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Prediction of Forest Fire Occurrence in Southwestern China

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Abstract: Southwestern China is an area heavily affected by forest fires, having a complex combination of fire sources and a high degree of human interference. The region is characterized by karst topography and a mixture of agricultural and forested areas, as well as diverse and dynamic mountainous terrain. Analyzing the driving factors behind forest fire occurrences in this area and conducting fire risk zoning are of significant importance in terms of implementing effective forest fire management. The Light Gradient Boosting Machine (LightGBM) model offers advantages in terms of efficiency, low memory usage, accuracy, scalability, and robustness, making it a powerful predictive algorithm that can handle large-scale data and complex problems. In this study, we used nearly 20 years of forest fire data in Southwestern China as the data source. Using mathematical statistics and kernel density analysis, we studied the spatiotemporal distribution characteristics of forest fires in Southwestern China. Considering 16 variables, including climate, vegetation, human factors, and topography, we employed the LightGBM model to predict and zone forest fire occurrences in Southwestern China. The results indicated the following conclusions: (i) Forest fires in Southwestern China are primarily concentrated in certain areas of Sichuan Province (such as Liangshan Yi Autonomous Prefecture and Panzhihua City), Guizhou Province (such as Qiannan Buyi and Miao Autonomous Prefecture), Yunnan Province (such as Puer City, Xishuangbanna Dai Autonomous Prefecture, and Wenshan Zhuang and Miao Autonomous Prefecture), and Chongqing Municipality. (ii) In terms of seasonality, forest fires are most frequent during the spring and winter, followed by the autumn and summer. (iii) The LightGBM forest fire prediction model yielded good results, having a training set accuracy of 83.088080%, a precision of 81.272437%, a recall of 88.760399%, an F1 score of 84.851539%, and an AUC of 91.317430%. The testing set accuracy was 79.987694%, precision was 78.541074%, recall was 85.978470%, F1 score was 82.091662%, and AUC was 87.977684%. These findings demonstrate the effectiveness of the LightGBM model in predicting forest fires in Southwest China, providing valuable insights regarding forest fire management and prevention efforts in the area.

Keywords: forest fire; light gradient boosting; spatial analysis; Southwestern China

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1. Introduction

Forests play an indispensable role in providing raw materials used in production, maintaining the ecological balance of the earth, responding to global climate change, and protecting biodiversity [1–3]. Forests are susceptible to various natural disasters, with forest fires being the most destructive, leading to extensive losses of forest resources and the disruption of forest ecosystems [4], as well as soil erosion [5]. As climate warming [6,7], adverse weather [8,9], and detrimental human activities [10,11] are on the rise, forest fires

have become more frequent and severe. This problem poses challenges to the economy, firefighting, and rescue efforts [12]. Predicting and forecasting these fires is crucial in terms of providing early warnings, maintaining personnel safety, and achieving efficient resource allocation. Climate change significantly influences the occurrence of forest fires [13–15].

Forest fires require specific conditions: ignition, which can have natural or human causes; sufficient combustible material meeting quantity thresholds; and an environment with the appropriate climate and topography. These fires are complex and non-linear processes influenced by various factors. In the past, research into the factors influencing forest fires mainly focused on individual meteorological factors [16–19]. Fire weather forecasts are often based on historical data and meteorological models, which may not accurately predict sudden wildfires or specific situations [20,21]. However, with the continuous advancements in forest fire research, an increasing number of scholars have begun to comprehensively analyze multiple factors, including vegetation, climate, topography, and human activities [22–24]. Additionally, there is evidence indicating that drought, when combined with various factors, such as forest productivity, topography, fire weather, and management activities, influences the frequency of fires [25]. Traditional forest fire prediction models mainly rely on manual rules [26] and statistical methods [27], such as Hurdle models [28,29], Bayesian models [30,31], Poisson regression models [32–34], and logistic regression models [35–37]. However, these methods have some drawbacks, primarily due to their excessive reliance on manual experience and data quality, making it difficult to make accurately predictions under complex conditions. Machine learning models can comprehensively consider multiple factors, such as weather conditions, topography, vegetation status, and human activities [38–42].

