

Article

Forest Fire Spread Hazard and Landscape Pattern Characteristics in the Mountainous District, Beijing

Bo Wang ^{1,2}, Weiwei Li ², Guanghui Lai ³, Ning Chang ⁴, Feng Chen ^{2,4,5}, Ye Bai ^{4,*} and Xiaodong Liu ^{2,4,5,*}

¹ School of Emergency Technology and Management, North China Institute of Science and Technology, Langfang 065201, China; wangboslfh@163.com

² Beijing Key Laboratory for Forest Resources and Ecosystem Processes, Beijing Forestry University, Beijing 100083, China; liweiweiorg@126.com (W.L.); chenfeng19851208@163.com (F.C.)

³ Beijing Municipal Forestry and Parks Planning and Resource Monitoring Center, Beijing Municipal Forestry Carbon Sinks and International Cooperation Affairs Center, Beijing 100029, China; laigh@126.com

⁴ Key Laboratory of Forest and Grassland Fire Risk Prevention Ministry of Emergency Management, China Fire and Rescue Institute, Beijing 102202, China; changningzgxfjyxy@163.com

⁵ State Key Laboratory of Efficient Production of Forest Resources, Beijing Forestry University, Beijing 100083, China

* Correspondence: xd_liu@bjfu.edu.cn (X.L.); 13681132378@163.com (Y.B.)

Abstract: Objective: This study established an index system for assessing forest fire spread hazards and conducted a forest fire spread hazard assessment in the mountainous district of Beijing (including Fangshan, Mentougou, Changping, Yanqing, Huairou, Miyun, and Pinggu). The relationship between forested landscape spatial pattern and forest fire spread hazard was explored; this method provided the basis for the establishment of a landscape forest fire security guarantee system. Methods: The forest fire spread hazard assessment index system was constructed from four aspects: forest fuel, meteorological factors, topographic factors, and fire behavior. The weighted comprehensive evaluation method and area-weighted average method were used to calculate the forest fire spread hazard indices at the subcompartment scale and township scale. Moran's I index was selected as the spatial autocorrelation index to analyze the autocorrelation degree and spatial distribution of the forest fire spread hazard index. Eleven representative landscape pattern indices were selected to analyze the main landscape spatial pattern affecting forest fire spread hazard by correlation analysis and principal component analysis. Results: (1) The areas with high, medium-high, medium-low, and low forest fire spread hazard grades accounted for 39.87%, 33.10%, 11.37%, and 15.66% of the study area, respectively, at the subcompartment scale and for 52.36%, 22.58%, 18.39%, and 6.67% of the study area, respectively, at the township scale. (2) The forest fire spread hazard index results obtained at the subcompartment and township scales in the Mountainous District of Beijing showed a spatial agglomeration distribution law. (3) The forest fire spread hazard was influenced mainly by landscape diversity (SHDI and PRD), landscape aggregation (AI, CONTAG, and PD), and landscape area (TA). Conclusions: The overall forest fire spread hazard in the mountainous district of Beijing showed a gradual increase from plains to mountainous areas. The land types of the high-spread hazard subcompartment mainly included general shrubbery and coniferous forestlands, and the dominant species in the high-spread hazard arbor forest subcompartment were mainly *Platycladus orientalis*, *Pinus tabulaeformis*, and *Quercus mongolica*.



Citation: Wang, B.; Li, W.; Lai, G.; Chang, N.; Chen, F.; Bai, Y.; Liu, X. Forest Fire Spread Hazard and Landscape Pattern Characteristics in the Mountainous District, Beijing. *Forests* **2023**, *14*, 2139. <https://doi.org/10.3390/f14112139>

Academic Editor: Manuel Marey-Pérez

Received: 7 September 2023

Revised: 17 October 2023

Accepted: 25 October 2023

Published: 27 October 2023



Copyright: © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Keywords: Beijing mountainous district; forest fire; spread hazard; spatial autocorrelation; landscape pattern

1. Introduction

The forest fire spread hazard refers to the possibility of a forest fire spreading (assuming that a forest fire has already begun) [1–6]. Under the influence of climate change and land use changes, the occurrence probability and intensity of extreme fires have increased

significantly [7–13]. Under the combined action of flammable vegetation types, special dangerous terrains, and harsh meteorological conditions, the probability of forest fires spreading rapidly and out of control has increased significantly, seriously threatening forest resources and the habitats of wild animals and plants, as well as life and property security and homeland ecological security [14–18]. The number of extreme fires is expected to increase by 30% worldwide by the end of 2050, according to a new report by the United Nations Environment Programme, *Spreading Like Wildfire: The Rising Threat of Extraordinary Landscape Fires* [19]. Therefore, scientific assessments of forest fire spread hazards can determine the areas where forest fires may spread easily and provide a basis for the construction of forest fire barrier systems, fire-extinguishing resources, and emergency force rational layouts; such studies thus have important theoretical and application value [20].

Forest fire hazards refer to the possibility of a disaster causing adverse effects, and the core is the degree of disaster-causing activity [21–23]. Generally, the forest fire intensity combines the two characteristics of fuel consumption and the forest fire spread speed to provide key information on forest fire behavior that may occur in different areas; this index is commonly used to measure fire hazards [24]. Scott et al. [25] defined the forest fire hazard as a physical situation in which a forest fire may cause losses and proposed a method to represent the forest fire hazard by combining the two indices of burning probability and forest fire intensity. Jolly et al. [26] constructed the severe fire danger index (SFDI) based on the two related indices of forest fire intensity and forest fire spread possibility and found that the index could predict extreme fire hazards and had a good prediction effect on the trapping and death of firefighters. Shafapourtehrany [27] used decision tree (DT) and support vector machine (SVM) methods to assess forest fire hazards in Queensland, Australia, and used the area under curve method (area under the receiver operating characteristic curve) to evaluate the accuracy of their results; they found that the accuracies reached 89.21% and 83.78%, respectively. According to the “Rank of the Regionalization on Nationwide Forest Fire Risk”, Zhang et al. [28] selected tree species burning type, population density, road network density, monthly average precipitation during the fire prevention period, temperature, and wind speed to complete the forest fire danger rating and fire hazard assessment in Chifeng City, Inner Mongolia.

Forest fire spread is an important index of forest fire behavior, which can provide basic information for forest fire risk assessment and is of great significance for the scientific planning of forest fire management and the rational allocation of fire-fighting resources [29,30]. Calkin et al. [31] summarized the methods of incorporating forest fire spread, forest fire intensity, and changes in important disaster-bearing bodies into the risk framework, and conducted assessment and application in Oregon, USA. Tao et al. [32] calculated the probability of canopy fire occurrence and potential canopy fire behavior characteristics of major coniferous forests in the Beijing mountainous area under different gradient burning conditions on the basis of an in-depth understanding of the spatial distribution of fuels in different layers and established the canopy hazard index model of major coniferous forests by using the canopy fire spread critical index model. Hysa et al. [2,5] used the wildfire ignition probability index and wildfire spreading capacity index to assess wildfire risk in northern Albania’s broad-leaved forests and the wildfire vulnerability of vegetated serpentine soils in the Balkan peninsula. Aparício et al. [33] quantified the impact of spatial arrangement of fuels on fire spread connectivity based on wildfire behavior simulations and network analysis methods, providing a basis for reducing the risk of fire spread and the potential impact of extreme fires. Rodrigues et al. [29] divided wildfire management areas into four types: comprehensive management, human ignition prevention, intensive fuel management, and fire reintroduction areas based on the modeling outcomes of wildfire occurrence, initial attack success, and wildfire transmission, providing a basis for wildfire management in Mediterranean regions.

Landscape heterogeneity and landscape patterns are at the core of landscape ecology. These factors also interact with each other. Different landscape heterogeneity conditions form different landscape patterns, and different landscape patterns determine different

ecological processes. It is therefore of great theoretical and practical significance to study the relationships between forest fire disturbances and landscape heterogeneity and diversity [34–36]. The methods used to research landscape patterns mainly include landscape pattern spatial statistical analyses and landscape pattern index analyses. Spatial statistical analyses of landscape patterns can describe the spatial distribution of landscape patterns and the extent to which landscape patterns are affected by spatial autocorrelation. Common methods include geostatistics, wavelet analysis, trend surface analysis, and autocorrelation analysis [37–39]. Analyses of landscape pattern indices can reflect the structural composition and spatial distribution characteristics of landscape elements, including the patch level, type level, and landscape level [40,41]. Long et al. [42] analyzed the spatial pattern of the forest fire risk in Yunnan Province by using a spatial trend surface analysis and a spatial autocorrelation model. Zhang et al. [43] conducted wavelet analysis on forest grassland fire statistics in China from 1993 to 2016 and discussed the influences of different time series on forest grassland fires under various fire-influencing factors. Steel et al. [44] analyzed the spatial pattern of forest fire severity in *Ponderosa pine* and mixed coniferous forests after forest fires in California from 1984 to 2015 based on five landscape pattern indices. Benali et al. [45] evaluated how different landscape-level fuel treatment strategies can reduce wildfire hazards in Alvares. However, no correlation analysis between forest fire spread hazards and forested landscape spatial patterns has yet been performed.

The Mountainous District of Beijing is an ecological conservation area, green ecological security barrier, and drinking water source protection area for the capital of China; this area is the key to ensuring the sustainable development of Beijing. The Mountainous District of Beijing (including Fangshan, Mentougou, Changping, Yanqing, Huairou, Miyun, and Pinggu) is the object of this study. In this study, we establish an index system to assess the forest fire spread hazard, carry out a forest fire spread hazard assessment in the Mountainous District of Beijing, and explore the spatial correlation model of the forest fire spread hazard index through a spatial autocorrelation analysis. Eleven representative horizontal landscape pattern indices are selected and calculated by Fragstats 4.2.1 software (Informer Technologies, Inc., Los Angeles, CA, USA). Pearson correlation analysis and principal component analysis are used to analyze the main landscape pattern indices affecting the forest fire spread hazard. The research results can provide a basis for the establishment of landscape-scale forest fire security systems.

