fire

Article

Forest Fire Driving Factors and Fire Risk Zoning Based on an Optimal Parameter Logistic Regression Model: A Case Study of the Liangshan Yi Autonomous Prefecture, China

Fuhuan Zhang [1,2,3], Bin Zhang [1,2,3], Jun Luo [1,2,3,*], Hui Liu [1,2,3], Qingchun Deng [1,2,3], Lei Wang [1,2,3] and Ziquan Zuo [1,2,3]

[1] Sichuan Provincial Engineering Laboratory of Monitoring and Control for Soil Erosion in Dry Valleys, China West Normal University, Nanchong 637009, China; fuhuan.z@stu.cwnu.edu.cn (F.Z.)
[2] Liangshan Soil Erosion and Ecological Restoration in Dry Valleys Observation and Research Station, Xide 616753, China
[3] School of Geographical Sciences, China West Normal University, Nanchong 637009, China
* Correspondence: luojunxmx@126.com

Abstract: Planning the analyses of the spatial distribution and driving factors of forest fires and regionalizing fire risks is an important part of forest fire management. Based on the Landsat-8 active fire dataset of the Liangshan Yi Autonomous Prefecture from 2014 to 2021, this paper proposes an optimal parameter logistic regression (OPLR) model, conducts forest fire risk zoning research under the optimal spatial analysis scale and model parameters, and establishes a forest fire risk prediction model. The results showed that the spatial unit of the optimal spatial analysis scale in the study area was 5 km and that the prediction accuracy of the OPLR was about 81%. The climate was the main driving factor of forest fires, while temperature had the greatest influence on the probability of forest fires. According to the forest fire prediction model, mapping the fire risk zoning, in which the medium- and high-risk area was 6021.13 km^2, accounted for 9.99% of the study area. The results contribute to a better understanding of forest fire management based on the local environmental characteristics of the Liangshan Yi Autonomous Prefecture and provide a reference for related forest fire prevention and control management.

Keywords: forest fires; Landsat 8 active fires; forest fire factors; logistic regression; risk zoning

check for updates

Citation: Zhang, F.; Zhang, B.; Luo, J.; Liu, H.; Deng, Q.; Wang, L.; Zuo, Z. Forest Fire Driving Factors and Fire Risk Zoning Based on an Optimal Parameter Logistic Regression Model: A Case Study of the Liangshan Yi Autonomous Prefecture, China. *Fire* **2023**, *6*, 336. https://doi.org/10.3390/fire6090336

Academic Editors: Guoxiong Zhou, Liujun Li, Weiwei Cai and Yanfeng Wang

Received: 1 August 2023
Revised: 19 August 2023
Accepted: 22 August 2023
Published: 26 August 2023

1. Introduction

As an important factor shaping forest ecosystems, forest fires play a vital role in forest renewal, succession, and biodiversity [1]. Nevertheless, forest fires will inevitably destroy the ecological services of forests, not only by causing natural disasters and threatening human life and property safety [2], but also by facilitating secondary disasters [3,4] such as soil erosion, debris flows and landslides [5,6]. Therefore, the occurrence patterns and spatial structure laws of forest fires should be understood, and forest fires should be monitored and forecasted accordingly [7]. The fire risk regionalization of forest fires is an effective technical means of forest fire prevention and control [8,9]. Exploring the factors driving forest fires, forest fire prediction, and fire risk zoning [2,9–12] can provide a scientific basis for planning fire prevention, deploying firefighting forces, and guiding forest fire prevention work.

Various complex factors determine the occurrence of forest fire disasters, including terrain, climate, vegetation, human activities, and so on [13,14]. The climate is an important factor in forest fires, and global warming may further aggravate forest fires [15]. Therefore, meteorological variables are widely considered in the study of forest fires [16]. Temperature, precipitation, wind speed, and other factors may affect the formation and flammability conditions of combustibles, thus resulting in fires with different probabilities [17]. Topographic factors also play an important role in forest fires. Altitude, slope direction, and slope can lead to the spatial differentiation of vegetation and also change the flammability conditions of fuels by affecting the local meteorological environment [18,19]. The quantity and structure of forest vegetation, as the most direct influencing factors of combustibles and combustible conditions, have an important influence on the occurrence and spread of forest fires [14,20]. Human variables are also significant driving factors of fires, and their impact on fires is related to population density and human activity. In areas with a high population density, human activities tend to be more frequent, leading to a higher frequency of fires [21]. Indeed, human activities will not only change the frequency of fires, either by extinguishing the fires or ignition points caused by human intervention, but also change their intensity and distribution [21,22].

Due to the complexity of forest fire generation and its driving factors, numerous scholars have attempted to use different research methods to explore forest fire prediction models and regionalization, such as Bayesian networks for fire risk mapping [23], a weights-of-evidence approach to modeling, and mapping the probability of fire occurrence [24]. Multiple overlapping solution methods to predict the growth of wildland fires [25], neural networks, and machine learning have also been applied to study forest fires [10,26]. Logistic regression models are among the most commonly used models in forest fire studies because of their good explanatory and predictive accuracy, and examples of these include multiclass logistic regression (RAFFIA) [27], binary logistic regression (BLR) [28], kernel logistic regression [29], semi-parametric logistic (SPL) regression models [30], and geographically weighted logistic models [31,32].

Logistic regression models have been widely used in forest research, but the construction strategies of the model may vary, especially when exploring the importance of variables. The presence or absence of a prior hypothesis will directly affect the selection of model construction strategies [33]. Moreover, regression coefficients for ordered categorical variables are easier to understand than one-unit changes for continuous variables [34]. Therefore, considering the degree of influence of an independent variable on the dependent variable, the continuous independent variable will generally not be directly incorporated into the model but will be transformed into ordered multiclassification variables and then incorporated into the model. However, during the analysis process, continuous parameter variables will mostly be processed based on professional experience [12,28,29,35], which is highly subjective.

Forest fire studies have been conducted at different spatial scales [7] in global [15,22], national [10,20], regional [1,36], or ecological zones [11,29] to assess fire indicators and a series of explanatory factors. Relevant studies have shown that heterogeneity exists in different spatial scales. The interaction and explanatory power of explanatory variables also vary on different scales [32,37]. Therefore, carrying out research on forest fires in local areas is both essential and of important strategic significance to understand the spatial distribution of forest fires in different regional scale environments and to better analyze and predict the laws of forest fire occurrence. The Liangshan Yi Autonomous Prefecture is an area of frequent forest fires in China as a result of its special geographical environment, climatic conditions, and rich forest resources. Forest fire prevention has always been extremely severe, and several scholars have conducted research on this issue. Sun et al. [36] used an adaptive forest fire spreading simulation algorithm to simulate and predict the spread of forest fires in the Coronation County area of Liangshan. Tian et al. [13] used multisource remote sensing imagery to monitor and quantify the dynamic spread of forest fires in Muli County. Cheng et al. [38] used a MEC-based image recognition algorithm for the monitoring and early warning of hill fires in Muli County. Li et al. [39] completed a spatial and temporal dynamic assessment of leaf fuel loads (FFL). However, there are still some questions about the fire in Liangshan Prefecture. What factors have affected the occurrence of the fires? What is the probability of fires? These issues need to be further explored. Even so, there are few studies on the drivers and spatial distribution of forest fires, which leads to the fact that fires in this area have not been fully studied and the inability to establish a scientific forest fire prevention and extinguishing system. Therefore, we hope to determine the driving factors of forest fires and their influence degree by exploring the fires in this area and obtaining the forest fire risk zoning map according to the probability of predicting the occurrence of forest fires to further study on the local area fires.

Although logistic regression models have been widely used to study forest fires, quantitative evaluations and modeling research on the variables involved in model construction from a data-driven perspective are still lacking. Therefore, this paper proposes the optimal parameter logistic regression (OPLR) model. Different from the regular binary logistic regression, OPLR discretizes continuous variables from the data-driven perspective, avoids subjectivity in professional experience processing, and better explores the factors driving forest fires at the regional scale. A logistic regression model constructed by using the optimal discretization parameters can effectively improve the performance of the model and generate a more accurate forest fire danger zoning map. The results can provide a scientific basis, support in decision making, and guidance for forest fire prevention and control management for the local government of the Liangshan Yi Autonomous Prefecture.

2. Materials and Methods

2.1. Study Area

The Liangshan Yi Autonomous Prefecture (26°03′~29°18′ N, 100°03′~103°52′ E) is located in the southwest of Sichuan Province, China, and on the northeast margin of the southwest Hengduan Mountain Region between the Sichuan Basin and the central Plateau of Yunnan Province; the total area is 60,423 km^2 (Figure 1). The terrain is high in the northwest and low in the southeast. Its landforms are complex and diverse; the highest elevation point in the territory is the Chalangdorj Peak in Muli County, reaching an altitude of 5958 m, while the lowest elevation point is at the bottom of Jinsha River Valley in Danyandong, Leibo County, at only 325 m, with a maximum relative height difference of 5653 m. The Liangshan Yi Autonomous Prefecture is characterized by a subtropical monsoon climate with distinct dry and wet features, but the boundary between the four seasons is not obvious. Due to its topographic differentiation and complex and diverse landforms, the Liangshan Yi Autonomous Prefecture has obvious vertical characteristics associated with a mountain climate. The annual average temperature is about 16–17 °C, the precipitation is about 1003 mm, and the sunshine hours are as high as 1967.2 h. Among them, in Huili, Huidong, Ningnan, Puge, and other dry and hot valley areas, the average annual temperature is 20–27 °C, and the annual precipitation is only 600–800 mm. Coupled with the influence of atmospheric circulation, it also has a complex and diverse climate. At the same time, the Liangshan Yi Autonomous Prefecture has a vast territory and rich forest resources, making it one of the three major forest regions in Sichuan Province. However, Liangshan Prefecture belongs to a forest-fire-prone area and endures severe forest fires, which have become especially commonplace in recent years. In March 2019, a forest fire in Muli resulted in the deaths of 31 rescue workers and damaged a forest area of 43.90 hectares. In March 2020, a forest fire in Xichang resulted in the deaths of 19 people, a damaged forest area of 791.6 hectares, and direct losses of up to CNY 97.32 million. Since 1951, the annual average surface temperature in China has shown a significant upward trend with an average increase of 0.26 °C per decade. The number of precipitation days has decreased, but the intensity of precipitation has increased significantly [40]. With the continuous emergence of extreme weather, the prevention and control of forest fires is becoming increasingly important.

