.13% of the total. January (10,711 fire points) and December (9,659 fire points) were the next most fire-prone months, representing 21.09% of the total. In contrast, August (993 fire points) and July (721 fire points) showed the lowest incidence, comprising only 1.77% of the total. The daily variation trend (Figure 3 [Figure 3: see original paper]) demonstrates fluctuating increases between days 1–41 and 71–101 of each year, followed by decreasing trends between days 101–131 and 151–181. Notably, more than 300 days per year experienced over 127 fire points, representing 67.07% of all days. The peak single-day fire occurrences were on days 43, 62, 94, and 63, with a cumulative total of 5,075 fire points over the 20-year period. Conversely, the lowest fire occurrences were recorded on days 202, 201, 189, and 195, with a combined total of only 61 fire points.

[Figure 2: see original paper] Monthly statistics of forest fire points in China

2.1.2 Distribution Patterns Across Different Ecological Geographic Zones

Based on climate type classification, China was divided into eight ecological geographic zones (Figure 4 [Figure 4: see original paper]). Statistical analysis reveals significant variations in forest fire distribution among these zones. The subtropical evergreen broadleaf forest zone, tropical monsoon rainforest zone, and cold temperate coniferous forest zone exhibited the highest fire point densities, accounting for 71.64%, 9%, and 8.71% of the total, respectively. These patterns likely relate to climatic conditions, forest vegetation types, and human activities in these regions. In contrast, the Qinghai-Tibet alpine vegetation zone and temperate desert zone showed the lowest fire point occurrences, representing only 0.06% and 0.04% of the total, respectively, presumably due to their harsh climatic conditions and vegetation characteristics.

[Figure 4: see original paper] Statistics of different ecological geographic zones and fire point proportions in China (R1: Temperate grassland zone; R2: Temperate desert zone; R3: Cold temperate coniferous forest zone; R4: Temperate coniferous and deciduous broadleaf mixed forest zone; R5: Warm temperate deciduous broadleaf forest zone; R6: Qinghai-Tibet alpine vegetation zone; R7: Subtropical evergreen broadleaf forest zone; R8: Tropical monsoon rainforest and rainforest zone)

2.1.3 Distribution Patterns Across Different Provinces

Forest fire distribution varies substantially among Chinese provinces (Figure 5 [Figure 5: see original paper]). The highest concentrations occurred in Yunnan (17.07%), Guangdong (16.77%), Guangxi (11.17%), Heilongjiang (11.13%), Jiangxi (9.44%), Hunan (8.86%), and Fujian (6.89%). These provinces are predominantly located in southern China. Yunnan and Guangxi feature complex terrain and diverse forest vegetation types with frequent human-caused fires, while Guangdong and Fujian have relatively high temperatures and extensive agricultural burning activities. Heilongjiang, situated in Northeast China, possesses abundant forest resources and experiences numerous summer lightning fires, making it one of the most fire-prone regions in the country.

[Figure 5: see original paper] Provincial distribution of forest fire points in China (excluding Hong Kong, Macau, and Taiwan)

2.1.4 Distribution Across Different Elevations

The distribution of forest fires across elevation gradients shows that the 200–500 m range had the highest fire point density, accounting for 39.71% of the total. The <200 m, 500–1000 m, and 1000–3500 m ranges represented 19.91%, 18.64%, and 20.93% of fire points, respectively. In contrast, areas above 3500 m exhibited minimal fire activity, with only 0.81% of total fire points, essentially indicating negligible fire occurrence.

[Figure 6: see original paper] Elevation distribution of forest fire points in China (excluding Hong Kong, Macau, and Taiwan)

2.1.5 Distribution Across Different Slopes

Forest fire distribution across slope gradients reveals the highest concentration on slopes of 5–15°, representing 42.18% of fire points. The <5° and 15–25° slopes accounted for 26.86% and 24.01%, respectively. The lowest fire occurrences were observed on slopes exceeding 35° and 45°, comprising only 0.84% of the total, with virtually no fire activity. Slope influences both fire propagation and the time lag of precipitation, thereby affecting fuel moisture content. Steeper slopes typically feature drier climates and more abundant fuel loads, creating conditions conducive to forest fires that are difficult to control and extinguish.