By analyzing vast amounts of data, these models can identify and understand the complex relationships between these factors. Utilizing large-scale data to perform training and learning enables machine learning models to make more comprehensive predictions and assessments of forest fire occurrence risks. Ensemble learning can reduce a model's sensitivity to outliers and noisy data, thereby improving the model's generalization ability. A boosting algorithm is a branch of ensemble learning, through which a series of weak classifiers are sequentially trained, and the weights of subsequent classifiers are adjusted based on the results of the previous classifier, gradually improving the overall performance of the classifier [43–45]. Examples of boosting algorithms include Gradient Boosting and XGBoost (Extreme Gradient Boosting) [46,47]. Indeed, the LightGBM algorithm excels in terms of performance, efficiency, and running speed relative to GBDT (Gradient Boosting Decision Trees), XGBoost, and other traditional machine learning methods [48,49]. It is true that the application of the LightGBM model in the field of forest fire prediction is relatively limited, especially in the prediction of forest fire occurrences in Southwestern China, where no reports have been published. Southwestern China, including Yunnan Province, Sichuan Province, Chongqing Municipality, etc., is a frequent occurrence area for forest fires [50].

Due to the complex weather conditions in the region, such as cloudiness, fog, and heavy rainfall, obtaining high-quality remote sensing data in a timely manner can often be challenging [51]; this limitation hinders the feasibility of practical applications for forest fire risk prediction models based on remote sensing data. The difficulty in obtaining timely and high-quality data in Southwestern China may affect the accuracy and effectiveness of such predictive models, posing challenges to their real-world implementation. As a result, alternative approaches or supplementary data sources may need to be considered to improve the reliability and applicability of forest fire risk prediction models in this region.

Therefore, in order to effectively predict forest fire risk in Southwestern China, the following steps are proposed: (i) In-depth exploration of the spatiotemporal patterns of forest fire occurrences in the region. This approach involves analyzing past fire records and relevant data to reveal seasonal and interannual variations, as well as hotspots of forest fires in Southwestern China. (ii) To improve prediction accuracy, a LightGBM forest fire prediction model will be constructed by integrating multiple factors, including

meteorological conditions, land surface cover, and human activities. This approach aims to develop a comprehensive forecast of forest fire occurrences in Southwestern China.

2. Resources and Methods

2.1. The Study Area

Southwestern China, according to its administrative and geographical divisions, includes provinces and municipalities such as Sichuan, Yunnan, Guizhou, Chongqing, and Tibet (Figure 1). It is situated between 78°42′ E and 110°11′ E (longitude) and 21°13′ N and 36°53′ N (latitude) [52]. The region has complex and diverse topography, including high mountains, hills, basins, plateaus, and gorges, among other landform types [52]. The main climate types in Southwestern China are subtropical monsoon climate and plateau climate. The summers are hot and humid, while the winters are relatively warm. The region receives abundant rainfall, making it one of the rainiest areas in China. However, due to the influence of topography, the distribution of rainfall is uneven. The eastern and southern parts of the region experience higher precipitation, while the western and northern parts receive relatively less rainfall [53]. Southwestern China possesses abundant human resources and a diverse ethnic culture. It is also rich in forestry resources, with a variety of forest types, including subtropical evergreen broadleaf forests, coniferous forests, and mixed conifer-broadleaf forests [54,55].