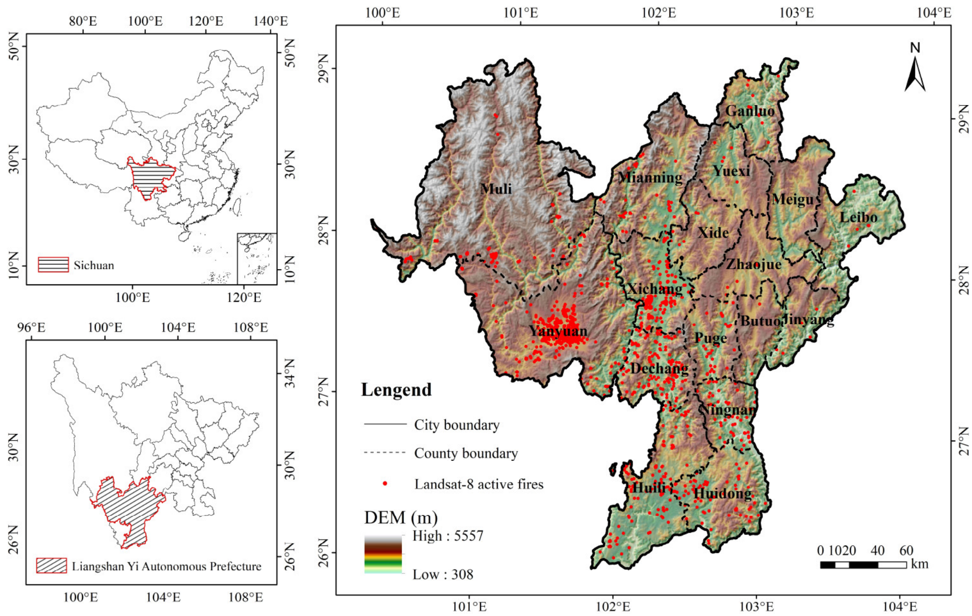

Figure 1. Landsat 8 active fires (2014–2021) in the Liangshan Yi Autonomous Prefecture.

2.2. Data Sources

The 2014–2021 Landsat 8 active fire datasets were from the Institute of Remote Sensing and Digital Earth (RADI), Chinese Academy of Sciences (http://satsee.radi.ac.cn/, accessed on 22 July 2023). Using Landsat 8 OLI sensor data with a spatial resolution of 30 m according to the spectral characteristics of fire spots in near-infrared and shortwave infrared bands, the improved Normalized Burning Ratio Short-wave (NBRS) results were used to adaptively determine the threshold to extract suspected fire spots. Then, the peak relationship of fire spots in short-wave infrared was used to eliminate false-positive points to obtain the final fire spot product. The fire dataset contained the following attributes: id, latitude, longitude, date, time, t1 (inversion temperature, unit: Kelvin), area, confidence, version, and imguri (background image location, URL connection). The Landsat 8 fire dataset with confidence greater than 50 fires in the study area was selected; to avoid creating control points that were the same as or near the ignition point, a buffer zone of 500 m around the fire point was placed as a barrier, excluding control points that fell into the buffer zone [41]. Finally, a total of 1187 fire point data were selected.

The normalized difference vegetation index (NDVI), monthly temperature, and precipitation data from 2014–2021 were derived from National Tibetan Plateau Data Center (http://data.tpdc.ac.cn/; accessed on 22 July 2023); and the monthly NDVI dataset was based on the maximum-value composite method to obtain the maximum monthly NDVI. The values were calculated as:

$$MNDVI_i = Max(NDVI_1, NDVI_2) \tag{1}$$

where $NDVI_i$ is the maximum value of $NDVI$ in the first half of month i; i is the number of months, $i \in (1{,}12)$; and $NDVI_1$ and $NDVI_2$ are the $NDVI$ values of the first and second halves of the i month, respectively. Based on the monthly $NDVI$, the annual $NDVI$ was obtained with the maximum-value composite method.

The road data were vector road data acquired from OpenStreetMap (https://www.openstreetmap.org/; accessed on 5 May 2022). The distance of each image element's center value from the nearest road was obtained using the distance analysis tool in ArcGIS v10.7 with an Euclidean distance calculation. In addition, the 2015 and 2019 population density data, vegetation type data, and land use remote sensing monitoring data were gathered from the data center of the Institute of Geographical Sciences and Resources, Chinese Academy of Sciences (https://www.resdc.cn/; accessed on 22 July 2023). The monthly wind and relative humidity data from 2014–2020 were obtained from the National Earth System Science Data Center (http://www.geodata.cn/; accessed on 22 July 2023). All the above data hade a uniform Albers Equal Area Conic projection and 500 × 500 m raster pixels.

Sections 3.1 and 3.2 of this article are based on RStudio 4.2.1 for analysis and drawing, Sections 3.3–3.5 are based on Statistical Product and Service Solutions (SPSS) 26 for analysis and mapping, and Sections 2.1 and 3.6 use ArcGIS 10.7 software for drawing.

2.3. Optimal Parameter-Based Geographical Detector Model

A geographical detector model is an efficient tool for spatially stratified heterogeneity analyses, and it mainly consists in dividing the study space into sub-regions according to variables and comparing the spatial variance within each sub-region and between different sub-regions to assess the influence of potential explanatory variables [42]. An optimal parameter-based geographical detector (OPGD) model was established based on the application and development of geographic detectors, and the OPGD model included five components: a factor detector, parameter optimization, an interaction detector, a risk detector, and an ecological detector [43].

The OPGD model's parameter optimization included an optimization of the spatial discretization and optimization of the spatial scale. The best combination of the discretization method and the number of interruptions of each geographically continuous variable was selected as the best discretization parameter as determined by the Q value calculated using the factor detector. The discretization methods included a series of supervised and unsupervised discretization methods, which could be set up with a discrete integer series according to the actual requirements. The value of the variable Q was calculated as:

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

where N_v and σ_v^2 are the number and population variance of observations within the whole study area, and $N_{v,j}$ and $\sigma_{v,j}^2$ are the number and population variance of observations within the jth (j = 1, . . ., M) sub-region of variable v. A large Q value means a relatively high importance of the explanatory variable due to a small variance within sub-regions and a large variance between sub-regions.

Based on the evaluation of forest fire risks and the actual geographical environment of the Liangshan Yi Autonomous Prefecture, we selected a total of 12 forest fire impact factors, namely the elevation (EL), slope, aspect, vegetation cover type (Veg), NDVI, annual mean temperature (Temp), precipitation (Prec), wind speed (Wind), relative humidity (Rhum), land use type (LandUT), population density (Popd), and distance from road (DisFR); of these, the Veg, aspect, and LandUT were discrete data, while the other continuous variables were discretized using the OPGD model to identify the optimal parameters.

2.4. Logistic Forest Fire Regression Prediction Model

The scenarios used in the logistic model were mostly dependent variables of binary or multiclassification, and the multiple independent variables affecting dependent variables could consist of qualitative or quantitative data. Because the regression coefficient of ordered categorical variables is easier to understand than the unit change of continuous variables, and considering the influence of independent variables on dependent variables, continuous independent variables are generally not directly incorporated into the model but instead transformed into ordered multicategory variables and then incorporated into the model.

In this study, the optimal combination of the discretization method and the number of outages of each geographically continuous variable was selected as the optimal discretization parameter. The Q value calculated with the geographic factor detector was used to determine the optimal parameter combination. A combination of a set of discretization methods and the number of interrupts was provided for each continuous variable to calculate their respective Q values. The optional discretization method could be a list of supervised and unsupervised discretization methods, and the optional breakpoint number could be an integer sequence of observation and actual requirements.

Therefore, the optional combination could cover almost all available options. For continuous variables, the parameter combination with the highest Q value in all combinations was selected for spatial discretization because from the perspective of spatial stratification heterogeneity, this parameter combination represents the highest importance of the variable. A logistic regression model constructed by using the discrete optimal parameters can effectively avoid subjectivity in the process of processing data with professional experience.

The probability of forest fire occurrence was taken as the binary dependent variable of the model, and 1 or 0 was used to indicate whether or not a forest fire occurred so that the probability was between 0 and 1.

$$ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_i x_i \tag{3}$$

where P is the probability of occurrence of a forest fire; $x_1, x_2 \cdots x_i$ is the independent variable; $\beta_1, \beta_2 \cdots \beta_i$ is the regression coefficient of the independent variable; and i is the number of independent variables.