2. Methods

2.1. Study Areas

Beijing (39°28′–41°05′ N, 115°25′–117°30′ E) is located in the northern part of the North China Plain, bordering Tianjin on the southeast and neighboring Hebei Province on the other borders. The total area of Beijing is 16,410 km², of which the mountainous area is approximately 10,072 km², accounting for 61.4% of the total area. According to the National Forest Fire Prevention Plan (2016–2025), there are no high-hazard areas in the key areas of forest fire prevention in Beijing, but there are seven high-risk areas, namely, the seven mountainous districts (Fangshan, Mentougou, Changping, Yanqing, Huairou, Miyun, and Pinggu), as shown in Figure 1. The geographical location and ecological location of the Beijing Mountainous District are extremely important, with superior natural conditions. The average elevation is 1000–1500 m, and the highest elevation is 2303 m on Dongling Mountain. The zonal soil is brown soil. The climate type is a warm, temperate, subhumid, continental monsoon climate with dry and windy spring and winter seasons, large temperature differences between day and night, low vegetation moisture contents, and winds mainly from the northwest direction, which easily cause forest fires. The Mountainous District of Beijing is rich in forest resources, with a forest coverage rate of 59% and an obvious vertical distribution law. The main dominant species are *Pinus tabulaeformis*, *Platycladus orientalis*, *Betula* spp., *Quercus* spp., *Populus davidiana*, and so on.

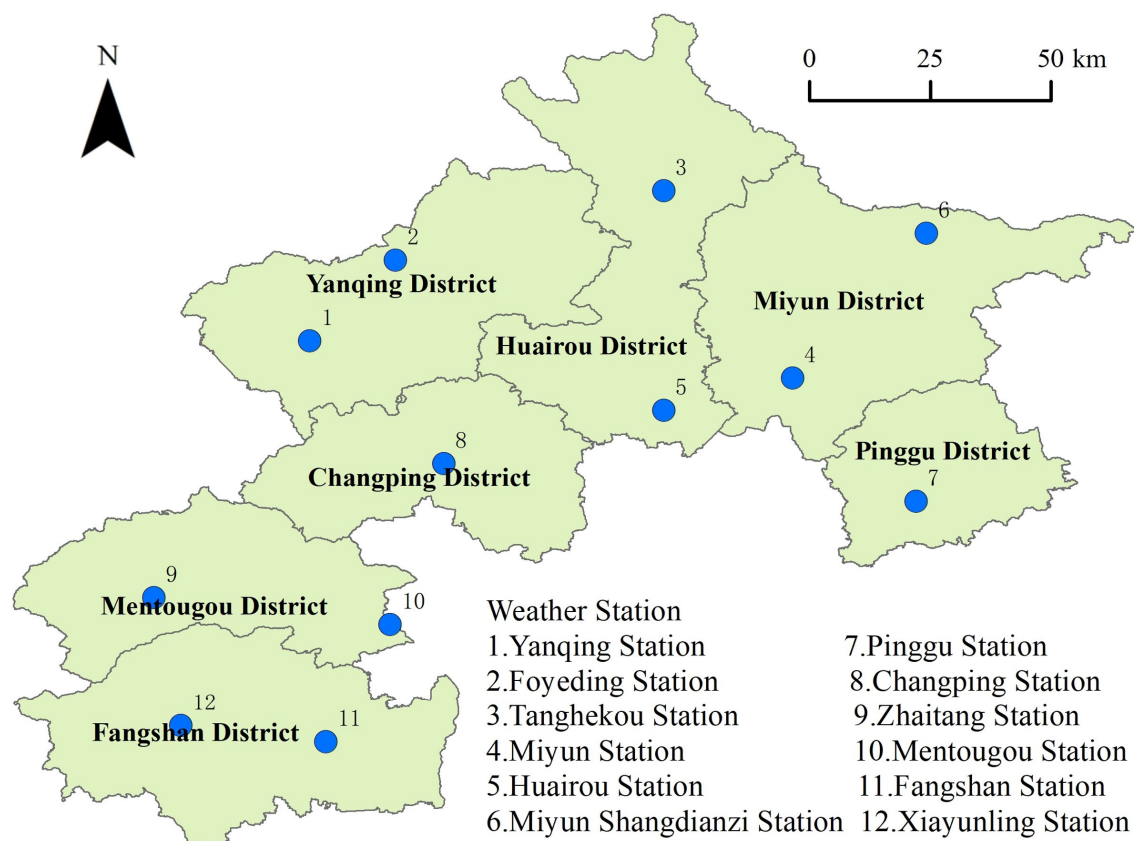


Figure 1. Research location.

2.2. Data Sources

The subcompartment data of the second-class forest resources survey in 2019 were collected from the Beijing Landscaping Planning and Resource Monitoring Center. The attribute indices included the land class, area, dominant tree species (group), tree species composition, origin, age group, canopy density, and total coverage of shrub and grass vegetation.

Forest fuel data and important ignition point data were obtained from the data results of the Beijing Forest Fire Risk Survey Project. The forest fuel data included surface fuel load data. The important ignition point data included the number of scattered graves, cemeteries, and rural traditional burial sites in townships.

The 30-meter-resolution digital elevation data were obtained from the Geospatial Data Cloud Platform of the Computer Network Information Center, Chinese Academy of Sciences (<http://www.gscloud.cn>).

The meteorological data were collected from the monthly minimum relative humidity, monthly average wind speed, monthly gale days, monthly precipitation, and monthly average maximum temperature data recorded at 12 meteorological stations (Yanqing, Foyeding, Tanghekou, Miyun, Huairou, Miyun Shangdianzi, Pinggu, Changping, Zhaitang, Mentougou, Fangshan, and Xiayunling) during the fire prevention period (November–May of the following year) from 2011 to 2020 provided by the Beijing Meteorological Service Center. The kriging interpolation method was used for the spatial interpolation of these meteorological data, data resampling was carried out, and raster data with a 50 m resolution were masked.

2.3. Forest Fire Spread Hazard Assessment

2.3.1. Forest Fire Spread Hazard Assessment Index

Forest fire spread hazards are affected mainly by four factors: forest fuel, meteorological factors, terrain factors, and fire behavior [1,6,46]. Forest fuels are the material basis that support the spread of forest fires, and a continuous distribution of fuels in the horizontal

direction is the basic condition for the spread of forest fires. Forest combustibility is an index used to measure the energy released by forest combustion. Meteorological factors are important factors affecting the spread of forest fires and change quickly with time and space. High temperatures, drought, and strong winds are the main factors leading to the rapid spread of forest fires that become out of control. Topographic factors can directly affect the spread and intensity of forest fires. Moreover, small changes in topographic factors can also cause the redistribution of ecological factors and result in significant changes in the composition of local environmental fuels and microclimate conditions, thus affecting the spread of forest fires. Fire behavior refers to the various phenomena and characteristics of forest fuels during the whole forest fire process, from igniting to developing to extinguishing. Here, the potential fire behavior was simulated using BehavePlus 5.0 software (Missoula Fire Sciences Laboratory, U.S. Forest Service, Missoula County, MT, USA). The wind speed was determined based on the local average wind speed of 3 m/s, and the slope was obtained based on the subcompartment data of the second-class forest resources survey.

In this study, thirteen secondary indices were selected to assess the forest fire spread hazard, as shown in Table 1.

Table 1. The assessment indices of the forest fire spread hazard.

Primary Index	Secondary Index	Calculation/Unit
Forest fuel	Surface fuel load	Amount of surface fuel (shrub, herb, and litter) per unit area, in t/hm ² .
	Total coverage of shrub and grass vegetation	Total coverage of the shrub and grass layer in the forested land, in %.
	Forest flammability	How easy it is for the forest to catch fire, and the state of burning (fire type), burning speed, and fire intensity. Can also measure the amount of energy released by burning forests, without dimensionality.
Meteorological factors	Monthly gale days during the fire prevention period	During the fire prevention period, the monthly average number of weather days with instantaneous wind force 5 or above, in days.
	Monthly precipitation during the fire prevention period	The monthly average total rainfall during the fire prevention period, in mm.
	Monthly mean maximum temperature during the fire prevention period	Average daily maximum temperature during the fire prevention period, in °C.
Topographical factors	Elevation	The vertical distance above sea level, in m.
	Slope	The ratio of the vertical height to the horizontal width of a slope, in °.
	Aspect	Orientation of slope, without dimensionality.
	Slope position	The landform on which a slope is located, without dimensionality.
Fire behavior	Surface fire spread speed	The distance that the surface fire line moves forward per unit time, in m·min ^{−1} .
	Fireline intensity	Heat release rate per unit length of fire head front, in kW·m ^{−1} .
	Flame height	Continuous flame height perpendicular to the ground, in m.

2.3.2. Standardization of Evaluation Index

To eliminate the dimensional influence among evaluation indices, data should be standardized so that the value of each index is distributed within the range of [0, 1]. Based on previous research results [47,48], seven stand factors, including plant (tree species) composition, canopy density, stand age, forest type, aspect, slope, and altitude, were selected as the burning property components, and the forest flammability metric of subcompartments in Beijing Mountainous Districts was divided into five grades: strong combustion, flammable, combustible, flame retardant, and noncombustible; then, the isometric assignment method

was used to convert forest combustibility into numerical values for evaluation. The assignment methods for the slope aspect and slope position were based on the method described in “the First National Comprehensive Risk Survey of Natural Disasters—Forest Fire Hazard Assessment”. Other indices were processed by the deviation standardization method.

$$X_{ij}' = \frac{X_{ij} - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} (\text{positive standardization}) \quad (1)$$

$$X_{ij}' = \frac{\max(X_{ij}) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} (\text{negative standardization}) \quad (2)$$

where X_{ij}' is the normalized value of the i th index value of the j th factor; X_{ij} is the i th index value of the j th factor; $\min(X_{ij})$ is the minimum value of the i th index; and $\max(X_{ij})$ is the maximum value of the i th index.

2.3.3. Determine the Weight of the Evaluation Index

In this study, subjective and objective weighting methods were combined with the analytic hierarchy process (AHP), and the entropy weight method was applied comprehensively to determine the weights of the evaluation indices [49]. First, the analytic hierarchy process was used to calculate the subjective weight of each index [50], and then the entropy weight method was used to determine the objective weight of the index combined with the statistical data at the subcompartment scale [51]. Finally, the equal weight of the subjective weight and the objective weight was fused to obtain the comprehensive weight value, which was then used as the weight value of the evaluation index. The calculation formula of the entropy weight method is expressed as follows:

$$P_{ij} = \frac{X_{ij}'}{\sum_{i=1}^m X_{ij}'} \quad (3)$$

$$g_i = 1 - (-k \sum_{i=1}^m p_{ij} \ln p_{ij}) \quad (4)$$

$$w_i = \frac{g_i}{\sum_{j=1}^m g_i} \quad (5)$$

where P_{ij} is the proportion of the index value of the j th index in the i th item; g_i is the difference coefficient of item i ; w_i is the weight of the i th index; m is the number of subcompartments in the evaluation area; and $k = 1/\ln m$.