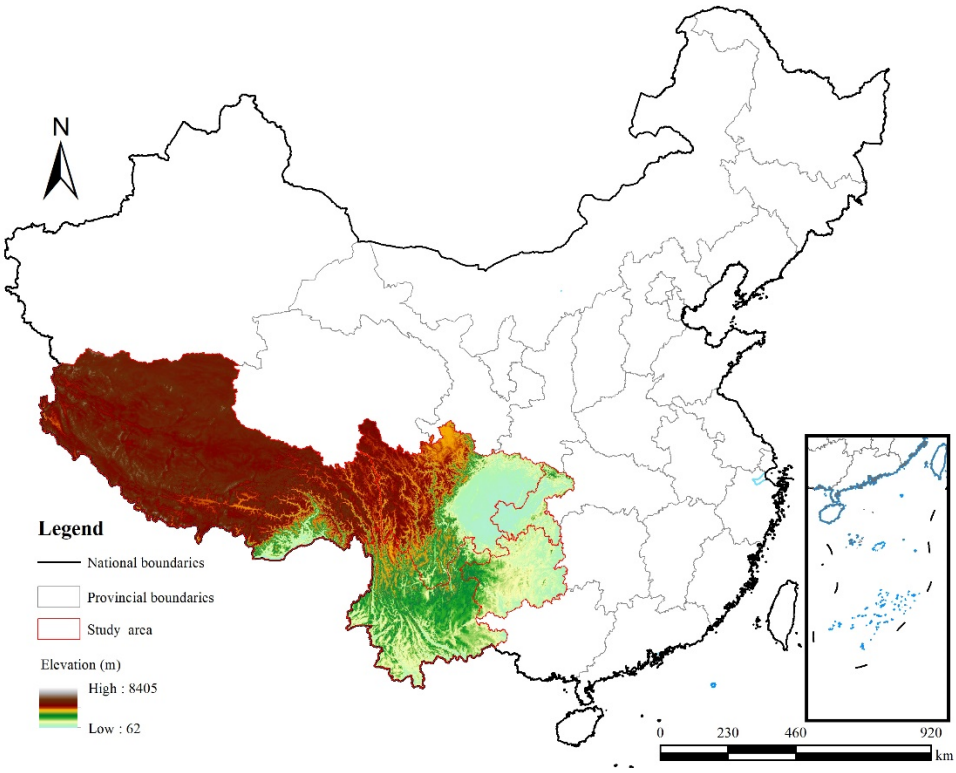

Figure 1. Study area.

2.2. Data Sources (Table 1)

Fire Dataset: This study employed NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) forest fire product, which is accessible through their website (https://earthdata.nasa.gov/, accessed on 1 January 2021). This dataset encompasses essential details, including fire occurrence dates, fire location coordinates (latitude and longitude), confidence levels, brightness, and other pertinent information [55]. These products document fire distribution in Southwestern China from 2000 to 2019. This study extracted 19,787 high-confidence fire points (confidence level > 80%) from the dataset spanning 2001

to 2019. After analyzing fire frequency within the southwestern forest area, these data were used to perform model training and validation.

Geographical data: The land use dataset, terrain data, and NDVI (normalized difference vegetation index) data used in this study were obtained from the Resource and Environment Data Center of the Chinese Academy of Sciences. The primary class accuracy of these datasets exceeds 93%, indicating high data quality and reliability [56]. In this study, the aforementioned dataset was utilized to extract the forest areas in Southwestern China. The terrain data used in the study have a resolution of 1 km and were employed to extract slope and aspect information.

Climatic data: The meteorological data used in this study were obtained from the National Meteorological Center (http://data.cma.cn, accessed on 9 January 2020). Specifically, the dataset used was the China Ground Climate Data (V3.0), which provided daily data on various meteorological indicators, including temperature, precipitation, humidity, air pressure, sunshine hours, wind speed, etc.

Social and cultural data: For the social and economic factors related to fire incidents, the study selected indicators such as residential areas, population density, special holidays (such as Tomb-Sweeping Day, Lantern Festival, Chinese New Year, etc.), and GDP (Gross Domestic Product). These indicators were important in terms of understanding the impact of fire occurrences on local communities and the overall socioeconomic conditions in the region [57]. The population and GDP data were obtained from the Resource and Environment Data Center of the Chinese Academy of Sciences (https://www.resdc.cn/, accessed on 9 January 2020), having a spatial resolution of 1 km. The road and residential area datasets were sourced from the National Geographic Information Resources Catalog System website (http://www.webmap.cn, accessed on 1 January 2019). To address significant differences between the input and output data scales, balance the contributions of various factors, and eliminate dimensional issues between these factors, all data were normalized. The normalization was performed to transform the range of all variables to 0:1. This normalization process ensured that each variable was equally treated and its influence on the final analysis was appropriately considered, regardless of its initial scale or unit [57].

Table 1. Description of datasets used in this study.

Classification	Data	Source
Fire point data	MODIS active fire	https://earthdata.nasa.gov/ (accessed on 1 January 2021)
Land cover data	Multi-period land cover dataset for China	https://www.resdc.cn (accessed on 9 January 2020)
Climatic	Daily average ground surface temperature, daily average relative humidity, daily maximum surface temperature, sunshine hours, etc.	https://data.cma.cn (accessed on 10 October 2021)
Socioeconomic	Population, gross domestic product, special holiday, toad network, residential area, etc.	https://www.resdc.cn (accessed on 9 January 2020) https://www.webmap.cn (accessed on 1 January 2019)
Vegetation	Fractional vegetation cover	https://www.resdc.cn (accessed on 9 January 2020)
Topographic	Slope, elevation, aspect, etc.	https://www.resdc.cn (accessed on 9 January 2020)