2.5. Spearman Rank Correlation Coefficient

The Spearman rank correlation coefficient (r_s) is a non-parametric or non-distributed rank statistical measure for the intensity and direction of any monotonic correlation between two rank variables or one rank variable and one measurement variable. In principle, the Spearman correlation coefficient is only a special case of the Pearson coefficient. Before the correlation coefficient is calculated, the sample is converted to rank [44]. However, it does not need to make any assumptions about the frequency distribution and the linear relationship between the two variables, nor does it need to be measured on the interval scale. The simple expression of r_s based on the difference between the two ranking variables is as follows:

$$r_s = 1 - \frac{6\sum d_i^2}{N(N^2-1)} \tag{4}$$

where $d_i = X_i' - Y_i'$ is the difference between each pair of ranked variables, and N is the total number of samples. It is a measure of a monotonic relationship that can be used when the characteristics of a pair of variables (such as frequency distribution and/or linear distribution) make Pearson's r_s misleading or unpopular. In addition to non-parametric privileges, the main advantage of this measurement method is that it is more convenient to use because it does not require the data to be sorted.

2.6. Multicollinearity Analysis

Multicollinearity refers to a significant correlation between two or more explanatory variables, which has a serious influence on the quasi-certainty of the regression model. The severity of collinearity is commonly measured using the variance inflation factor (VIF), which is defined as:

$$VIF_i = \frac{1}{1-R_i^2} \tag{5}$$

where R_i^2 denotes the R^2 index when the ith explanatory variable is regressed on the remaining independent variables. A larger VIF value indicates a stronger correlation between the variable and the other independent variables.

2.7. Receiver Operator Characteristic (ROC) Curve Analysis

The receiver operator characteristic (ROC) curve was calculated according to the predicted value as the possible judgment threshold, and the corresponding sensitivity and specificity were drawn with 1-specificity as the abscissa and sensitivity as the ordinate. The area under the ROC curve (AUC) could be used to evaluate the accuracy of the model. Its value ranged from 0 to 1. The larger the value was, the higher the fitting accuracy of the model. The Youden index was calculated by subtracting 1 from the sum of the sensitivity and specificity of the ROC curve, which was used to determine the best indicator threshold in the upper left corner of the ROC curve to obtain the accuracy of the model prediction.

3. Results

3.1. Spatial Unit and Discretization of Optimal Parameters

The optimal spatial scale was based on the calculation of the 90% quantile of the Q values of all explanatory variables on a spatial scale, comparing the overall Q trends on different spatial scales, and selecting the spatial scale where the 90% quantile of Q values of all explanatory variables reached the highest value as the optimal spatial scale. The dataset in this study was processed into six different sizes of grid data. The results of the effect comparison between these different sizes of data by the OPGD model showed that the Q values of most variables increased from 0.5 km space units to 5 km space units. When the space unit was 5 km, the 90% quantile of the Q value reached the highest value (Figure 2). Therefore, a 5 km spatial grid was used as the best spatial unit for the analysis of factors driving forest fires.

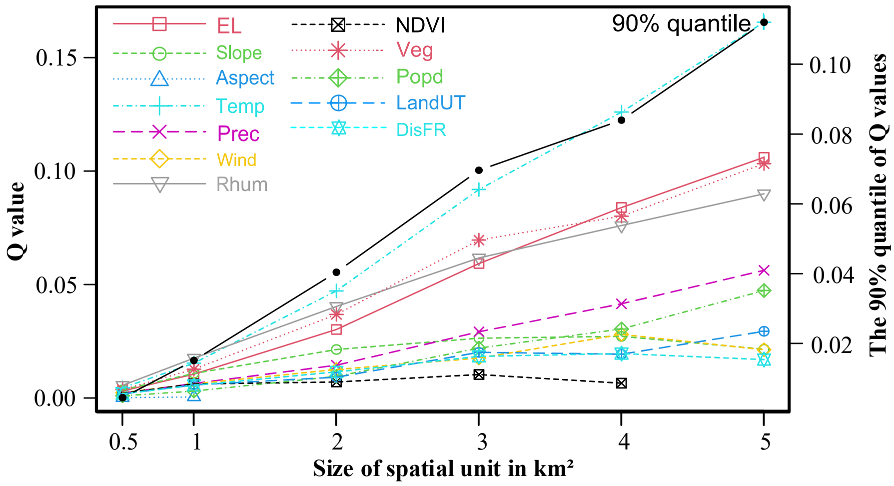

Figure 2. Comparative results of Q values and 90% quantile effects of explanatory variables at different spatial unit scales, including elevation (EL), slope, aspect, temperature (Temp), precipitation (Prec), wind speed (Wind), relative humidity (Rhum), vegetation cover type (Veg), NDVI, land use type (LandUT), population density (Popd), and distance from road (DisFR).

The OPGD model involved six discretization methods for continuous variables in the spatial analysis: the equal break method, the natural break method, the quantile method, the geometric break method, the standard deviation method, and the manual break method. Several spatially continuous variables were considered in this study, and all were optimized using the OPGD model for spatial discretization parameters (Figure 3). The results showed that the optimal parameter combinations of discretization methods and the number of interruptions differed for different explanatory variables. EL, Temp, and DisFR used the quantile break with nine, eight, and nine intervals, respectively; slope and Prec used the standard deviation method with eight intervals; Wind and Rhum used the equal break with nine interruptions; NDVI used the natural break with nine intervals, and Popd used the geometric break with nine intervals.

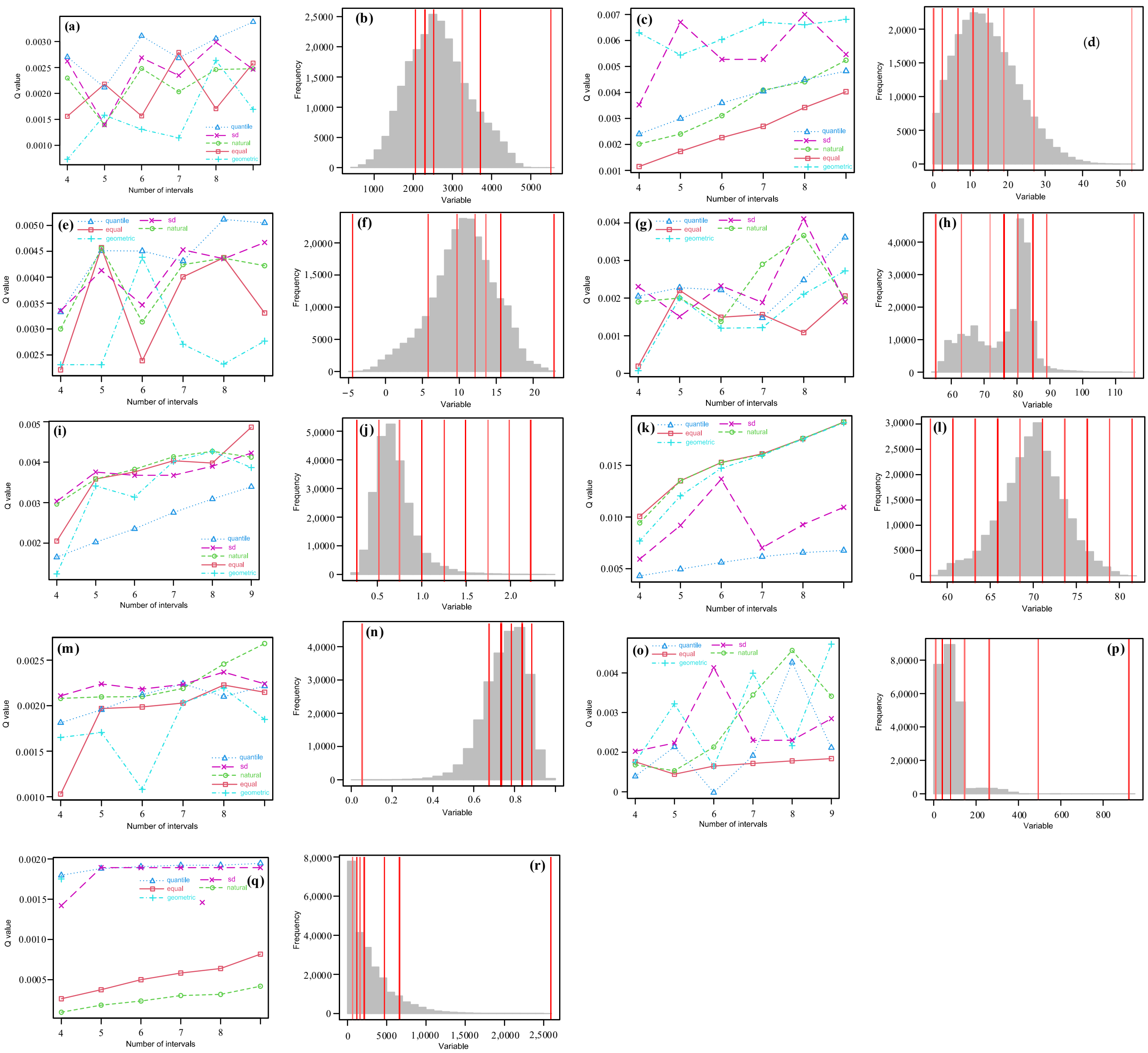

Figure 3. Results of the discretization process of explanatory variables: (**a**,**b**) elevation (EL); (**c**,**d**) slope; (**e**,**f**) temperature (Temp); (**g**,**h**) precipitation (Prec); (**i**,**j**) wind speed (Wind); (**k**,**l**) relative humidity (Rhum); (**m**,**n**) NDVI; (**o**,**p**) population density (Popd); (**q**,**r**) distance from road (DisFR).