[Figure 7: see original paper] Slope distribution of forest fire points in China (excluding Hong Kong, Macau, and Taiwan)

2.1.6 Distribution Across Different Aspects

The distribution of forest fires across aspect categories shows the highest fire point densities on south-facing (15.27%), southeast-facing (14.52%), and southwest-facing (12.67%) slopes. Northeast-facing and northwest-facing slopes accounted for 11.82% and 11.21%, respectively, while north-facing slopes had the lowest occurrence at only 5.89%. These results demonstrate that aspect significantly influences fire distribution, as different aspects cause variations in environmental factors such as precipitation, temperature, and solar radiation, which subsequently affect vegetation growth, desiccation levels, and ultimately fire occurrence and spread.

[Figure 8: see original paper] Aspect distribution of forest fire points in China (excluding Hong Kong, Macau, and Taiwan)

2.1.7 Distribution Across Different Temperature Ranges

Forest fire distribution across temperature ranges indicates the highest concentrations at average temperatures of 15–25°C (37.55%) and 10–15°C (20.45%). In contrast, fire point numbers gradually decreased at average temperatures below 0°C or above 25°C. While elevated temperatures reduce humidity and fuel moisture content, thereby increasing fire risk, the high-rainfall conditions during China's hot summer months maintain high vegetation moisture, resulting in fewer fires despite high temperatures.

[Figure 9: see original paper] Distribution of forest fire points across different temperature ranges

2.1.8 Distribution Across Different Precipitation and Wind Speed Conditions

Forest fire distribution across precipitation levels shows that fires were most frequent when precipitation was less than 5 mm, accounting for 80% of all fire points. Relatively fewer fires occurred in the 5–10 mm and 10–15 mm precipitation intervals. Precipitation directly affects fuel moisture content, and insufficient rainfall leads to vegetation desiccation, facilitating fire expansion.

[Figure 10: see original paper] Distribution of forest fire points across different precipitation levels

Analysis of wind speed conditions reveals that fire points were most common at average wind speeds of 1–2 m/s (43.87%) and 2–3 m/s (19.9%). Within the 0–2 m/s range, fire occurrence increased with wind speed. However, when wind speed exceeded 7 m/s, fire probability approached zero, with virtually no fire activity recorded. Wind speed is a critical factor in fire behavior, as increased wind accelerates fire spread and diffusion, making fire suppression more challenging.

[Figure 11: see original paper] Distribution of forest fire points across different average wind speeds

2.1.9 Distribution Across Different Socio-Cultural Contexts

Forest fire distribution relative to road distance shows concentrated fire points within 500 m (9.28%), 500–1000 m (11.84%), and 1000–1500 m (11.91%) of roads. Secondary concentrations occurred at 2000–2500 m (9.02%) and 2500–3000 m (7.52%). Beyond 5000 m from roads, fire point numbers declined rapidly. Road presence is a significant fire factor, as roads correlate strongly with human ignition sources such as cooking, discarded cigarettes, ritual activities, and incense burning near roadways. In tourist areas or densely populated regions, human activities near roads substantially increase fire risk.

[Figure 12: see original paper] Distribution of forest fire points by distance from roads

Analysis of fire distribution by distance from settlements indicates that fire points were heavily concentrated 4000–7000 m from residential areas, representing 41.5% of the total. Additionally, fire point numbers showed an increasing trend within 0–5000 m of settlements. The distance from settlements significantly influences fire spread rate, fire intensity, and threats to human safety. Moreover, the complex environments surrounding settlements increase fire suppression difficulties.

[Figure 13: see original paper] Distribution of forest fire points by distance from settlements

Forest fire distribution during special holidays shows a total of 4,444 fire points, with Qingming Festival accounting for the highest number at 2,749. The Lantern Festival, second day of Chinese New Year, first day of Chinese New Year, and New Year's Eve followed in frequency, while the Ghost Festival had the lowest occurrence. These patterns reflect China's unique traditional customs, including ritual activities and holiday celebrations. For instance, fireworks during Spring Festival and tomb-sweeping activities during Qingming Festival, particularly the burning of paper money, significantly increase fire probability. Such activities conducted in natural environments are difficult to control and extinguish once ignited.