2.3.4. Forest Fire Spread Hazard Index Calculation

The weighted comprehensive evaluation method is a common disaster risk assessment method, with the advantages of systematicness and clear results. According to the contribution degree of each evaluation index to the overall goal, a corresponding weight coefficient was assigned, the value was multiplied by the quantitative value of each index corresponding to the evaluation index, and the results were summed [52]. The forest fire spread hazard index at the subcompartment scale in the Mountainous District of Beijing was calculated by the weighted comprehensive evaluation method, and the forest fire spread hazard index at the township scale was calculated by the weighted average area method.

The calculation formula of the forest fire spread hazard index at the subcompartment scale is expressed as follows:

$$HI = \sum_{i=1}^n w_i \times H_i' \quad (6)$$

where HI is the forest fire spread hazard index at the subcompartment scale; w_i is the weight value of the i th index in the secondary index of forest fire spread hazard; and H_i' is the index value of item i after normalization.

The calculation formula for the forest fire spread hazard index converted from the subcompartment scale to the township scale is expressed as follows:

$$HI' = \frac{\sum_{i=1}^n (HI_i \times M_i)}{\sum_{i=1}^n M_i} \quad (7)$$

where HI' is the forest fire spread hazard index at the township scale; HI_i is the forest fire spread hazard index of subcompartment i within the township; M_i is the area of subcompartment i within the township; and n is the number of subcompartments comprising woodlands within the township.

2.3.5. Forest Fire Spread Hazard Classification

The natural breakpoint classification method takes the discontinuous places in the dataset as the classification basis through continuous iteration, emphasizes the natural breakpoints and groups, and requires little human intervention; this method can thus reduce the differences within the same level and increase the differences between different levels [53]. In this study, the natural breakpoint classification method was used to classify the forest fire spread hazard into four levels: high, medium-high, medium-low, and low.

2.3.6. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis refers to the correlation degree analysis of a certain attribute value of a certain unit in a space and its surrounding units; such analyses can reveal the statistical distribution rules of spatial units and the interaction mechanism between spatial units, providing a measure of the degree of agglomeration in a given spatial scope [54,55].

Spatial autocorrelation analysis includes global spatial autocorrelation and local spatial autocorrelation. Global spatial autocorrelation can reflect the overall correlation degree and significance of the specified attribute values in the whole research area, while local spatial autocorrelation can reflect the spatial aggregation and differentiation of a certain phenomenon in a local area.

In this study, Moran's I index was selected as the spatial autocorrelation index, and ArcGIS 10.2 software (Environmental Systems Research Institute, Inc., Redlands, CA, USA) was used to analyze the autocorrelation degree and spatial distribution of the forest fire spread hazard index at the subcompartment and township scales in the Mountainous District of Beijing; in addition, a significance test was conducted.

$$Global\ Moran\ I = \frac{\sum_{i=1}^n \sum_{j=1}^n (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (8)$$

where n is the number of area units; x_i and x_j are the observed values of regions i and j ; $\bar{x}$ is the average value; S^2 is the variance of the sample; and w_{ij} is the spatial weight matrix.

$$Local\ Moran\ I_i = \frac{(x_i - \bar{x})}{s_i^2 \sum_{i=1, j \neq 1}^n w_{ij}(x_i - \bar{x})} \quad (9)$$

where n is the number of area units; x_i is the observed value of region i ; $\bar{x}$ is the average value; S^2 is the variance of the sample; and w_{ij} is the spatial weight matrix.

2.4. Correlation Analysis of the Forest Landscape Spatial Pattern and Forest Fire Spread Hazard

2.4.1. Classification of Forest Landscapes in the Mountainous District of Beijing

Based on the subcompartment data of the second-class forest resources survey in 2019, the forest landscape was divided into coniferous forests, broad-leaved forest, mixed forests, shrublands, other forests and nonforested lands based on the vegetation type, forest fuels and forest fire spread characteristics.

The three land classes of general shrubland, economic shrubland, and shrubland above the tree distribution line were merged into shrubland. The nine land classes of nursery lands, woodlands, unforested lands, clear-cut lands, burned lands, other lands, failed plantation lands, other suitable lands, and planned forests were merged into other forest lands. The eight land classes of grasslands, cultivated lands, construction lands for urban and rural residents, industrial and mining construction lands, transportation construction lands, water areas, other lands, and unused lands were merged into nonforested lands.

2.4.2. Selection and Calculation of the Landscape Pattern Index

Currently, the most widely used landscape pattern analysis software, Fragstats, can calculate more than 50 landscape pattern indices; usually, an index can summarize the entire landscape system in only one of a few aspects of information, but some of the ecological significance of the index is not clear or even contradictory, and a large amount of redundancy occurs between different landscape pattern indices. Therefore, it is very important to select appropriate and relevant landscape pattern indices [56].

Based on previous research results combined with the ecological implications of different landscape pattern indices [57,58], this study selected eleven landscape pattern indices (TA, NP, PD, LPI, LSI, CONTAG, DIVISION, PR, PRD, SHDI, and AI) at the landscape level to analyze the spatial pattern of forested landscapes in the Mountainous District of Beijing. The landscape pattern indices were calculated by Fragstats 4.2.1 software.

2.4.3. Correlation Analysis of the Forested Landscape Spatial Pattern and Forest Fire Spread Hazard

Pearson correlation analysis and principal component analysis were used to analyze the main factors affecting the spread hazard of forest fires. The data processing and statistical analysis were completed by R 4.0.5 (R Foundation for Statistical Computing, Vienna, Austria). The research workflow diagram is shown in Figure 2.

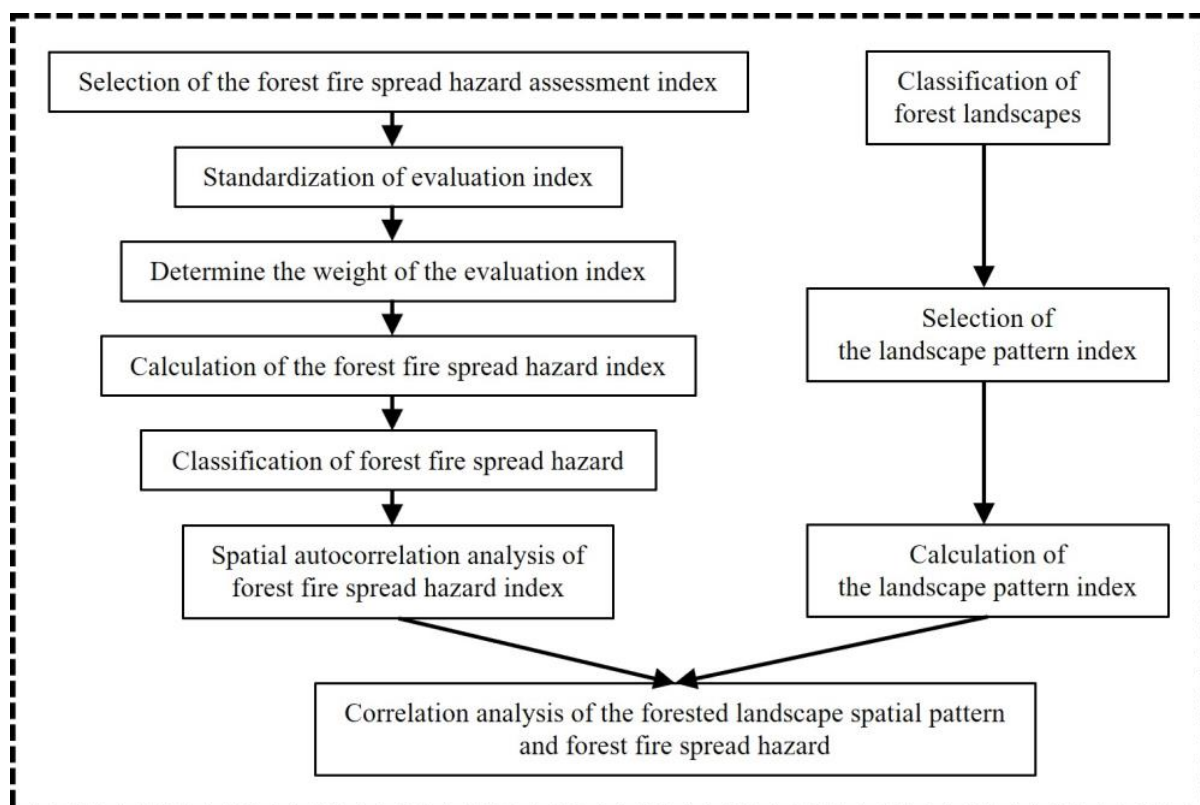


Figure 2. Research workflow diagram.

3. Results

3.1. Determination of the Weights of the Forest Fire Spread Hazard Indices

The weights of the indices used to evaluate the forest fire spread hazard are shown in Table 2.

Table 2. Forest fire spread hazard assessment index weights.

Primary Index	Comprehensive Weight of Primary Index	Secondary Index	Chromatography Analysis Weight of Secondary Index	Entropy Weight of Secondary Index	Comprehensive Weight of Secondary Index
Forest fuel	0.1909	Surface fuel load	0.0812	0.0404	0.0608
		Total coverage of shrub and grass vegetation	0.1132	0.0598	0.0865
		Forest flammability	0.0735	0.0137	0.0436
Meteorological factors	0.1434	Monthly gale days during the fire prevention period	0.1153	0.0405	0.0779
		Monthly precipitation during the fire prevention period	0.0524	0.0210	0.0367
		Monthly mean maximum temperature during the fire prevention period	0.0501	0.0075	0.0288
Topographical factors	0.2520	Elevation	0.0126	0.0038	0.0082
		Slope	0.1249	0.1813	0.1531
		Aspect	0.0508	0.0384	0.0446
		Slope position	0.0522	0.0400	0.0461
Fire behavior	0.4137	Surface fire spread speed	0.1265	0.2103	0.1684
		Fireline intensity	0.0781	0.2103	0.1442
		Flame height	0.0692	0.1330	0.1011

From Table 2, it can be seen that the comprehensive weights of the four primary indices of the forest fire spread hazard, namely, forest fuels, meteorological factors, topographical factors, and fire behavior, are 0.1909, 0.1434, 0.2520, and 0.4137, respectively. The comprehensive weights of the four secondary indices, namely, the slope, surface fire spread speed, fireline intensity, and flame height, are all greater than 0.1000, indicating that the slope and fire behavior indices are the main factors affecting the forest fire spread hazard.