In addition to the above-mentioned continuous spatial data optimized using OPGD model parameters, the spatial distribution data of Veg were sorted into nine categories according to the code table of source data Veg, while LandUT data were sorted into eight categories according to the land use classification system of the Resource Environmental Science Data Center. The aspect data were generated using the surface tool in ArcGIS v10.7 software based on the DEM, which was divided into nine categories. A total of 12 factors contributing to the occurrence of forest fires were classified, and the results of the reclassification of factors driving forest fires were obtained according to the classification (Figure 4).

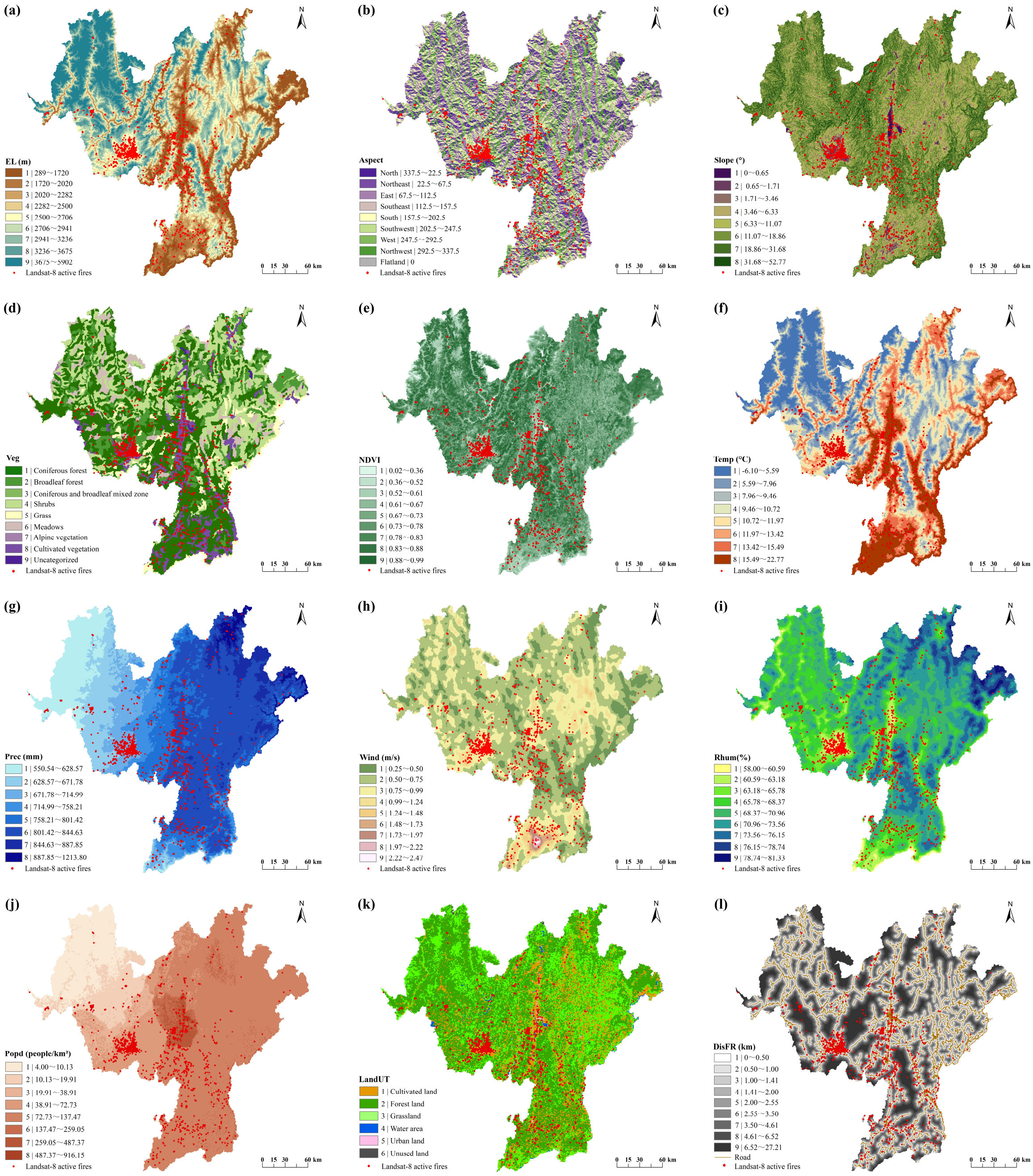

Figure 4. Reclassification of driving factors: (**a**) EL; (**b**) aspect; (**c**) slope; (**d**) Veg; (**e**) NDVI; (**f**) Temp; (**g**) Prec; (**h**) Wind; (**i**) Rhum; (**j**) Popd; (**k**) LandUT; (**l**) DisFR.

3.2. Results of the Spearman Rank Correlation Coefficient

According to the results of the Spearman correlation analysis (Figure 5), the variables of EL except aspect were extremely significant (P < 0.01), and the average correlation coefficient was 0.289. To avoid the conflict variables with high correlation, which resulted in overfitting of the future model, the EL variable was eliminated.

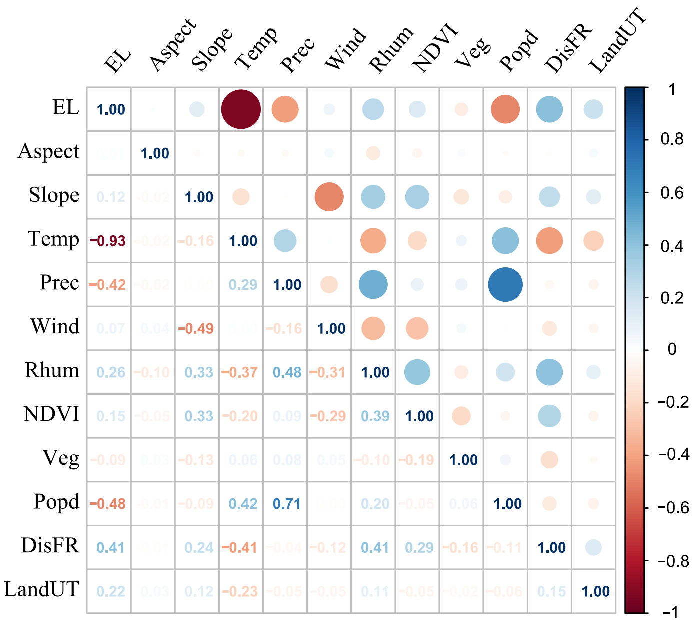

Figure 5. Spearman correlation analysis results.

3.3. Results of the Driving Factor Multicollinearity Diagnosis

VIF is an important index to measure multicollinearity. If the VIF value is greater than 10, there is a collinearity problem between independent variables [11,45]. The results of the multicollinearity diagnostic test showed that the EL and Temp were relatively high: the VIF value for each factor was 10.683 and 10.098, respectively. Therefore, it was necessary to deal with the collinearity of the driving factors. After eliminating the EL factor, the collinearity diagnosis results showed that the VIF values of all the remaining factors were less than 5 (Table 1) and that the average VIF value was 1.844. Consequently, the collinearity test was passed.

Table 1. Multicollinearity diagnostic.

Type	Factors	Coding	VIF
Topographic factors	Elevation	EL	*1
	Aspect	-	1.027
	Slope	-	1.487
Vegetation factors	Vegetation cover type	Veg	1.105
	NDVI	-	1.361
Meteorological factors	Temperature	Temp	2.159
	Precipitation	Prec	3.646
	Wind speed	Wind	1.460
	Relative humidity	Rhum	3.053
Human factors	Population density	Popd	2.488
	Land use type	LandUT	1.087
	Distance from road	DisFR	1.408

*1 Null value after eliminating variables.

3.4. Construction and Evaluation of the OPLR Forest Fire Prediction Model

Based on the optimal spatial scale analysis unit determined by the OPGD model, a total of 4748 data point sets were screened for participation in model building, and the sample data included fire point data and non-fire point data with a ratio of about 1:3. Moreover, to reduce the influence of data spatial autocorrelation on model accuracy, the dataset was randomly divided into 70% model samples and 30% test samples, and the random division was repeated three times to reduce the influence of sample distribution. The Wald forward principle was adopted for data sample model fitting. According to the three sample data fitting results, significant variables were selected as the influence factors of the whole sample fitting, including slope, Temp, Prec, Rhum, Veg, Popd, and LandUT (Table 2).

Table 2. Fitting results of the whole sample model.

Model Variable	Coefficient	Standard Error	Wald Test	Degree of Freedom	Significance	Exp(β)
Rhum (X_1)	−0.462	0.038	147.829	1	0.000	0.630
Temp (X_2)	0.292	0.027	113.877	1	0.000	1.339
Slope (X_3)	−0.171	0.023	57.404	1	0.000	0.843
Popd (X_4)	0.206	0.043	22.729	1	0.000	1.229
LandUT (X_5)	−0.158	0.049	10.352	1	0.001	0.854
Veg (X_6)	−0.033	0.015	4.635	1	0.031	0.968
Prec (X_7)	−0.081	0.040	4.068	1	0.044	0.922
Constant	−0.192	0.255	0.568	1	0.451	0.825

The results of the mixed test of the model coefficients showed that the significance value was 0.05. The chi-square value obtained from the model calculation at 7 degrees of freedom was 1349.23, much larger than the chi-square critical value of 14.067 for 7 degrees of freedom in this confidence level group. Its corresponding significance value of 0.000 was less than 0.05, so the model coefficients passed the test at a significance level of 0.05. In the significance test, the significance values corresponding to each influence factor were less than 0.05 at a significance level of 0.05 and therefore passed the Wald test.