[Figure 14: see original paper] Distribution of forest fire points during special holidays

2.2 Trend Test

The Mann-Kendall (M-K) mutation test is a robust method for time series data analysis, offering strong resistance to outliers and anomalies while providing advantages of simple operation, broad applicability, high precision, minimal human influence, and strong quantification capabilities [7]. The calculated sequence d_k is a random order series that follows a normal distribution, with $UF(d_k)$ computed as:

$$UF(d_k) = \frac{[d_k - E(d_k)]}{\sqrt{Var(d_k)}}$$

where UF or UB values greater than or less than 0 indicate upward or downward trends, respectively. Values exceeding the critical significance level line denote significant changes, with the temporal range of such changes identifiable as mutation periods.

[Figure 15: see original paper] M-K mutation test curves
[Figure 16: see original paper] Cumulative anomaly curve

As shown in Figures 15 and 16, UF values were positive during 2001–2014, indicating an upward trend in fire point numbers, while negative values during 2015–2019 indicate a downward trend. The UF curve exceeded the 0.05

confidence line (+1.96) in 2004, 2008, and 2009, signifying significant increasing trends in these years. The intersection of UF and UB curves occurred in 2015 within the confidence interval, and combined with the cumulative anomaly curve, confirms 2015 as the mutation point for national forest fire numbers over the past two decades.

2.3 Kernel Density Analysis

Point pattern analysis represents a fundamental method in spatial analysis for investigating distribution patterns, spatial relationships, and evolutionary trends of point features in space. Among density calculation methods, kernel density estimation demonstrates superior performance compared to quadrat density methods and Voronoi diagram-based approaches [8]. Kernel density analysis is a density-based algorithm that reveals spatial distribution characteristics using the formula:

$$f(x) = \sum \frac{1}{\pi r^2} \Phi\left(\frac{d_{ix}}{r}\right) \quad (2)$$

where r is the search radius, n is the total number of fire point samples, d_{ix} is the distance between fire point i and location x, and Φ is the distance weight function.

Figure 17 [Figure 17: see original paper] presents the kernel density analysis of forest fires in China, revealing high-density regions primarily in Yunnan Province, Guangxi Zhuang Autonomous Region, Guangdong Province (Heyuan, Shaoguan, Huizhou), Fujian Province (Nanping, Sanming), Hunan Province (Yongzhou, Chenzhou), Jiangxi Province (Ji'an, Fuzhou), Heilongjiang Province (Daxing'anling, Heihe), and parts of Hulunbuir in Inner Mongolia. These results align closely with the spatial distribution of fire points.

[Figure 17: see original paper] Kernel density analysis map of forest fires in China (excluding Hong Kong, Macau, and Taiwan)

2.4 Standard Deviation Ellipse and Barycentric Shift

The Standard Deviational Ellipse (SDE) is a spatial statistical method that precisely reveals the concentration and dispersion degree of spatial data [9], with the ellipse center representing the barycenter of forest fire occurrence. The position change and movement direction of the barycenter are calculated as follows [10-12]:

$$\mathrm{var}(x) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n}, \quad \mathrm{cov}(x,y) = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{n}$$

where x and y are coordinates of variable i, $(\bar{X}, \bar{Y})$ represents the mean center, and n is the total number of variables.

The long axis direction of the standard deviation ellipse reflects the primary trend direction of forest fire occurrence, while the major and minor axes represent the distribution range. The formulas for ellipse distribution along the x and y axes are [11][12]:

$$SDE_x = \sqrt{\sum_{i=1}^{n}(x_i - \bar{X})^2}, \quad SDE_y = \sqrt{\sum_{i=1}^{n}(y_i - \bar{Y})^2}$$

where X and Y represent the longitude and latitude coordinates of forest fire points, and X_i and Y_i represent the coordinates of grid fire points.

The ratio of long to short axes represents the oblateness; greater oblateness indicates more concentrated spatial distribution of forest fires. The direction angle is calculated as [11][12]:

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

Table 2 and Figure 18 [Figure 18: see original paper] present the standard deviation ellipse and barycentric shift results for Chinese forest fire points from 2001 to 2019. The findings indicate that the azimuth angle fluctuated within the 20°–30° range throughout the study period. Although the angle increased to 40.75° in 2012, the relatively small oblateness value for that year suggests this does not indicate a northeast-southwest shift but rather a reduced fire occurrence range with concentration toward the south. The short semi-axis fluctuated primarily within 600–700 km, while the long semi-axis showed an overall shortening trend from 2001–2019, with minor expansions during 2001–2002, 2002–2003, and 2008–2009, and more substantial expansions during 2005–2006, 2009–2010, and 2014–2015. Analysis of short and long semi-axis variations reveals an intermittent contraction trend in the north-south direction and relative stability in the east-west direction for national forest fire occurrence during 2001–2019.