3.2. Forest Fire Spread Hazard Assessment in the Mountainous District, Beijing

3.2.1. Forest Fire Spread Hazard Assessment at the Subcompartment and Township Scales

The thirteen forest fire spread hazard indices selected were calculated by weighted comprehensive calculation at the subcompartment scale, and the weighted-average area method was used to calculate the forest fire spread hazard index at the township scale. Then, the forest fire spread hazard levels at the subcompartment and township scales in the Mountainous District of Beijing were obtained, as shown in Figures 3 and 4.

As shown in Figure 3, the forest fire spread hazard in the Mountainous District of Beijing presents a law of gradually increasing from the plain area to the mountainous area, and the high-spread-hazard area is distributed mainly in the mountainous area. The areas with high-, medium-high-, medium-low-, and low-grade hazards account for 39.87%, 33.10%, 11.37%, and 15.66% of the area, respectively.

The land classes with high-spread-hazard subcompartments included general shrublands, coniferous forests, broadleaf forests, mixed forests, and open forests, accounting for 41.70%, 24.30%, 17.91%, 15.85%, and 0.24%, respectively. The dominant species of the subcompartments corresponding to the high-spread-hazard forests were *Platycladus orientalis*, *Pinus tabuliformis*, and *Quercus mongolica*, accounting for 34.98%, 19.89%, and 16.67%, respectively. The high-spread hazard side of *Platycladus orientalis* was dominated by artificial young forests and natural young forests, accounting for 72.09% and 10.61%, respectively. The high-spread-hazard side of *Pinus tabuliformis* was dominated by artificial near-mature forests, artificial mature forests, artificial young forests, and artificial mature forests, accounting for 31.59%, 24.96%, 22.55%, and 13.19%, respectively. The high-spread-hazard side of *Quercus mongolica* was dominated by natural young forests and natural immature timber, accounting for 50.94% and 36.46%, respectively.

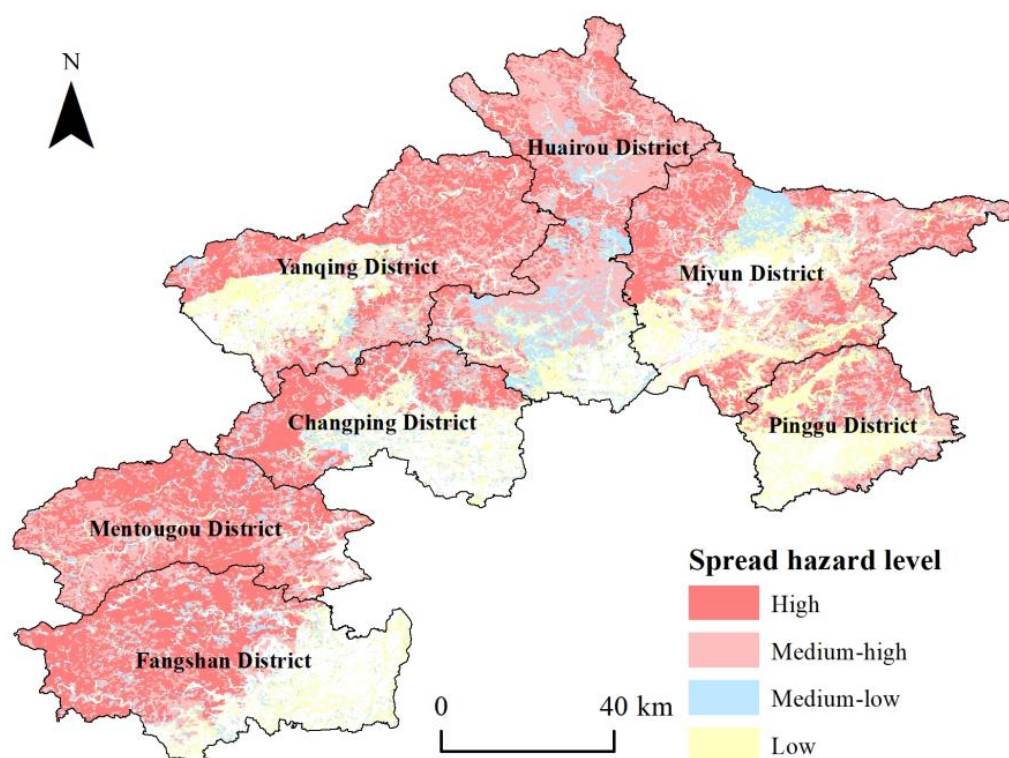


Figure 3. Forest fire spread hazard level map at the subcompartment scale in the Mountainous District of Beijing.

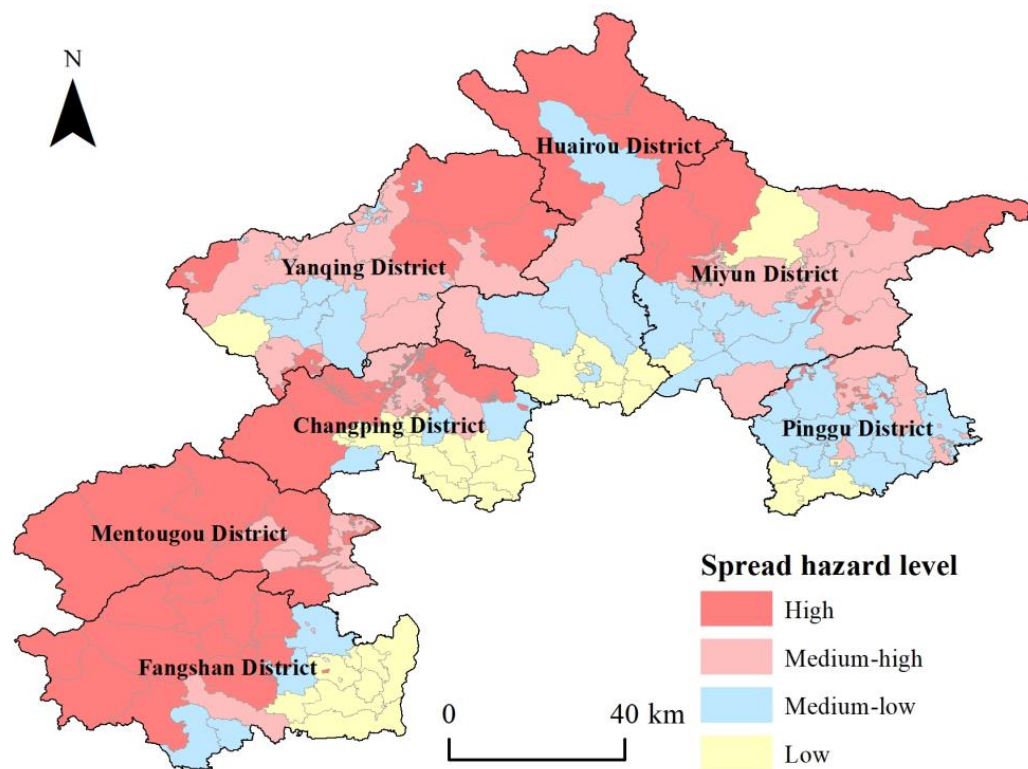


Figure 4. Forest fire spread hazard level map at the township scale in the Mountainous District of Beijing.

As shown in Figure 4, at the township scale, the areas with high, medium-high, medium-low, and low spread hazard grades accounted for 52.36%, 22.58%, 18.39%, and 6.67%, respectively. Townships with high spread hazards were distributed in the western and northern mountainous areas and scattered in the northwestern area of Yanqing, the eastern area of Miyun, and central Pinggu.

3.2.2. Spatial Autocorrelation of the Forest Fire Spread Hazard

The global spatial autocorrelation analysis results of the forest fire spread hazard indices in the Mountainous District of Beijing are shown in Table 3, and the local spatial autocorrelation analysis results are shown in Figures 5 and 6.

Table 3. Global spatial autocorrelation indices of the forest fire spread hazard index in the Mountainous District of Beijing.

Index	Moran's I index	Z	P
Forest fire spread hazard index at the subcompartment scale	0.6057	464.6000	0.0000
Forest fire spread hazard index at the township scale	0.4978	10.1603	0.0000

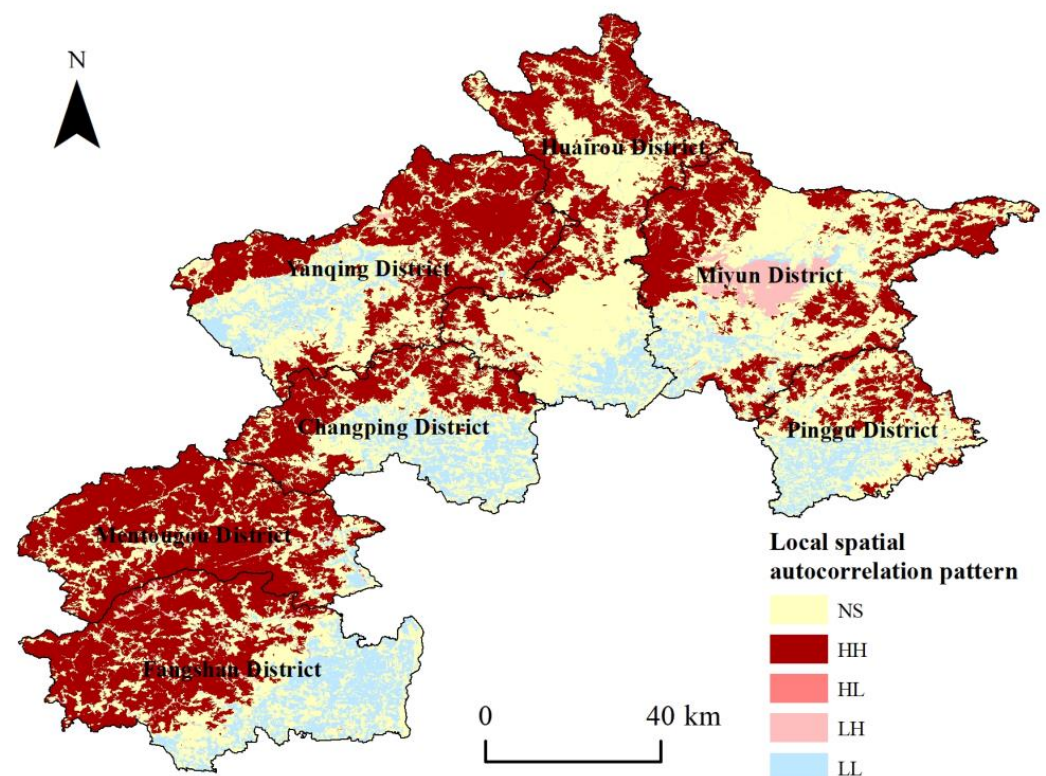


Figure 5. Local spatial autocorrelation pattern of the forest fire spread hazard index at the subcompartment scale in the Mountainous District of Beijing.