The model fitting results showed that the slope, Temp, Rhum, and Popd had extremely significant relationships with the probability of forest fire occurrence ($P < 0.01$), and the Prec, Veg, and LandUT were also significant ($P < 0.05$). The Temp and Popd were positively correlated with the probability of forest fire occurrence, and the Exp(β) values were all greater than 1. Compared with other factors, Temp and Popd had a greater impact on the probability of forest fire occurrence. The slope, Prec, Rhum, Veg, and LandUT were negatively correlated with forest fire occurrence probability. According to the fitting results in Table 3, the OPLR model was established as follows:

$$ln\left(\frac{P}{1-P}\right) = -0.462X_1 + 0.292X_2 - 0.171X_3 + 0.206X_4 - 0.158X_5 - 0.033X_6 - 0.081X_7 - 0.192 \quad (6)$$

Table 3. Evaluation of the forest fire prediction model.

Sample Group	Predicted								AUC	Youden Index
	Training				Validation					
	Fire	0	1	Percentage correct	Fire	0	1	Percentage correct		
Sample 1	0	2285	208	91.65	0	986	82	92.32	0.831	0.527
	1	440	397	47.43	1	186	164	46.86		
Overall percentage				80.54				81.1		
Sample 2	0	2279	205	91.75	0	994	83	92.29	0.832	0.529
	1	415	425	50.6	1	199	148	42.65		
Overall percentage				81.35				80.2		
Sample 3	0	2277	205	91.74	0	1007	72	93.33	0.837	0.525
	1	425	439	50.81	1	181	142	43.96		
Overall percentage				81.17				81.95		
Whole sample	0	3269	292	91.8					0.83	0.521
	1	615	572	48.19						
Overall percentage				80.9						

3.5. ROC Curve Analysis

The fitting results of the ROC curves showed that the AUC values of Sample 1, Sample 2, Sample 3, and the whole sample dataset were 0.831, 0.832, 0.837, and 0.830, respectively; the AUC values of the sample datasets were close to each other and were much higher than 0.5. The prediction accuracy of the test sample data of each sample group exceeded 80%, and the average value was 80.99% (Figure 6 and Table 3), which showed that the OPLR model fitted better and had a higher prediction accuracy.

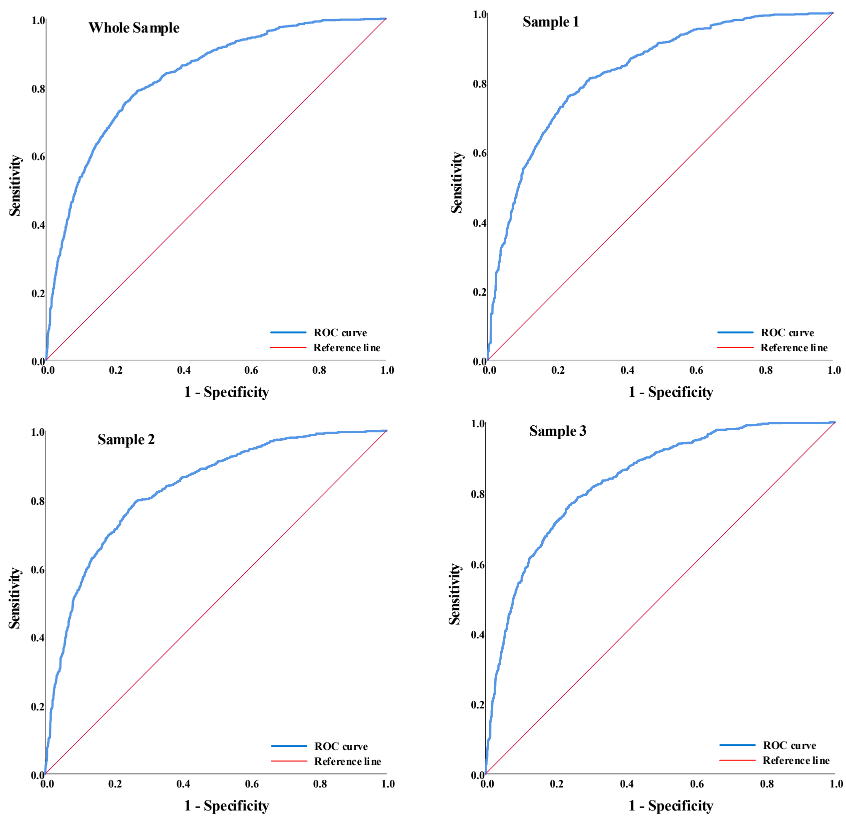

Figure 6. Receiver operator characteristic (ROC) curves of each sample.

3.6. Classification of Forest Fire Probability Risk Level

The probability of forest fire occurrence in the dataset was calculated according to the whole-sample OPLR model. The spatial distribution of the probability of forest fire occurrence in the Liangshan Yi Autonomous Prefecture was obtained using the kriging spatial interpolation method; an optimal threshold value of 0.521 was obtained by calculating the Youden index from the results of the whole-sample ROC curve. An area with a probability of forest fire occurrence exceeding this value could be considered prone to forest fires [35]. The fire risk was divided into five levels: Class I fire risk areas with basically no fire occurrence ($P \leq 0.2$), Class II fire risk areas with little fire occurrence ($0.2 < P \leq 0.4$), Class III fire risk areas with a possible fire occurrence ($0.4 < P \leq 0.521$), Class IV fire-prone areas ($0.521 < P \leq 0.6$), and Class V extremely fire-prone areas ($0.6 < P \leq 0.831$). On the whole, the forest fire risk areas were divided into low-risk fire areas (Class I and II fire risk areas), medium-risk fire areas (Class III fire risk areas), and high-risk fire areas (Class IV and V fire risk areas). In addition, the forest fire probability risk zoning was conducted according to the above division of fire risk levels (Figure 7).

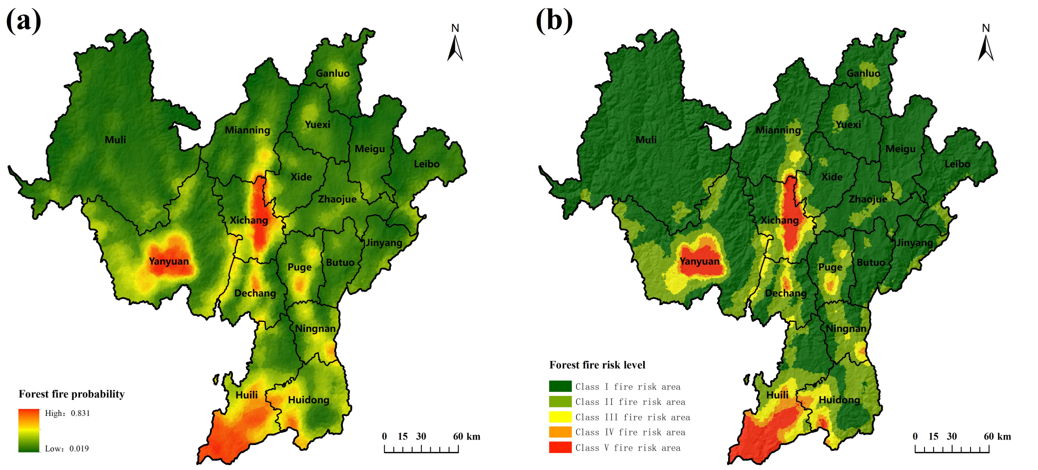

Figure 7. Spatial distribution of forest fire probability and risk level zoning: (**a**) forest fire probability; (**b**) forest fire risk level.

As shown by the forest fire probability risk level zoning, the medium- and high-risk fire risk areas in the Liangshan Yi Autonomous Prefecture were spatially clustered and mainly concentrated in the south, central, and midwest parts, among which Huili, Xichang, Yanyuan, and Huidong were high-risk forest fire-prone areas, mainly due to the IV and V fire risk level areas; Ningnan, Puge, Dechang, Mianning, and Xide were mostly characterized by Class III and IV areas of fire risk level zoning, so these areas were prone to fire. Furthermore, Muli, Meigu, Leibo, Jinyang, Zhaojue, and Butuo were classed as Class I or II fire risk zones, so the probability of fire in these areas was minimal.

The area of each risk level and its proportion indicated that in the fire risk zoning, the area of the Class I fire risk zone accounted for 68.87% (the largest proportion), while the area of the Class II fire risk zone accounted for 19.46%. That is, the low-risk fire areas accounted for 88.33% of the total. The proportion of third-level risk zones, namely the medium-risk fire areas, reached 5.16%; the proportions of Class IV and V risk zones were 2.15% and 2.68%, respectively; and the high-risk fire areas accounted for 4.83% (i.e., the medium- and high-risk areas were more than 1/5 of the total area of the Liangshan Yi Autonomous Prefecture (Table 4)). Therefore, attention to these medium-high-risk fire areas is needed. Indeed, fire prevention measures should be strengthened, and the forest fire controllability of these areas should be improved to better cope with the difficult forest fire situation in the prefecture.