2.3. Method

The methodological flowchart used in this study is illustrated in Figure 2. Firstly, all data related to forest fire risk, including various indicators, environmental factors, and geographical information, were stored in a database. The dataset was then randomly divided into a training set and a test set. The training set was used to perform parameter

training of the LightGBM model, while the test set was utilized to evaluate the model's performance and generalization ability. The constructed LightGBM model was trained using the training set through iterative optimization of model parameters to achieve better fitting of the training data. Then, the model's performance was evaluated using the validation set, and the model's hyperparameters were adjusted to enhance its generalization ability. Finally, forest fire risk mapping and zoning were conducted based on the trained model.

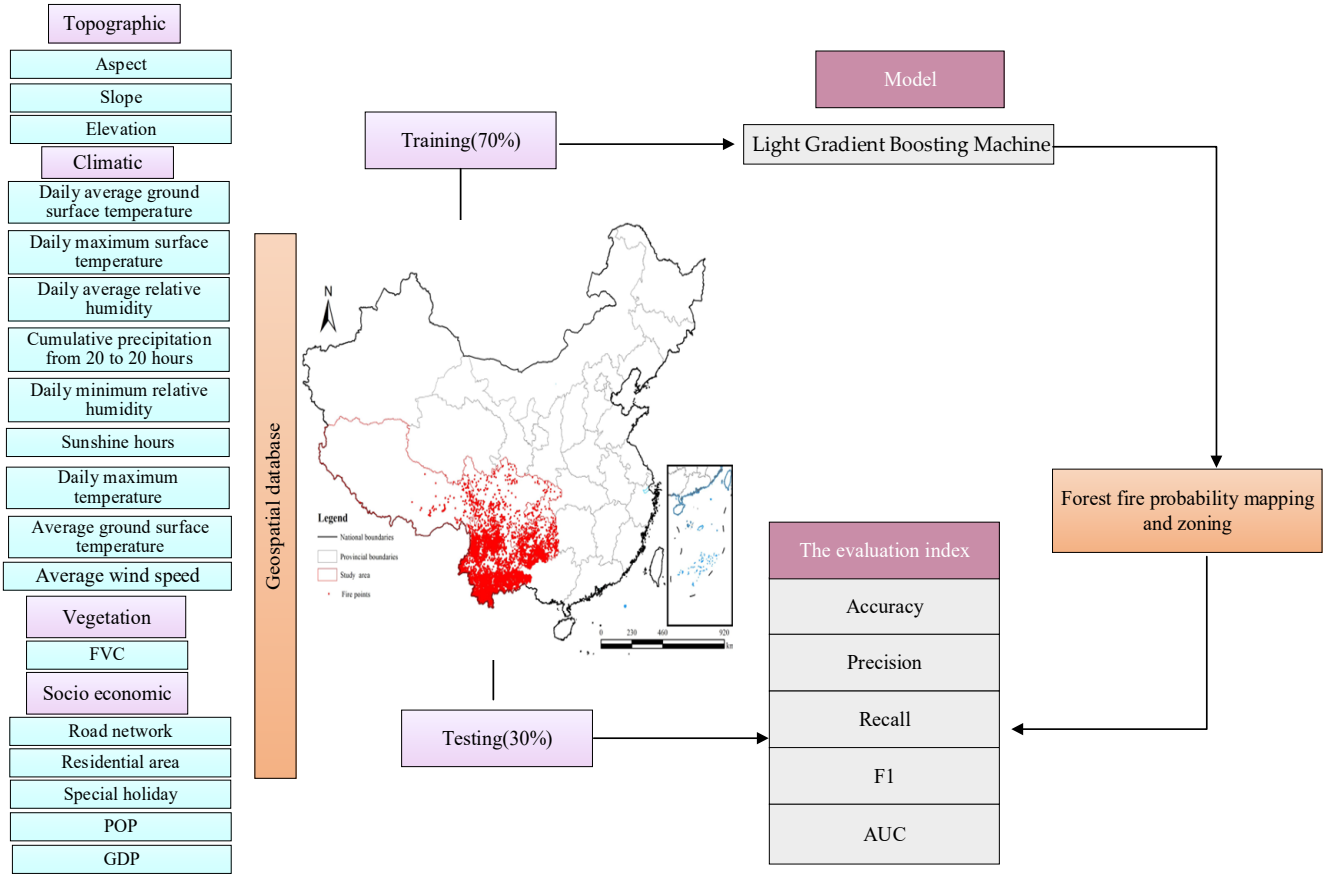

Figure 2. Technology roadmap.