As seen from Table 3, the Moran's I values of the global spatial autocorrelation index of the forest fire spread hazard index at the subcompartment scale and township scale in the Mountainous District of Beijing were positive, and the Z test results were extremely significant, indicating that the spatial distribution of the forest fire spread hazard index at the subcompartment scale and township scale in the Mountainous District of Beijing exhibited positive spatial autocorrelation, reflecting a clustered-distribution spatial law.

As shown in Figure 5, the spatial heterogeneity of the forest fire spread hazard index at the subcompartment scale was significant in the Mountainous District of Beijing. There were 37,648 HH (high-high) cluster subcompartments, and these subcompartments were concentrated and contiguous in the western and northern mountains and relatively

scattered in the eastern mountains. There were 32,163 very significantly clustered subcompartments ($p < 0.01$) and 5485 significantly clustered subcompartments ($p < 0.05$). There were 18,603 LL (low–low) cluster subcompartments, mainly distributed in the plain areas around the city. There were 10,080 very significantly clustered subcompartments ($p < 0.01$) and 8523 significantly clustered subcompartments ($p < 0.05$). The negative correlation-type clustered subcompartments of the forest fire spread hazard index in the Mountainous District of Beijing were staggered and formed a certain forest fire barrier effect. There were 646 HL (high–low) cluster subcompartments and 2099 LH (low–high) cluster subcompartments.

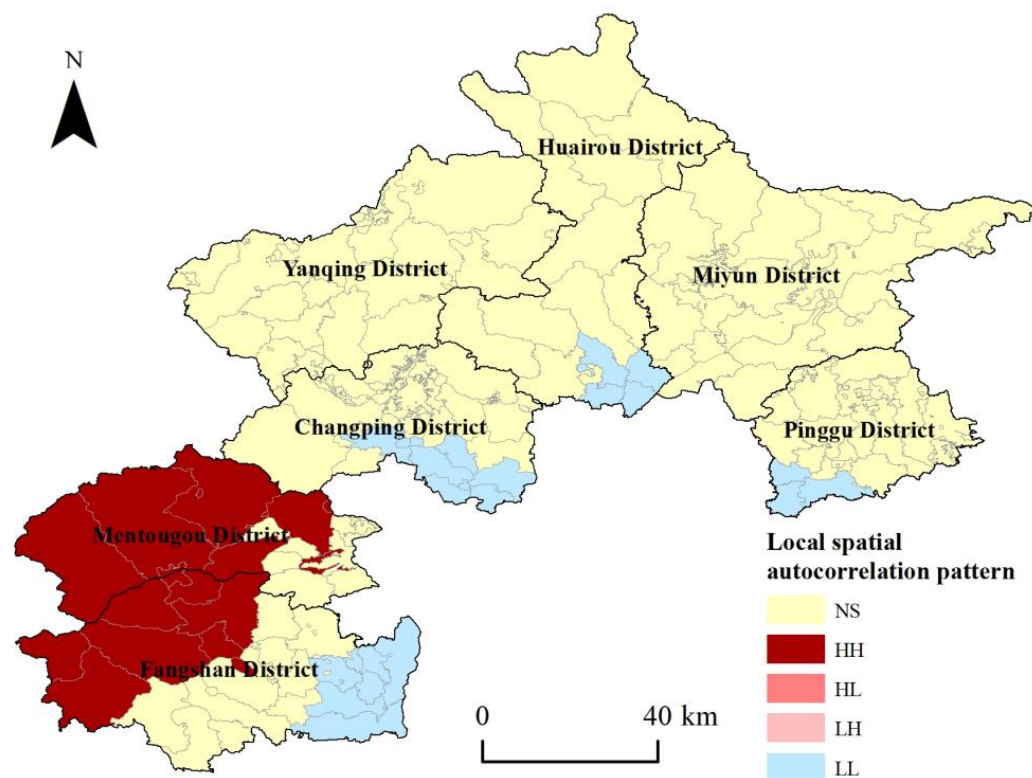


Figure 6. Local spatial autocorrelation pattern of the forest fire spread hazard index at the township scale in the Mountainous District of Beijing.

As shown in Figure 6, the forest fire spread hazard index at the township scale in the Mountainous District of Beijing presented a certain agglomeration law and the results all reflect positive correlation types, including 15 HH (high–high) agglomeration townships and 22 LL (low–low) agglomeration townships. The HH (high–high) cluster townships were distributed mainly in northwestern Fangshan and midwestern Mentougou. The LL (low–low) cluster townships were distributed mainly in eastern Fangshan, southeastern Changping, southeastern Huairou and southwestern Pinggu.

3.3. Correlation Analysis of the Forested Landscape Spatial Pattern and Forest Fire Spread Hazard in the Mountainous District of Beijing

3.3.1. Calculation and Statistics of the Landscape Pattern Index of Townships in the Mountainous District of Beijing

At the landscape level, eleven indices, including TA, NP, PD, LPI, LSI, CONTAG, DIVISION, PR, PRD, SHDI, and AI, were selected to calculate the forest landscape spatial pattern characteristics of townships in the Mountainous District of Beijing.

As shown in Table 4, the variation ranges of the landscape pattern indices of each township in the mountainous district of Beijing were identified as follows: the total landscape area (TA) ranged from 6.3900–37,349.8000, the patch number (NP) ranged from 2.0000–3383.0000, the patch density index (PD) ranged from 0.6205–32.3600, the maximum patch index (LPI) ranged from 5.1456–99.7673, the landscape shape index (LSI) ranged from

1.3347~38.8390, the spread index (CONTAG) ranged from 0.0000~98.4728, the landscape fragmentation index (DIVISION) ranged from 0.0046~0.9844, the landscape abundance index (PR) ranged from 1.0000~6.0000, the landscape abundance density index (PRD) ranged from 0.0161~31.2989, the Shannon diversity index (SHDI) ranged from 0.0000~1.7504, and the aggregation index (AI) ranged from 91.3310~99.7948.

Table 4. Landscape horizontal landscape spatial pattern characteristics of townships in the Mountainous District of Beijing.

Landscape Pattern Index	Maximum Value	Median Value	Minimum Value	Average Value	Standard Deviation	Coefficient of Variation (%)
TA	37,349.8000	6509.9800	6.3900	8566.7259	7671.0216	89.5444
NP	3383.0000	585.0000	2.0000	706.6950	637.0348	90.1428
PD	32.3600	8.3113	0.6205	9.4364	6.2420	66.1485
LPI	99.7673	25.4143	5.1456	36.2719	25.4719	70.2249
LSI	38.8390	18.8652	1.3347	18.7565	8.8651	47.2640
CONTAG	98.4728	55.6657	0.0000	57.9148	11.1045	19.1739
DIVISION	0.9844	0.8930	0.0046	0.7822	0.2341	29.9263
PR	6.0000	6.0000	1.0000	5.6950	0.8940	15.6974
PRD	31.2989	0.0922	0.0161	0.4907	2.7369	557.7276
SHDI	1.7504	1.3755	0.0000	1.2532	0.3599	28.7155
AI	99.7948	96.1721	91.3310	96.1040	1.3874	1.4437

The variation coefficient (CV) represents the spatial variability in a landscape pattern index as well as the degree of variation. CV values between 0 and 20% are generally considered to indicate weak variability; those between 20% and 50% indicate moderate variability; and those >50% indicate strong variability. The landscape total area (TA), patch number (NP), patch density index (PD), maximum patch index (LPI), and landscape abundance density index (PRD) exhibited strong variability, and the landscape shape index (LSI), landscape fragmentation index (DIVISION), and Shannon diversity index (SHDI) exhibited moderate variability. The spread index (CONTAG), landscape abundance index (PR), and aggregation index (AI) exhibited weak variability.

3.3.2. Correlation Analysis between Landscape Spatial Pattern Characteristics and Forest Fire Spread Hazard in the Mountainous District of Beijing

The Pearson correlation analysis method was used to analyze the correlation between the landscape pattern index and the forest fire spread hazard index and to explore the relationship between the landscape spatial pattern characteristics and the forest fire spread hazard in the Mountainous District of Beijing. The correlation analysis results are shown in Table 5.

Table 5. Correlation analysis between the landscape pattern indices and the forest fire spread hazard index.

Landscape Pattern Index	TA	NP	PD	LPI	LSI	CONTAG	DIVISION	PR	PRD	SHDI	AI
Correlation coefficient	0.358 **	0.016	−0.614 **	−0.550 **	0.045	−0.204 *	0.488 **	0.005	−0.175 *	0.357 **	0.426 **

* $p < 0.05$; ** $p < 0.01$.

As shown in Table 5, the landscape total area (TA), landscape fragmentation index (DIVISION), Shannon diversity index (SHDI), and aggregation index (AI) were very significantly negatively correlated with the forest fire spread hazard index ($p < 0.01$). The patch density index (PD) and maximum patch index (LPI) were very significantly negatively correlated with the forest fire spread hazard index ($p < 0.01$), and the spread index (CONTAG) and landscape abundance density index (PRD) were negatively correlated with the forest fire spread hazard index ($p < 0.05$). The patch number (NP), landscape shape index (LSI), and landscape abundance index (PR) had no significant correlation with the forest fire spread hazard index.

3.3.3. Analysis of the Main Factors Affecting the Forest Fire Spread Hazard

The results of the collinearity test performed using the variance inflation factor (VIF) diagnosis showed that LPI and DIVISION had serious collinearity. After excluding the factors unrelated to the forest fire spread hazard (NP, LSI, and PR) and the factors with severe collinearity (LPI and DIVISION), a principal component analysis was conducted for the six remaining landscape pattern indices. Table 6 shows the results of the principal component analysis of factors affecting the forest fire spread hazard, illustrating the influence of different indices on the spread hazard.

Table 6. Principal component analysis results of the factors influencing the forest fire spread hazard.