Table 4. The proportion of forest fire risk level zoning areas.

Fire Risk Probability (P)	Fire Risk Class	Area (km^2)	Area Percentage (%)
$P \leq 0.2$	Class I fire risk areas	41,511.25	68.87
$0.2 < P \leq 0.4$	Class II fire risk areas	11,729.25	19.46
$0.4 < P \leq 0.521$	Class III fire risk areas	3109.50	5.16
$0.521 < P \leq 0.6$	Class IV fire risk areas	1298.00	2.15
$0.6 < P \leq 0.831$	Class V fire risk areas	1613.63	2.68

4. Discussion

4.1. Effects of Meteorological Factors on Forest Fires

The meteorological factors considered in this study were temperature, precipitation, wind, and relative humidity, which are important factors driving the occurrence of forest fires, of which temperature has a stronger contribution. Air temperature will directly affect the water contents of fuels. A high temperature will intensify the transpiration of plants and lead to a decrease in plant water contents, reducing the critical value of the fuel ignition point and making the forest more prone to fire. In turn, precipitation will increase the amount of water in the fuel, reducing the likelihood of forest fires [46]. In addition to temperature and precipitation, wind speed and humidity also directly affect the water content of the fuel [17]. Because combustibles exist in the atmosphere, they exchange energy and matter with the surrounding environment and maintain water balance. When combustibles burn, water evaporates and decomposes into combustible gases. Therefore, the lower the relative humidity, the lower the energy required for fuel combustion or the lower the evaporation potential, the higher the risk of fire [47]. In general, the higher the wind speed, the higher the plant transpiration, resulting in more oxygen, increasing the risk of fire [48]. However, the wind speed in the results of this study was not a significant factor affecting fires because the intensity and spread direction of fires will change sharply with the change in wind [49] and the near-surface wind in mountainous terrain has certain fluctuations in small-scale time and space [50], which leads to uncertainty regarding wind speed and wind direction in fire fields, and forest fires are prone to sudden changes in behavior. Therefore, the monitoring and forecasting of fine mountain wind fields before the fire has become an urgent need. This can not only effectively prevent the occurrence of forest fires but also provide scientific guidance for the deployment of forest fire fighting and rescue.

4.2. Effects of Topographic Factors and Vegetation Factors on Forest Fires

The vegetation factor has also become an important indicator of forest fire probability [14]. The type of vegetation in an area has a certain influence on the probability of forest fire occurrence. The main regional vegetation type of fire in the Liangshan Prefecture is coniferous forest. This is because the special climatic conditions in the Liangshan Prefecture provide a suitable living environment for Yunnan pine, resulting in an area of Yunnan pine as high as 1.275 million hm^2, accounting for 40.3% of the total forest stock volume in the Liangshan Prefecture. Because of the large amount of litter, it is not easy for it to decompose, and it becomes the origin of the main forest fires. The distribution of vegetation can reflect the trend in forest fires during the spatial development process. The topographic factors considered here were mainly elevation and slope, and differences in these may lead to changes in local meteorological elements such as solar radiation, temperature, and precipitation. As is well known, temperature will decrease with increasing altitude. Altitude not only directly changes the moisture contents of fuel by affecting the temperature but also changes the distribution of vegetation [51]. In general, high-altitude areas have more than enough combustible materials and stronger connectivity between fuels, but high-altitude areas are limited by conditions such as humidity and temperature and do not easily produce ignition sources and thus fires [52]. In the study of the Penticton Creek watershed in southeastern BC, Canada, Spittlehouse and Dymond found that the fire risk decreased significantly with the increase in altitude regardless of the historical data results or future projections [53]. On the other hand, high altitudes are sparsely populated, and almost none of the fires at these elevations are caused by human activity [54]. But as the altitude increases, the possibility of fire caused by lightning will increase [55]. In addition, slopes will affect the soil's water-holding capacity, which will change the demand conditions for the growth and development of vegetation and affect the spatial patterns of vegetation distribution, resulting in fluctuations in the probability of forest fires [56].

4.3. Effects of Human Factors on Forest Fires

Relevant studies have shown that population density is usually positively correlated with the probability of forest fires because of human activities such as living fires, ancestral worship, garbage incineration, and land burning, which will greatly increase the probability of forest occurrence [21,57]; this was consistent with the results of this study. As one of China's key poverty alleviation areas, the government has been focused on the urbanization of the Liangshan Yi Autonomous Prefecture and the development of characteristic regional industries since it achieved certain results of poverty alleviation in 2018. Areas with a high population were mostly concentrated in urban centers, industrial parks, or developed areas with high degrees of urbanization. Therefore, the possibility of fires caused by frequent human activities caused by high population concentration will be very high. However, human-caused fires are not always the result of arson [21,22]. These fires may also be caused by a lack of education and basic forest protection knowledge, resulting in activities such as garbage incineration, land burning, discarding unextinguished cigarette butts, etc. Population density is not surprising as an important driver of fires, as most fires are caused by human activity [14]. The land use type and the distance from roads were also identified as important factors controlling the probability of forest fires [56,58]. The spatial clustering of human-caused fires is high around the accessibility network [59]. Ricotta et al. analyzed the interaction between roads and land cover in driving fire ignition and found that in all classes of land use types, the impact of roads on fire spatial patterns was not the same [60]. However, this study identified the DisFR as a positive driver of forest fires. A greater distance from human infrastructure translates into an area being more remote with more spatially continuous vegetation distribution and a higher likelihood of fires starting and continuing to spread [61]. Owing to China's policy support, the on-duty road bayonet or sentry booth enforcement personnel in the Liangshan Yi Autonomous Prefecture area can strictly control the source of a fire in the field. Furthermore, building vigorous fire channels and isolating these have become an effective means of preventing and controlling forest fires [62].

4.4. Limitations and Future Developments

Time, cost, and ethnic policy factors in the Liangshan Yi Autonomous Prefecture region prevented us from exploring additional potential impact factors in the model, such as human entertainment activities, planned burning policies released in April 2020, and other variables related to human activities. The complexity of forest fires not only dictates that the same variables cannot be used in models for different regions [63] but also implies that over time, new influencing variables may appear in models for the same region or that the relationship between variables may also change, requiring that the models be updated periodically to improve their quality. The OPLR model proposed in this paper can effectively determine the optimal spatial analysis scale and eliminate the subjectivity of model construction, but since forest fires are generated through interactions of multiple factors, the applicability and interpretation of each forest fire prediction model will differ according to the geographical conditions. At present, in addition to statistical models, numerous studies on forest fire prediction models have been carried out by scholars using machine learning models such as artificial neural network (ANN) models, random forest (RF) models, and deep belief network (DBN) models [10,26,64] to define nonlinear characteristics among the driving factors of forest fires. However, a single algorithm lacks a proper representation of the input data, which may lead to a model that does not correctly represent the actual spatial distribution of the sample set. In the future, a combination of linear regression and machine learning methods could be considered to explore optimal interpretation models of forest fire prediction.

5. Conclusions

The OPLR model presented in this study was based on the optimal spatial analysis scales and optimal model parameters to identify the factors driving forest fires in the Liangshan Yi Autonomous Prefecture and to establish a prediction model on a larger temporal scale using four aspects of terrain, vegetation, climate, and human influence. Seven different factors driving forest fires (slope, Veg, Temp, Prec, Rhum, Popd, and LandUT) were determined. Five forest fire risk levels were identified based on the prediction model. The results showed that the logistic forest fire regression model based on the optimal parameters had a good performance. Pan et al. [12] and Chang et al. [35] used the logistic regression methods to predict forest fires in Shanxi and Heilongjiang, respectively. Both obtained prediction models with an accuracy rate of about 70% and an AUC of about 0.75. The prediction accuracy of the OPLR model proposed in this paper was about 81%, and the AUC was about 0.83. The performance of the model was significantly improved. According to the results of the evaluation of the factors affecting fire occurrence, the climate factor was the main driver behind the occurrence of forest fires within the region, among which Temp was the most influential factor. The slope, Temp, Rhum, and Popd had an extremely significant effects on the occurrence of forest fires ($P < 0.01$), while Prec, Veg, and LandUT had comparatively weak effects on the latter ($P < 0.05$). According to the spatial division of forest fire risk probability, the medium- and high-risk areas in Liangshan Yi Autonomous Prefecture comprise 6021.13 km^2, accounting for 9.99% of the total. Fire sources should be strictly controlled and managed in these areas, fire prevention infrastructure should be strengthened, forest fire prevention education should be carried out to improve people's fire prevention awareness, and various measures should be taken to ensure the long-term security of the forests. Although forest fires remain random and uncertain and are extremely difficult to fully control, estimating the fire risk conditions and building a prediction model of fire risks can help prevent the possible losses caused by the fires, better allocate fire prevention resources, and thus reduce the fire hazard. The OPLR model presented in this paper provides a fire risk zoning scheme for forest fires, and the quantitative evaluation of fires will serve to analyze the comprehensive situation of forest fires, understand the spatial distribution and degree of damage of forest fires, and provide a scientific basis and technical support for forest fire prevention and management.