The overall oblateness trend decreased initially then increased. Minor east-west expansions occurred during 2001–2003 and 2016–2019, while 2003–2016 showed a general oblateness decrease, indicating gradual concentration of fire occurrence areas with reduced north-south influence. The standard deviation ellipse distribution and trajectory changes from 2001–2019 demonstrate that forest fires primarily followed a northeast-southwest orientation. The fire occurrence range gradually shifted southward during 2003–2016, with a notable northeastward expansion after 2016. Barycentric movement analysis reveals a primary southwestward shift with a northeastward tendency from 2001–2019. Specifically: 2001–2003 showed a 268.2 km northeastward shift, indicating increased fire occurrence in the northeast; 2003–2005 exhibited a 1027.5 km southwestward shift, reflecting significant fire expansion in Southwest China; 2005–2008 involved a

500.6 km northeastward shift followed by a 470.8 km southwestward shift, culminating in a 189.8 km northeastward movement during 2007–2008; 2008–2012 featured primarily east-west movements, with a 435.2 km westward shift during 2008–2010, a 483.8 km eastward shift during 2010–2011, and a 545.2 km westward shift during 2011–2012; 2012–2013 showed a 218.9 km northeastward shift; 2013–2017 movements were predominantly north-south, with northward shifts in most years except for a southward movement in 2014; and 2017–2019 involved a 228.8 km southwestward shift followed by a 108.4 km westward shift.

[Figure 18: see original paper] Barycentric shift map of forest fires from 2001–2019 (excluding Hong Kong, Macau, and Taiwan)
Standard deviation ellipse parameters for forest fires in China: XStdDist (km), YStdDist (km), Rotation, Oblateness

3 Conclusions

To explore the influencing factors and spatio-temporal distribution characteristics of forest fires in China, this study analyzed MODIS-monitored fire point data from 2001–2019 to examine intrinsic relationships between forest fires and influencing factors. Integrating multiple disaster-causing factors including topography, climate, vegetation, and socio-cultural elements, we conducted qualitative and quantitative analyses of forest fire occurrence in China. Through spatial analysis techniques (standard deviation ellipse, kernel density, etc.), we investigated spatio-temporal distribution and evolution patterns, enabling assessment and quantification of forest fire risk spatio-temporal dynamics and revealing activity patterns and distribution characteristics. The results demonstrate:

(1) Forest fires in China exhibited an overall fluctuating downward trend from 2001–2019, with an upward trend during 2001–2014 and a downward trend during 2015–2019.

(2) Forest fire points were predominantly distributed within specific ranges: elevation 200–500 m, slope 5–15°, south to southeast aspects, temperature 10–15°C, precipitation less than 5 mm, distance from roads 500–1500 m, and distance from settlements 4000–7000 m.

(3) The majority of forest fires occurred in Southwest China, South China, Northeast China, and East China, with high concentrations in Yunnan, Guangdong, Guangxi, Heilongjiang, and Fujian provinces. Fires were concentrated in subtropical evergreen broadleaf forest zones, tropical monsoon rainforest zones, cold temperate coniferous forest zones, and temperate coniferous-deciduous broadleaf mixed forest zones. Nationally, forest fire occurrence showed an intermittent contraction trend in the north-south direction while remaining relatively stable in the east-west direction from 2001–2019.

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Author Contributions

Feng Zhongke and Shao Yakui: Conceived the research idea and designed the study framework.
Shao Yakui, Sun Linhao, and Yang Xuanhan: Conducted the experiments.
Ma Tiantian: Collected, cleaned, and analyzed the data.
Shao Yakui, Sun Linhao, Ma Tiantian, and Yang Xuanhan: Drafted the manuscript.
Shao Yakui and Feng Zhongke: Revised the final version of the paper.

Note: Figure translations are in progress. See original paper for figures.