	Index	First Principal Components	Second Principal Components	Third Principal Components
Load matrix	TA	0.185	0.480	0.319
	PD	0.309	−0.629	
	CONTAG	−0.508	−0.148	−0.324
	PRD	−0.176	−0.397	0.839
	SHDI	0.546	0.268	0.127
	AI	−0.532	0.350	0.271
Contribution rate	Variance root extraction of principal component	1.526	1.308	0.957
	Variance contribution rate	0.388	0.285	0.153
	Cumulative variance contribution rate	0.388	0.673	0.826

According to the principle that the cumulative variance contribution rate should be greater than 80%, three principal components were selected, and the cumulative variance contribution rate was 82.6%. As shown in Table 6, the coefficients of SHDI, AI, and CONTAG in the first principal component were all greater than 0.5, mainly reflecting the influence of landscape diversity and landscape aggregation on the spread hazard. Among the second principal components, the coefficients of PD and TA were the largest, at 0.629 and 0.480, respectively, while the coefficients of the other indices were all less than 0.4; these results mainly reflected the influence of the landscape aggregation and landscape area on the spread hazard. Among the third principal component, the coefficient of PRD reached 0.839, significantly higher than those of the other indices, reflecting the impact of landscape diversity on the spread hazard. The forest fire spread hazard was thus affected mainly by landscape diversity (SHDI and PRD), landscape aggregation (AI, CONTAG, and PD), and landscape area (TA).

4. Discussion

The spread of forest fires is affected by fuel, weather, terrain, human activities, and other factors [1,6,46]. In this study, the subjective and objective weighting method combining the analytic hierarchy process (AHP) and entropy weight method was used to determine the weights, and the results showed that the slope and fire behavior were the main factors affecting the forest fire spread hazard; this finding was consistent with the research results of Chen et al. [59] and Scott et al. [24]. The influence of the local topography and intraforest microclimate on the forest fire spread was very strong. The annual mean values of the meteorological data from meteorological stations were used to perform a spatial interpolation, and the assessment was carried out in combination with the subcompartment topographic data. In the process of further analyzing the forest fire spread hazard at a finer scale, the influence of the spatial variations in local topography and of dynamic changes in the forest microclimate and forest fuels on the forest fire spread was also taken into account.

In this study, it was found that the subcompartments with high spread hazards were dominated by *Platycladus orientalis*, *Pinus tabulaeformis*, and *Quercus mongolica* forest, which

was consistent with the research results of Li et al. [60] and Liu et al. [61]. The main reason is that *Pinus tabulaeformis* and *Platycladus orientalis* are the main conifer species in Beijing mountainous areas, with dense weeds under the forest and poor fire resistance of the young forest. The *Quercus mongolica* forest is mainly distributed in mountainous areas with high stand closure and high potential energy. The analytic hierarchy process (AHP) [50] and entropy weight method [51] to determine index weights have been widely used in forest fire hazard and risk assessment, but no subjective and objective weighting method combining AHP and the entropy weight method has been widely used in forest fire hazard and risk assessment. They have been widely used in flood risk [62], tobacco quality [63], crop disasters [64], and public transportation passenger satisfaction assessments [65] and have achieved good results.

Forest fuel is an important material basis for forest fire occurrence and spread, and the fuel situation directly affects the distribution of regional fires [66,67]. Considering the actual forest fire management situation in Beijing, the number of forest fires is generally small, and low-intensity surface fires are dominant. In this study, three indices, including the surface fuel load, total coverage of shrub and grass vegetation, and forest flammability, are selected to represent the overall characteristics of forest fuels without considering the related indices of canopy fuels (the canopy volume density, canopy base height, and canopy fuel load) [68]. Further studies on the spatial continuity (horizontal continuity and vertical continuity) of fuels in different stands are needed in the future [69].

Forest fire behavior comprises both the fire characteristics and fire site changes during fire development. In this study, BehavePlus 5.0 software was used to simulate surface fire behavior, and the three most commonly used fire behavior indices, namely, surface fire spread speed, fireline intensity, and flame height, were selected, resulting in good evaluation results being obtained. The weight of fire behavior in the forest fire spread hazard assessment reached 0.4137, and this factor was the main factor affecting the forest fire spread. In the future, based on assessments of surface fire behavior and canopy fire behavior, the role of stand coupling in affecting the potential fire behavior should be further analyzed in forest fire spread hazard assessments, and the forest fire spread hazard should be further divided into large-area forest fire spread hazards (whether fire spreads to a location) and high-intensity forest fire spread hazards (whether the location will burn entirely). The forest fire spread hazard should be analyzed from both the horizontal and vertical dimensions.

The spatial distribution pattern of the forest fire spread hazard index has an important reference value for forest fire management. In this study, Moran's I index was used for spatial autocorrelation analysis to reveal the spatial correlation degree of the forest fire spread hazard index. The results of the global spatial autocorrelation index can reflect the overall correlation degree of the regional forest fire spread hazard index. The stronger the clustering degree is, the weaker the interlacing degree of the subcompartments of forest fire spread hazards among different sizes is, the smaller the forest fire blocking effect is, and the greater the threat of spread hazards is; these relations lay the foundation for landscape-scale assessments. The results of the local spatial autocorrelation index can reflect the type and specific location of a cluster within the region of interest. A HH (high–high) cluster area is a contiguous distribution area with a high spread hazard, where fire easily spreads to a large disaster area once a forest fire occurs. HL (high–low) and LH (low–high) agglomeration areas show staggered distributions of high and low spread hazards, respectively, and can exert forest fire blocking effects. In particular, the HL (high–low) agglomeration areas, in which high-value space units are adjacent to low-value space units, are an ideal model for exerting the forest fire blocking effect.

Usually, forest fire spreads in a specific spatial way in forests. The ecological process of forest fire spread can be best understood by analyzing the regularity and characteristics of different vegetation types and forest fuel types at the landscape scale, such as their relative layout, connectivity, size, and shape. A thorough understanding of the relationships between forest fire disturbances and landscape spatial patterns is not only critical

for clarifying forest fire management methods and scales but can also provide a theoretical basis for landscape pattern planning and design. Deng et al. [70] summarized the impact of landscape patterns on forest fires. They found that relatively high landscape heterogeneity, a high fragmentation degree, a great number of patches, a rich ecosystem type, and high landscape diversity are associated with relatively strong stability and strong anti-interference ability. This is consistent with the findings in this study that forest fire spread hazards are affected mainly by landscape diversity, landscape aggregation, and landscape area. Chen et al. [71] found that the CONTAG, DIVISION, SHDI, PR, and PRD indices could best express the fire resistance of forested landscapes by analyzing the gray correlation degree and correlation between the landscape pattern index and forest fire risk index; their results were consistent with the results of this study. DIVISION and SHDI are very significantly correlated with the forest fire spread hazard, while CONTAG and PRD are significantly correlated with the forest fire spread hazard. It is suggested that the relationship between the landscape pattern index at the class level and the forest fire spread hazard be further analyzed and that the influence of landscape pattern indices on the forest fire spread hazard be further explored.

The scientific and accurate classification of forest fuel types is the basis of studying the spatial patterns of forested landscapes and the forest fire spread hazard, building fire risk rating systems, and predicting fire behaviors. Canada, the United States, Greece, Australia, and other countries have long studied the classification of forest fuels. Tian et al. [72] used a land use map of Beijing and Landsat TM images to classify forest fuels into six types, including O-1 grassland, O-2 grassland, S-1 shrub, S-2 young forest, C-1 coniferous forest, M-1 coniferous broad-leaved forest, and B-1 broad-leaved forest. The classification results basically met the demands of forest fire risk grade forecasting, but it is still necessary to further classify coniferous forests according to the burning properties of the stands, the vertical structure of the stands, and the distribution state of the fuels to forecast fire behavior. Chen [58] studied the relationship between landscape security and fire hazards in the Beijing Miaofeng Mountain forest farm, took Gaofen-No. 1 remote sensing data in August 2016 as the basic data source, and comprehensively considered the land use types, vegetation community types, etc. According to forest fire spread differences, under the environment of ENVI 5.1, the forest fuel types of the Miaofeng Mountain forest farm in Beijing were divided into five types: coniferous forests, broad-leaved forests, mixed forests, other shrub forests, roads and buildings, using the object-oriented classification method based on samples. In further analyses of the relationships between the spatial pattern characteristics of the forested landscape and the large-area spread hazard and high-intensity spread hazard of forest fires, it will still be necessary to further improve the classification accuracy of forest fuel types according to the characteristics of the forest burning properties, forest fuel spatial continuity, and fuel distribution.

The landscape pattern index is an important tool used to study landscape pattern characteristics. It can highly concentrate landscape pattern information and reflect the causes and ecological implications of landscape spatial heterogeneity. With the rapid development of computer technology and geographic information technology, a large number of landscape pattern indices have been studied, but correlations and redundancies exist among many landscape pattern indices. The calculation results of some landscape pattern indices are difficult to explain ecologically, and the ecological significance of a single landscape pattern index is obviously different from those of multiple landscape pattern indices. The existence of these problems increases the difficulty of researchers in selecting landscape pattern indices and thus affects the accuracy of landscape pattern research results and limits the application degree of landscape pattern research results. Due to the complex interactions among factors affecting forest fire behaviors and forest fire hazards at the landscape scale, only a few studies have studied the relationship between forest fire spread and landscape patterns. We suggest that the application values of different landscape pattern indices be further analyzed in forest fire research in the future, that the landscape pattern indices that can highly concentrate forest fire-related information be clarified, and

that the internal connections between these indices be identified to provide a basis for landscape-scale forest fire research.

5. Conclusions

This study establishes a forest fire spread hazard assessment index system based on thirteen secondary indices from four aspects: forest fuels, meteorological factors, topographical factors, and fire behaviors. The evaluation results can be used to identify areas where forest fires are prone to spreading, thereby providing a basis for precise forest fire prevention and control. Eleven representative landscape-level landscape pattern indices were selected, the landscape pattern indices of each township in the Beijing Mountainous District were calculated, and the main landscape pattern indices that affect the forest fire spread hazard were analyzed, thus providing a basis for establishing a landscape-scale forest fire security guarantee system.

The results showed that (1) the overall spread hazard of forest fire in the Mountainous District of Beijing showed a gradual increase from plains to mountainous areas. The land types of the high-spread hazard subcompartment were mainly general shrubbery and coniferous forestlands, and the dominant species of the high-spread hazard forest subcompartment included mainly *Platycladus orientalis*, *Pinus tabulaeformis*, and *Quercus mongolica*. (2) The forest fire spread hazard indices at the subcompartment scale and township scale in the Mountainous District of Beijing showed an agglomeration distribution spatial law. HH (high–high) cluster subcompartments were distributed in the western and northern mountainous areas but scattered in the eastern mountainous areas. HH (high–high) cluster townships were distributed in the northwest of Fangshan and central and western Mentougou. (3) The correlation analysis between the spatial pattern of forest landscapes and the forest fire spread hazard showed that the forest fire spread hazard was influenced mainly by landscape diversity (SHDI and PRD), landscape aggregation (AI, CONTAG, and PD), and landscape area (TA).