Author Contributions: Conceptualization, B.Z.; Methodology, F.Z. and J.L.; Software, F.Z.; Validation, F.Z., H.L. and Z.Z.; Formal analysis, Q.D. and L.W.; Investigation, all authors; Resources, B.Z. and J.L.; Data curation, B.Z.; Writing—original draft, F.Z.; Writing—review and editing, J.L. and B.Z.; Visualization, H.L. and Z.Z.; Supervision, Q.D. and L.W.; Project administration, J.L.; Funding acquisition, B.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the National Natural Science Foundation of China (grant number 41971015) and the Innovation Team Funds of China West Normal University (grant number KCXTD 2022-1).

Data Availability Statement: The data used in this study are available from the corresponding author upon reasonable request.

Acknowledgments: We thank the anonymous reviewers for their constructive feedback. This project was supported by the National Natural Science Foundation of China (grant number 41971015) and the Innovation Team Funds of China Weat Normal University (grant number KCXTD 2022-1).

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

References

1. Hong, H.; Tsangaratos, P.; Ilia, I.; Liu, J.; Zhu, A.-X.; Xu, C. Applying Genetic Algorithms to Set the Optimal Combination of Forest Fire Related Variables and Model Forest Fire Susceptibility Based on Data Mining Models. The case of Dayu County, China. *Sci. Total Environ.* **2018**, *630*, 1044–1056. [CrossRef] [PubMed]
2. Sowmya, S.; Somashekar, R. Application of Remote Sensing and Geographical Information System in Mapping Forest Fire Risk Zone at Bhadra Wildlife Sanctuary, India. *J. Environ. Sci.* **2010**, *31*, 969–974.
3. Li, J.Y.; Chen, C. Modeling the Dynamics of Disaster Evolution Along Causality Networks with Cycle Chains. *Phys. A Stat. Mech. Its Appl.* **2014**, *401*, 251–264. [CrossRef]
4. Zhang, J.-H.; Li, J.; Liu, Z. Multiple-Resource and Multiple-depot Emergency Response Problem Considering Secondary Disasters. *Expert Syst. Appl.* **2012**, *39*, 11066–11071. [CrossRef]
5. Rengers, F.K.; McGuire, L.A.; Oakley, N.S.; Kean, J.W.; Staley, D.M.; Tang, H. Landslides After Wildfire: Initiation, Magnitude, and Mobility. *Landslides* **2020**, *17*, 2631–2641. [CrossRef]
6. Dong, S.Y.; Jiang, Y.S.; Yu, X. Analyses of the Impacts of Climate Change and Forest Fire on Cold Region Slopes Stability by Random Finite Element Method. *Landslides* **2021**, *18*, 2531–2545. [CrossRef]
7. Pacheco, A.P.; Claro, J.; Fernandes, P.M.; de Neufville, R.; Oliveira, T.M.; Borges, J.G.; Rodrigues, J.C. Cohesive Fire Management within an Uncertain Environment: A Review of Risk Handling and Decision Support Systems. *For. Ecol. Manag.* **2015**, *347*, 1–17. [CrossRef]
8. Akay, A.E.; Wing, M.G.; Zengin, M.; Kose, O. Determination of Fire-access Zones along Road Networks in Fire-Sensitive Forests. *J. For. Res.* **2017**, *28*, 557–564. [CrossRef]

9. Enoh, M.A.; Okek, U.C.; Narinua, N.Y. Identification and Modelling of Forest Fire Severity and Risk Zones in the Cross-Niger Transition Forest with Remotely Sensed Satellite Data. *Egypt. J. Remote Sens. Space Sci.* **2021**, *24*, 879–887. [CrossRef]
10. Pang, Y.Q.; Li, Y.D.; Feng, Z.K.; Feng, Z.M.; Zhao, Z.Y.; Chen, S.L.; Zhang, H.Y. Forest Fire Occurrence Prediction in China Based on Machine Learning Methods. *Remote Sens.* **2022**, *14*, 5546. [CrossRef]
11. Guo, F.T.; Su, Z.W.; Wang, G.Y.; Sun, L.; Tigabu, M.; Yang, X.J.; Hu, H.Q. Understanding Fire Drivers and Relative Impacts in Different Chinese Forest Ecosystems. *Sci. Total Environ.* **2017**, *605*, 411–425. [CrossRef] [PubMed]
12. Pan, J.H.; Wang, W.G.; Li, J.F. Building Probabilistic Models of Fire Occurrence and Fire Risk Zoning Using Logistic Regression in Shanxi Province, China. *Nat. Hazards* **2016**, *81*, 1879–1899. [CrossRef]
13. Tian, Y.P.; Wu, Z.C.; Li, M.Z.; Wang, B.; Zhang, X.D. Forest Fire Spread Monitoring and Vegetation Dynamics Detection Based on Multi-Source Remote Sensing Images. *Remote Sens.* **2022**, *14*, 4431. [CrossRef]
14. Ciesielski, M.; Balazy, R.; Borkowski, B.; Szczesny, W.; Zasada, M.; Kaczmarowski, J.; Kwiatkowski, M.; Szczygiel, R.; Milanovic, S. Contribution of Anthropogenic, Vegetation, and Topographic Features to Forest Fire Occurrence in Poland. *Iforest Biogeosci. For.* **2022**, *15*, 307–314. [CrossRef]
15. Marchal, J.; Cumming, S.G.; McIntire, E.J.B. Turning Down the Heat: Vegetation Feedbacks Limit Fire Regime Responses to Global Warming. *Ecosystems* **2020**, *23*, 204–216. [CrossRef]
16. Girardin, M.P.; Ali, A.A.; Carcaillet, C.; Gauthier, S.; Hely, C.; Le Goff, H.; Terrier, A.; Bergeron, Y. Fire in Managed Forests of Eastern Canada: Risks and Options. *For. Ecol. Manag.* **2013**, *294*, 238–249. [CrossRef]
17. Shmuel, A.; Ziv, Y.; Heifetz, E. Machine-Learning-Based Evaluation of the Time-Lagged Effect of Meteorological Factors On 10-Hour Dead Fuel Moisture Content. *For. Ecol. Manag.* **2022**, *505*, 119897. [CrossRef]
18. Ng, J.; North, M.P.; Arditti, A.J.; Cooper, M.R.; Lutz, J.A. Topographic Variation in Tree Group and Gap Structure in Sierra Nevada Mixed-Conifer Forests with Active Fire Regimes. *For. Ecol. Manag.* **2020**, *472*, 118220. [CrossRef]
19. Loudermilk, E.L.; O'Brien, J.J.; Goodrick, S.L.; Linn, R.R.; Skowronski, N.S.; Hiers, J.K. Vegetation's Influence on Fire Behavior Goes Beyond Just Being Fuel. *Fire Ecol.* **2022**, *18*, 1–10. [CrossRef]
20. Liang, S.; Hurteau, M.D. Novel Climate-Fire-Vegetation Interactions and Their Influence on Forest Ecosystems in the Western USA. *Funct. Ecol.* **2023**, *37*, 2126–2142. [CrossRef]
21. Ying, L.X.; Han, J.; Du, Y.S.; Shen, Z.H. Forest Fire Characteristics in China: Spatial Patterns and Determinants with Thresholds. *For. Ecol. Manag.* **2018**, *424*, 345–354. [CrossRef]
22. Ganteaume, A.; Camia, A.; Jappiot, M.; San-Miguel-Ayanz, J.; Long-Fournel, M.; Lampin, C. A Review of the Main Driving Factors of Forest Fire Ignition Over Europe. *Environ. Manag.* **2013**, *51*, 651–662. [CrossRef] [PubMed]
23. Dlamini, W.M. Application of Bayesian Networks for Fire Risk Mapping Using GIS and Remote Sensing Data. *GeoJournal* **2011**, *76*, 283–296. [CrossRef]
24. Dickson, B.G.; Prather, J.W.; Xu, Y.; Hampton, H.M.; Aumack, E.N.; Sisk, T.D. Mapping the Probability of Large Fire Occurrence in Northern Arizona, USA. *Landsc. Ecol.* **2006**, *21*, 747–761. [CrossRef]
25. Bianchini, G.; Denham, M.; Cortés, A.; Margalef, T.; Luque, E. Wildland Fire Growth Prediction Method Based on Multiple Overlapping Solution. *J. Comput. Sci.* **2010**, *1*, 229–237. [CrossRef]
26. Abid, F. A Survey of Machine Learning Algorithms Based Forest Fires Prediction and Detection Systems. *Fire Technol.* **2021**, *57*, 559–590. [CrossRef]
27. Wang, L.; Zhao, Q.J.; Wen, Z.M.; Qu, J.M. RAFFIA: Short-term Forest Fire Danger Rating Prediction via Multiclass Logistic Regression. *Sustainability* **2018**, *10*, 4620. [CrossRef]
28. Pourghasemi, H.R. GIS-Based Forest Fire Susceptibility Mapping in Iran: A Comparison Between Evidential Belief Function and Binary Logistic Regression Models. *Scand. J. For. Res.* **2016**, *31*, 80–98. [CrossRef]
29. Bui, D.T.; Le, K.T.T.; Nguyen, V.C.; Le, H.D.; Revhaug, I. Tropical Forest Fire Susceptibility Mapping at the Cat Ba National Park Area, Hai Phong City, Vietnam, Using GIS-Based Kernel Logistic Regression. *Remote Sens.* **2016**, *8*, 347. [CrossRef]
30. Xiaowei, L.; Guobin, F.; Zeppel, M.J.B.; Xiubo, Y.; Gang, Z.; Eamus, D.; Qiang, Y. Probability Models of Fire Risk Based on Forest Fire Indices in Contrasting Climates over China. *J. Resour. Ecol.* **2012**, *3*, 105–117. [CrossRef]
31. Zhang, H.; Qi, P.; Guo, G. Improvement of Fire Danger Modelling with Geographically Weighted Logistic Model. *Int. J. Wildland Fire* **2014**, *23*, 1130–1146. [CrossRef]
32. Martínez-Fernández, J.; Chuvieco, E.; Koutsias, N. Modelling Long-term Fire Occurrence Factors in Spain by Accounting for Local Variations with Geographically Weighted Regression. *Nat. Hazards Earth Syst. Sci.* **2013**, *13*, 311–327. [CrossRef]
33. Stoltzfus, J.C. Logistic Regression: A Brief Primer. *Acad. Emerg. Med.* **2011**, *18*, 1099–1104. [CrossRef] [PubMed]
34. Royston, P.; Altman, D.G.; Sauerbrei, W. Dichotomizing Continuous Predictors in Multiple Regression: A Bad Idea. *Stat. Med.* **2006**, *25*, 127–141. [CrossRef]
35. Chang, Y.; Zhu, Z.; Bu, R.; Chen, H.; Feng, Y.-t.; Li, Y.; Hu, Y.; Wang, Z. Predicting Fire Occurrence Patterns with Logistic Regression in Heilongjiang Province, China. *Landsc. Ecol.* **2013**, *28*, 1989–2004. [CrossRef]
36. Sun, L.Y.; Xu, C.C.; He, Y.L.X.; Zhao, Y.J.; Xu, Y.; Rui, X.P.; Xu, H.W. Adaptive Forest Fire Spread Simulation Algorithm Based on Cellular Automata. *Forests* **2021**, *12*, 1431. [CrossRef]
37. Li, W.; Xu, Q.; Yi, J.-h.; Liu, J. Predictive Model of Spatial Scale of Forest Fire Driving Factors: A Case Study of Yunnan Province, China. *Sci. Rep.* **2022**, *12*, 19029. [CrossRef]