2.3.1. Nuclear Density Analysis

Kernel density estimation is a non-parametric statistical method used to estimate the probability density function of a random variable. It achieves this goal by treating each data point as the center of a kernel function (typically a Gaussian kernel) and superimposing all of the kernel functions to form a smooth density estimation curve [58]. Kernel density analysis could assess the concentration of fire points and reflect the distribution patterns of incidents in the surrounding area. The calculation was performed as follows [59]:

$$f(x) = \sum_{i=1}^{n} k\left(\frac{x - x_i}{h}\right)$$

where $f(x)$ is the kernel density value within the specified threshold range, n is the total number of forest fires within the threshold range, h is the specified search distance for the density value window, and k is the kernel function.

2.3.2. Standard Deviation Ellipse

The standard deviation ellipse method is a technique used to describe the spatial distribution characteristics of a study object. Through this method, we could visually

understand various features of the study object, such as centrality, distribution range, direction, and shape [60,61];

In this study, the center of gravity, distribution range, orientation, and change in forest fires in Southwestern China could be accurately measured, and the formula was defined as follows [62,63]:

Center of gravity:

$$\bar{X} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i}, \bar{Y} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}, \quad (1)$$

Azimuth angle:

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

X and Y axis standard deviation:

$$\sigma_x = \sqrt{\frac{2\sum_{i=1}^{n} (w_i \tilde{x}_i \cos\theta - w_i \tilde{y}_i \sin\theta)^2}{\sum_{i=1}^{n} w_i^2}}, \quad (3)$$

$$\sigma_y = \sqrt{\frac{2\sum_{i=1}^{n} (w_i \tilde{x}_i \sin\theta + w_i \tilde{y}_i \cos\theta)^2}{\sum_{i=1}^{n} w_i^2}}, \quad (4)$$

where n represents the number of prefecture-level cities, (x_i, y_i) represents the geographical coordinates (longitude and latitude) of each prefecture-level city, w_i represents the corresponding forest fire value of each prefecture-level city, $\left(\bar{X}, \bar{Y}\right)$ represents the weighted average centroid coordinates, θ represents the orientation angle of the ellipse, σ_x and σ_y represent the standard deviations of the ellipse along the x–axis and y–axis, and $\tilde{x}_i$ and $\tilde{y}_i$ represent the coordinate deviations of each prefecture-level city from the mean centroid.

2.3.3. Light Gradient Boosting Machine

The LightGBM model utilized the gradient boosting algorithm, in which each iteration fit a new decision tree using the residuals (negative gradient of the loss function) of the current model [64]. In this way, each new decision tree was built on top of the existing model, adding a new function to gradually approach the true values of the entire model's predictions. In forest fire prediction, dealing with a large amount of geographical information, meteorological data, and historical fire records is often necessary. LightGBM could quickly construct and train models, demonstrating strong capabilities in handling high-dimensional and sparse features, thus enhancing prediction speed and efficiency.

The objective function of LightGBM can be expressed as follows [65]:

$$\hat{y} = \sum_{k=1}^{K} f_k(x), f_k \in F, \quad (5)$$

where K represents the number of decision trees, F represents the collection of all decision trees, and f_k represents the k-th decision tree generated in the k-th iteration, which belongs to the function space F. The complexity of a tree was expressed as the number of leaf nodes T and the sum of squares of output results w for each leaf node of the tree [65], as shown in the following equation:

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{t} w_j^2, \quad (6)$$

2.3.4. Evaluation Index

Accuracy, precision, recall, F1, and AUC are performance evaluation indexes commonly used in machine learning and statistics to evaluate the performance of classification models. The formula was defined as follows [66]:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}, \quad (7)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}, \quad (8)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}, \quad (9)$$

$$\text{F1} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

Accuracy: Accuracy measures the overall correctness of the model's predictions. It is the ratio of correctly predicted samples to the total number of samples. However, in dealing with imbalanced datasets, accuracy may not be the optimal metric, as one class may dominate the majority of samples.