Author Contributions: B.W. and X.L. conceived the research ideas and constructed the evaluation systems; B.W., W.L., G.L., N.C. and F.C. conducted field surveys; B.W. and W.L. analyzed the data; X.L. reviewed thoroughly; G.L., N.C., F.C. and Y.B. provided insights, contacts, and resources; B.W. wrote the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Project of the National Key Research and Development Plan, grant number 2020YFC1511605.

Data Availability Statement: All data are available from the corresponding authors, upon reasonable request.

Acknowledgments: The authors would like to thank the Beijing Municipal Forestry and Parks Bureau for providing a variety of resource support, and Professor Chunming Shi from Beijing Normal University for his help in English editing.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Chuvieco, E.; Aguado, I.; Yebra, M.; Nieto, H.; Salas, J.; Martín, M.P.; Vilar, L.; Martínez, J.; Martín, S.; Ibarra, P.; et al. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecol. Model.* **2010**, *221*, 46–58. [\[CrossRef\]](#)
2. Hysa, A.; Baskaya, F.A.T. A GIS based method for indexing the broad-leaved forest surfaces by their wildfire ignition probability and wildfire spreading capacity. *Model. Earth Syst. Environ.* **2019**, *5*, 71–84. [\[CrossRef\]](#)
3. Hysa, A.; Spalevic, V.; Dudic, B.; Rosca, S.; Kuriqi, A.; Bilasco, S.; Sestras, P. Utilizing the available open-source remotely sensed data in assessing the wildfire ignition and spread capacities of vegetated surfaces in Romania. *Remote Sens.* **2021**, *13*, 2737. [\[CrossRef\]](#)
4. Hysa, A. Indexing the vegetated surfaces within WUI by their wildfire ignition and spreading capacity, a comparative case from developing metropolitan areas. *Int. J. Disaster Risk Reduct.* **2021**, *63*, 102434. [\[CrossRef\]](#)
5. Hysa, A.; Teqja, Z.; Bani, A.; Libohova, Z.; Cerda, A. Assessing wildfire vulnerability of vegetated serpentine soils in the Balkan peninsula. *J. Nat. Conserv.* **2022**, *68*, 126217. [\[CrossRef\]](#)

6. Guo, Z.X.; Zhong, X.C.; Fang, W.H.; Cao, X.; Lin, W. The research advances of wildfire spreading and wildfire risk assessment. *Prog. Geogr.* **2010**, *29*, 778–788.
7. Francis, E.J.; Pourmohammadi, P.; Steel, Z.L.; Collins, B.M.; Hurteau, M.D. Proportion of forest area burned at high-severity increases with increasing forest cover and connectivity in western US watersheds. *Landsc. Ecol.* **2023**, *38*, 2501–2518. [\[CrossRef\]](#)
8. Aparício, B.A.; Santos, J.A.; Freitas, T.R.; Sá, A.C.L.; Pereira, J.M.C.; Fernandes, P.M. Unravelling the effect of climate change on fire danger and fire behaviour in the Transboundary Biosphere Reserve of Meseta Ibérica (Portugal-Spain). *Clim. Chang.* **2022**, *173*, 5. [\[CrossRef\]](#)
9. Kharuk, V.I.; Shvetsov, E.G.; Buryak, L.V.; Golyukov, A.S.; Dvinskaya, M.L.; Petrov, I.A. Wildfires in the Larch Range within Permafrost, Siberia. *Fire* **2023**, *6*, 301. [\[CrossRef\]](#)
10. Whitman, E.; Parks, S.A.; Holsinger, L.M.; Parisien, M.A. Climate-induced fire regime amplification in Alberta, Canada. *Environ. Res. Lett.* **2022**, *17*, 055003. [\[CrossRef\]](#)
11. Bowman, D.M.J.S.; Williamson, G.J.; Abatzoglou, J.T.; Kolden, C.A.; Cochrane, M.A.; Smith, A.M.S. Human exposure and sensitivity to globally extreme wildfire events. *Nat. Ecol. Evol.* **2017**, *1*, 0058. [\[CrossRef\]](#) [\[PubMed\]](#)
12. Canadell, J.G.; Meyer, C.P.; Cook, G.D.; Dowdy, A.; Briggs, P.R.; Knauer, J.; Pepler, A.; Haverd, V. Multi-decadal increase of forest burned area in Australia is linked to climate change. *Nat. Commun.* **2021**, *12*, 6921. [\[CrossRef\]](#) [\[PubMed\]](#)
13. Ferreira, I.J.M.; Campanharo, W.A.; Barbosa, M.L.F.; Silva, S.S.d.; Selaya, G.; Aragão, L.E.O.C.; Anderson, L.O. Assessment of fire hazard in Southwestern Amazon. *Front. For. Glob. Chang.* **2023**, *6*, 1107417. [\[CrossRef\]](#)
14. Rodrigues, M.; Camprubi, À.C.; Balaguer-Romano, R.; Megía, C.J.C.; Castañares, F.; Ruffault, J.; Fernandes, P.M.; Dios, V.R.d. Drivers and implications of the extreme 2022 wildfire season in Southwest Europe. *Sci. Total Environ.* **2023**, *859*, 160320. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Fryirs, K.A.; Zhang, N.; Duxbury, E.; Ralph, T. Rivers up in smoke: Impacts of Australia’s 2019–2020 megafires on riparian systems. *Int. J. Wildland Fire* **2022**, *31*, 720–727. [\[CrossRef\]](#)
16. Alarcon-Aguirre, G.; Miranda Fidhel, R.F.; Ramos Enciso, D.; Canahuire-Robles, R.; Rodriguez-Achata, L.; Garate-Quispe, J. Burn severity assessment using sentinel-1 SAR in the southeast Peruvian Amazon, a case study of Madre de Dios. *Fire* **2022**, *5*, 94. [\[CrossRef\]](#)
17. Mamuji, A.A.; Rozdilsky, J.L. Wildfire as an increasingly common natural disaster facing Canada: Understanding the 2016 Fort McMurray wildfire. *Nat. Hazards* **2019**, *98*, 163–180. [\[CrossRef\]](#)
18. Canosa, I.V.; Biesbroek, R.; Ford, J.; McCarty, J.L.; Orttung, R.W.; Paavola, J.; Burnasheva, D. Wildfire adaptation in the Russian Arctic: A systematic policy review. *Clim. Risk Manag.* **2023**, *39*, 100481. [\[CrossRef\]](#)
19. United Nations Environment Programme. *Spreading like Wildfire—The Rising Threat of Extraordinary Landscape Fires. A UNEP Rapid Response Assessment*; United Nations Environment Programme: Nairobi, Kenya, 2022.
20. Wang, B.; Yang, X.Q.; Jiang, C.Y.; Liu, D.; Chen, F.; Bai, Y.; Liu, X.D. Forest fire spread risk in Yanqing District of Beijing based on GIS. *Sci. Silvae Sin.* **2023**, *59*, 90–101.
21. Nune, A.N.; Figueiredo, A.; Pinto, C.; Lourenço, L. Assessing wildfire hazard in the wildland-urban interfaces (WUIs) of central Portugal. *Forests* **2023**, *14*, 1106. [\[CrossRef\]](#)
22. Xofis, P.; Konstantinidis, P.; Papadopoulos, I.; Tsiourlis, G. Integrating remote sensing methods and fire simulation models to estimate fire hazard in a south-east mediterranean protected area. *Fire* **2020**, *3*, 31. [\[CrossRef\]](#)
23. Wibbenmeyer, M.; Robertson, M. The distributional incidence of wildfire hazard in the western United States. *Environ. Res. Lett.* **2022**, *17*, 064031. [\[CrossRef\]](#)
24. Scott, J.H.; Thompson, M.P.; Calkin, D.E. *A Wildfire Risk Assessment Framework for Land and Resource Management*; General Technical Reports RMRS-GTR-315; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2013; 83p.
25. Scott, J.; Helmbrecht, D.; Thompson, M.P.; Calkin, D.E.; Marcille, K. Probabilistic assessment of wildfire hazard and municipal watershed exposure. *Nat. Hazards* **2012**, *64*, 707–728. [\[CrossRef\]](#)
26. Jolly, W.M.; Freeborn, P.H.; Page, W.G.; Butler, B.W. Severe fire danger index: A forecastable metric to inform firefighter and community wildfire risk management. *Fire* **2019**, *2*, 47. [\[CrossRef\]](#)
27. Shafapourtehrany, M. Geospatial wildfire risk assessment from social, infrastructural and environmental perspectives: A case study in Queensland Australia. *Fire* **2023**, *6*, 22. [\[CrossRef\]](#)
28. Zhang, H.; Wang, X.; Zhang, X.; Yu, H.Z.; Zhou, M.; Wang, Y.X. Forest fire danger rating and fire hazard assessment in Chifeng City of Inner Mongolia. *J. Southwest For. Univ.* **2019**, *39*, 143–150.
29. Rodrigues, M.; Zúñiga-Antón, M.; Alcasena, F.; Gelabert, P.; Vega-Garcia, C. Integrating geospatial wildfire models to delineate landscape management zones and inform decision-making in Mediterranean areas. *Saf. Sci.* **2022**, *147*, 105616. [\[CrossRef\]](#)
30. Sá, A.C.L.; Aparicio, B.; Benali, A.; Bruni, C.; Salis, M.; Silva, F.; Marta-Almeida, M.; Pereira, S.; Rocha, A.; Pereira, J. Coupling wildfire spread simulations and connectivity analysis for hazard assessment: A case study in Serra da Cabreira, Portugal. *Nat. Hazards Earth Syst. Sci.* **2022**, *22*, 3917–3938. [\[CrossRef\]](#)
31. Calkin, D.E.; Ager, A.A.; Gilbertson, D.J. Wildfire risk and hazard: Procedures for the first approximation. In *General Technical Report RMRS-GTR-235*; U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station: Fort Collins, CO, USA, 2010; p. 62.