38. Cheng, C.; Zhou, H.; Chai, X.C.; Li, Y.; Wang, D.N.; Ji, Y.; Niu, S.C.; Hou, Y. Adoption of Image Surface Parameters Under Moving Edge Computing in the Construction of Mountain Fire Warning Method. *PLoS ONE* **2020**, *15*, e0232433. [CrossRef]
39. Li, Y.X.; Chen, R.; He, B.B.; Veraverbeke, S. Forest Foliage Fuel Load Estimation from Multi-Sensor Spatiotemporal Features. *Int. J. Appl. Earth Obs. Geoinf.* **2022**, *115*, 103101. [CrossRef]
40. CMA Climate Change Centre. *Blue Book on Climate Change in China*; Science Press: Beijing, China, 2022.
41. Kalabokidis, K.; Koutsias, N.; Konstantinidis, P.; Vasilakos, C. Multivariate Analysis of Landscape Wildfire Dynamics in a Mediterranean Ecosystem of Greece. *Area* **2007**, *39*, 392–402. [CrossRef]
42. Wang, J.; Xu, C. Geodetector: Principle and Prospective. *J. Geogr. Sci.* **2017**, *72*, 116–134. [CrossRef]
43. Song, Y.; Wang, J.; Ge, Y.; Xu, C. An Optimal Parameters-Based Geographical Detector Model Enhances Geographic Characteristics of Explanatory Variables for Spatial Heterogeneity Analysis: Cases with Different Types of Spatial Data. *GISci. Remote Sens.* **2020**, *57*, 593–610. [CrossRef]
44. Hauke, J.; Kossowski, T.M. Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data. *Quaest. Geogr.* **2011**, *30*, 87–93. [CrossRef]
45. Lieberman, M.G.; Morris, J.D. The Precise Effect of Multicollinearity on Classification Prediction. *Mult. Linear Regres. Viewp.* **2014**, *40*, 5–10.
46. Zumbrunnen, T.; Pezzatti, G.B.; Menéndez, P.; Bugmann, H.; Bürgi, M.; Conedera, M. Weather And Human Impacts on Forest Fires: 100 Years of Fire History in Two Climatic Regions of Switzerland. *For. Ecol. Manag.* **2011**, *261*, 2188–2199. [CrossRef]
47. Wang, Z.-b.; Zhang, X.; Xu, B. Spatio-Temporal Features of China's Urban Fires: An Investigation with Reference to Gross Domestic Product and Humidity. *Sustainability* **2015**, *7*, 9734–9752. [CrossRef]
48. Chang, C.; Chang, Y.; Xiong, Z.-p.; Ping, X.; Zhang, H.; Guo, M.; Hu, Y. Predicting Grassland Fire-Occurrence Probability in Inner Mongolia Autonomous Region, China. *Remote Sens.* **2023**, *15*, 2999. [CrossRef]
49. Wakes, S.J.; Maegli, T.; Dickinson, K.J.M.; Hilton, M. Numerical Modelling of Wind Flow Over a Complex Topography. *Environ. Model. Softw.* **2010**, *25*, 237–247. [CrossRef]
50. Forthofer, J.M.; Butler, B.W.; McHugh, C.W.; Finney, M.; Bradshaw, L.S.; Stratton, R.D.; Shannon, K.; Wagenbrenner, N. A Comparison of Three Approaches for Simulating Fine-Scale Surface Winds in Support of Wildland Fire Management. Part II. An Exploratory Study of the Effect of Simulated Winds on Fire Growth Simulations. *Int. J. Wildland Fire* **2014**, *23*, 982–994. [CrossRef]
51. Sebastián-López, A.; Salvador-Civil, R.; Gonzalo-Jiménez, J.; SanMiguel-Ayanz, J. Integration of Socio-Economic and Environmental Variables for Modelling Long-Term Fire Danger in Southern Europe. *Eur. J. For. Res.* **2008**, *127*, 149–163. [CrossRef]
52. Margolis, E.Q.; Swetnam, T.W. Historical Fire-Climate Relationships of Upper Elevation Fire Regimes in the South-Western United States. *Int. J. Wildland Fire* **2013**, *22*, 588–598. [CrossRef]
53. Spittlehouse, D.; Dymond, C. Interaction of Elevation and Climate Change on Fire Weather Risk. *Can. J. For. Res.* **2022**, *52*, 237–249. [CrossRef]
54. Schoenberg, F.P.; Peng, R.D.; Huang, Z.; Rundel, P.W. Detection of Non-Linearities in the Dependence of Burn Area on Fuel Age and Climatic Variables. *Int. J. Wildland Fire* **2003**, *12*, 1–6. [CrossRef]
55. Schwartz, M.W.; Butt, N.; Dolanc, C.R.; Holguin, A.J.; Moritz, M.A.; North, M.P.; Safford, H.D.; Stephenson, N.L.; Thorne, J.H.; Mantgem, P.J.V. Increasing Elevation of Fire in the Sierra Nevada and Implications for Forest Change. *Ecosphere* **2015**, *6*, 1–10. [CrossRef]
56. Maingi, J.K.; Henry, M.C. Factors Influencing Wildfire Occurrence and Distribution in Eastern Kentucky, USA. *Int. J. Wildland Fire* **2007**, *16*, 23–33. [CrossRef]
57. Pereira, M.G.; Malamud, B.D.; Trigo, R.M.; Alves, P. The History and Characteristics of the 1980-2005 Portuguese Rural Fire Database. *Nat. Hazards Earth Syst. Sci.* **2011**, *11*, 3343–3358. [CrossRef]
58. Miranda, B.R.; Sturtevant, B.R.; Stewart, S.I.; Hammer, R.B. Spatial and Temporal Drivers of Wildfire Occurrence in the Context of Rural Development in Northern Wisconsin, USA. *Int. J. Wildland Fire* **2012**, *21*, 141–154. [CrossRef]
59. Orozco, C.V.; Tonini, M.; Conedera, M.; Kanveski, M. Cluster Recognition in Spatial-Temporal Sequences: The Case of Forest Fires. *GeoInformatica* **2012**, *16*, 653–673. [CrossRef]
60. Ricotta, C.; Bajocco, S.; Guglietta, D.; Conedera, M. Assessing the Influence of Roads on Fire Ignition: Does Land Cover Matter? *Fire* **2018**, *1*, 24. [CrossRef]
61. Penman, T.D.; Bradstock, R.A.; Price, O.F. Modelling the Determinants of Ignition in the Sydney Basin, Australia: Implications for Future Management. *Int. J. Wildland Fire* **2013**, *22*, 469–478. [CrossRef]
62. Laschi, A.; Foderi, C.; Fabiano, F.F.C.; Neri, F.; Cambi, M.; Mariotti, B.; Marchi, E. Forest Road Planning, Construction and Maintenance to Improve Forest Fire Fighting: A Review. *Croat. J. For. Eng.* **2019**, *40*, 207–219.
63. Pourtaghi, Z.S.; Pourghasemi, H.R.; Aretano, R.; Semeraro, T. Investigation of General Indicators Influencing on Forest Fire and Its Susceptibility Modeling Using Different Data Mining Techniques. *Ecol. Indic.* **2016**, *64*, 72–84. [CrossRef]
64. Pundir, A.S.; Raman, B. Deep Belief Network For Smoke Detection. *Fire Technol.* **2017**, *53*, 1943–1960. [CrossRef]