32. Tao, C.S.; Niu, S.K.; Chen, F.; Li, L.Q.; Chen, L.; Zhang, P. Potential fire behavior and canopy hazard index of main coniferous forests in Beijing mountain area. *J. Beijing For. Univ.* **2018**, *40*, 55–62.
33. Aparício, B.A.; Pereira, J.M.C.; Santos, F.C.; Bruni, C.; Sá, A.C.L. Combining wildfire behaviour simulations and network analysis to support wildfire management: A Mediterranean landscape case study. *Ecol. Indic.* **2022**, *137*, 108726. [\[CrossRef\]](#)
34. Loehman, R.A.; Keane, R.E.; Holsinger, L.M.; Wu, Z.W. Interactions of landscape disturbances and climate change dictate ecological pattern and process: Spatial modeling of wildfire, insect, and disease dynamics under future climates. *Landsc. Ecol.* **2017**, *32*, 1447–1459. [\[CrossRef\]](#)
35. Pais, C.; Miranda, A.; Carrasco, J.; Shen, Z.J.M. Deep fire topology: Understanding the role of landscape spatial patterns in wildfire occurrence using artificial intelligence. *Environ. Model. Softw.* **2021**, *143*, 105122. [\[CrossRef\]](#)
36. Hood, S.M.; Varner, J.M.; Jain, T.B.; Kane, J.M. A framework for quantifying forest wildfire hazard and fuel treatment effectiveness from stands to landscapes. *Fire Ecol.* **2022**, *18*, 33. [\[CrossRef\]](#)
37. Shi, K.; Touge, Y. Characterization of global wildfire burned area spatiotemporal patterns and underlying climatic causes. *Sci. Rep.* **2022**, *12*, 644. [\[CrossRef\]](#) [\[PubMed\]](#)
38. Lee, J.; Kim, J.; Shin, J.; Cho, S.; Kim, S.; Lee, K. Analysis of wildfires and their extremes via spatial quantile autoregressive model. *Extremes* **2023**, *26*, 353–379. [\[CrossRef\]](#)
39. Tomar, J.S.; Kranjčić, N.; Đurin, B.; Kanga, S.; Singh, S.K. Forest fire hazards vulnerability and risk assessment in sirmaur district forest of Himachal Pradesh (India): A Geospatial Approach. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 447. [\[CrossRef\]](#)
40. He, Y.N.; Chen, G.; Cobb, R.C.; Zhao, K.G.; Meentemeyer, R.K. Forest landscape patterns shaped by interactions between wildfire and sudden oak death disease. *For. Ecol. Manag.* **2021**, *486*, 118987. [\[CrossRef\]](#)
41. Ghadban, S.; Ameztegui, A.; Rodrigues, M.; Chocarro, C.; Alcasena, F.; Vega-Garcia, C. Stand structure and local landscape variables are the dominant factors explaining shrub and tree diversity in Mediterranean forests. *Sustainability* **2021**, *13*, 11658. [\[CrossRef\]](#)
42. Long, T.T.; Yin, J.Y.; Ou, C.R.; Yang, Q.; Li, Y.; Wang, Q.H. Comprehensive assessment and spatial pattern study on forest fire risk in Yunnan Province. *China Saf. Sci. J.* **2021**, *31*, 167–173.
43. Zhang, H.; Qiao, G.W.; Zhang, Q.L. Studies on periodicity variation of forest and grassland fires in China based on wavelet analysis. *J. For. Eng.* **2019**, *4*, 139–145.
44. Steel, Z.L.; Koontz, M.J.; Safford, H.D. The changing landscape of wildfire: Burn pattern trends and implications for California's yellow pine and mixed conifer forests. *Landsc. Ecol.* **2018**, *33*, 1159–1176. [\[CrossRef\]](#)
45. Benali, A.; Sá, A.C.L.; Pinho, J.; Fernandes, P.M.; Pereira, J.M.C. Understanding the impact of different landscape-level fuel management strategies on wildfire hazard in central Portugal. *Forests* **2021**, *12*, 522. [\[CrossRef\]](#)
46. Adab, H.; Atabati, A.; Oliveira, S.; Gheshlagh, A.M. Assessing fire hazard potential and its main drivers in Mazandaran province, Iran: A data-driven approach. *Environ. Monit. Assess.* **2018**, *190*, 670. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Niu, S.K.; Cui, G.F.; Lei, M.; Li, X.B.; Zhao, S.T. Study on the forest combustibility and the fire districts in Labagoumen forest region. *J. Beijing For. Univ.* **2000**, *22*, 109–112.
48. Wang, X.L. Study on Combustibility of Forests in Beijing Mountain Area. Ph.D. Thesis, Beijing Forestry University, Beijing, China, 2010.
49. Xu, S.H.; Zhang, M.; Ma, Y.; Liu, J.P.; Wang, Y.; Ma, X.R.; Chen, J. Multiclassification method of landslide risk assessment in consideration of disaster levels: A case study of Xianyang city, Shaanxi Province. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 646. [\[CrossRef\]](#)
50. Nasiri, V.; Sadeghi, S.M.M.; Bagherabadi, R.; Moradi, F.; Deljouei, A.; Borz, S.A. Modeling wildfire risk in western Iran based on the integration of AHP and GIS. *Environ. Monit. Assess.* **2022**, *194*, 644. [\[CrossRef\]](#)
51. Xiang, K.X.; Zhou, Y.; Zhou, E.Z.; Lu, J.H.; Liu, H.; Huang, Y. A spatial assessment of wildfire risk for transmission-line corridor based on a weighted naïve bayes model. *Front. Energy Res.* **2022**, *10*, 829934. [\[CrossRef\]](#)
52. Li, X.H.; Li, M.J.; Cui, K.K.; Lu, T.; Xie, Y.L.; Liu, D.L. Evaluation of comprehensive emergency capacity to urban flood disaster: An example from Zhengzhou city in Henan Province, China. *Sustainability* **2022**, *14*, 13710. [\[CrossRef\]](#)
53. Bian, R.; Huang, K.Y.; Liao, X.; Ling, S.X.; Wen, H.; Wu, X.Y. Snow avalanche susceptibility assessment based on ensemble machine learning model in the central Shaluli Mountain. *Front. Earth Sci.* **2022**, *10*, 880711. [\[CrossRef\]](#)
54. Baek, S.; Yoon, H.; Hahm, Y. Assessment of spatial interactions in farmland abandonment: A case study of Gwangyang city, Jeollanam-do Province, South Korea. *Habitat Int.* **2022**, *129*, 102670. [\[CrossRef\]](#)
55. Fard, B.J.; Puvvula, J.; Bell, J.E. Evaluating changes in health risk from drought over the contiguous United States. *Int. J. Environ. Res. Public Health* **2022**, *19*, 4628. [\[CrossRef\]](#) [\[PubMed\]](#)
56. Asubonteng, K.O.; Pfeffer, K.; Ros-Tonen, M.A.F.; Baud, I.; Benefoh, D.T. Integration versus segregation: Structural dynamics of a smallholder-dominated mosaic landscape under tree-crop expansion in Ghana. *Appl. Geogr.* **2020**, *118*, 102201. [\[CrossRef\]](#)
57. Zhang, C.; Niu, S.K.; Chen, F.; Shao, X.; Wang, H. Effect of landscape pattern on forest fires in Yunnan province based on GIS. *Sci. Silvae Sin.* **2016**, *52*, 96–103.
58. Chen, L. Study on Pattern of Landscape Security and Fire Hazard in Miaofeng Mountain Forests. Master Thesis, Beijing Forestry University, Beijing, China, 2019.
59. Chen, Y.Y.; You, Y.S.; Tang, Y.H. Research of forest fire zoning based on local topography and fire numbers. *J. Nat. Disasters* **2015**, *24*, 228–234.

60. Li, L.Q.; Niu, S.K.; Chen, F.; Tao, C.S.; Chen, L.; Zhang, P. Analysis on surface potential fire behavior and combustion of Miaofeng Mountain Forest Farm in Beijing. *J. Beijing For. Univ.* **2019**, *41*, 58–67.
61. Liu, G.H. Study on the Mechanism of Surface Fire and Spread of Canopy Fire of Typical Tree Species in Beijing Area. Master's Thesis, Beijing Forestry University, Beijing, China, 2019.
62. Wu, J.R.; Chen, X.L.; Lu, J.Z. Assessment of long and short-term flood risk using the multi-criteria analysis model with the AHP-Entropy method in Poyang Lake basin. *Int. J. Disaster Risk Reduct.* **2022**, *75*, 102968. [[CrossRef](#)]
63. Li, X.N.; Shao, X.H.; Li, R.Q.; Gao, C.; Yang, X.; Ding, F.Z.; Yuan, Y.B. Optimization of tobacco water-fertilizer coupling scheme under effective microorganisms biochar-based fertilizer application condition. *Agron. J.* **2021**, *113*, 1653–1663. [[CrossRef](#)]
64. Zhang, L.; Huo, Z.G.; Zhang, L.Z.; Huang, D.P. Integrated risk assessment of major meteorological disasters with paprika pepper in Hainan province. *J. Trop. Meteorol.* **2017**, *23*, 334–344.
65. Zhang, X.H.; Liu, H.J.; Xu, M.M.; Mao, C.Y.; Shi, J.Q.; Meng, G.L.; Wu, J.H. Evaluation of passenger satisfaction of urban multi-mode public transport. *PLoS ONE* **2020**, *15*, e0241004. [[CrossRef](#)]
66. Jenkins, M.J.; Page, W.G.; Hebertson, E.G.; Alexander, M.E. Fuels and fire behavior dynamics in bark beetle-attacked forests in Western North America and implications for fire management. *For. Ecol. Manag.* **2012**, *275*, 23–34. [[CrossRef](#)]
67. Yang, X.Q.; Sun, Z.C.; Chai, Z.; Qiu, Y.W.; Jiang, C.Y. Research on the plot survey and load estimation of national forest fuels. *For. Resour. Manag.* **2022**, *6*, 1–6.
68. Heisig, J.; Olson, E.; Pebesma, E. Predicting wildfire fuels and hazard in a central European temperate forest using active and passive remote sensing. *Fire* **2022**, *5*, 29. [[CrossRef](#)]
69. Niu, S.K. Fire Behavior and Fuel Spatial Continuity of Major Forest Types in the Mountainous Area. Ph.D. Thesis, Beijing Forestry University, Beijing, China, 2012.
70. Deng, X.W.; Wen, D.Y.; Deng, S.W. A preliminary study of the relationship between forest fire and landscape pattern. *Fire Saf. Sci.* **2003**, *12*, 238–244+255.
71. Chen, L.; Chen, F.; Niu, S.K.; Li, L.Q.; Tao, C.S. Correlation analysis between the spatial characteristics of landscape pattern and risk of forest fire in Jiufeng Forest Park of Beijing. *J. Beijing For. Univ.* **2021**, *43*, 41–49.
72. Tian, X.R.; Dai, X.A.; Wang, M.Y.; Shu, L.F.; Gao, C.D. Study on the fuel types classification of forests in Beijing. *Sci. Silvae Sin.* **2006**, *42*, 76–80.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.