Precision: Precision focuses on the model's positive predictions and measures the proportion of correctly predicted positive samples among all samples predicted to be positive. Precision is a useful metric when the cost of misclassifying positive instances is high or minimizing false positives is crucial.

Recall (also known as sensitivity or the true positive rate): Recall measures the proportion of correctly predicted positive samples among all actual positive samples. Recall is useful when the cost of misclassifying negative instances is high or minimizing false negatives is important.

F1 Score: The F1 Score is the harmonic mean of precision and recall. It provides a single metric that combines precision and recall. The F1 Score seeks a balance between precision and recall and is useful when a balance between minimizing false positives and false negatives is needed.

AUC (area under the ROC curve): AUC is a metric commonly used to solve binary classification problems. It measures the model's performance at all possible classification thresholds. The ROC curve plots the relationship between the true positive rate (recall) and the false positive rate (1—specificity) at different thresholds. AUC represents the area under this curve, and a higher AUC indicates the better overall performance of the model.

3. Results

3.1. Changing Trends

In Figure 3, the seasonal variation in forest fires in Southwestern China from 2001 to 2019 is visualized. It is evident that forest fires in Southwestern China exhibit distinct seasonal patterns, with higher occurrences in spring and winter and relatively fewer incidents in summer and autumn. In terms of the overall trend, both spring and winter show similar changing patterns, but the number of fire points in spring is significantly higher than in winter, and both seasons exhibit fluctuating multi-peak patterns.

The highest peak of forest fires in spring occurred in 2010, which divides the period into two stages. From 2001 to 2010, the number of fire points showed an increasing trend, while from 2010 to 2019, it exhibited a decreasing trend, albeit with a rising tendency. In the winter season, three peaks occurred in 2005, 2010, and 2014, and the changing trend is symmetric around the year 2010. The occurrences of forest fires in summer and autumn are relatively less frequent, with minimal fluctuation, but there is a gradual upward trend, especially during summer, when the upward trend is prominent.

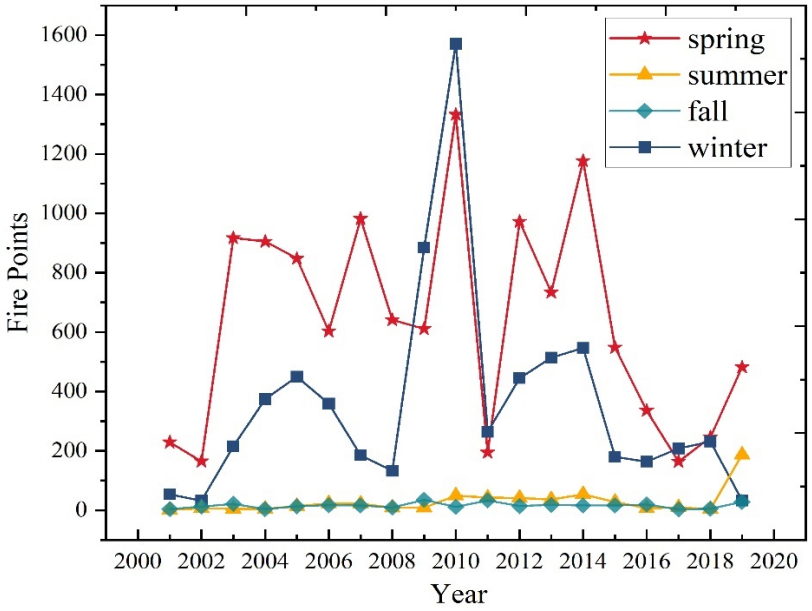

Figure 3. Cumulative distance leveling curve.

3.2. The Result of Standard Deviation Ellipse

As shown in Figure 4, based on the standard deviation ellipse, the calculation of forest fire occurrences in Southwestern China from 2001 to 2019 reflects the spatial aggregation characteristics and temporal changes in fire points in an intuitive manner. From the analysis of the centroid changes, the center of forest fire occurrences in Southwestern China is concentrated in Yunnan Province, and the overall trajectory forms a "mouth" shape. Specifically, from 2001 to 2005, the centroid moved 89.4 km in a southwestern direction, indicating a significant increase in forest fire occurrences in the southwestern part compared to 2001. From 2005 to 2010, the centroid moved 227.3 km in a northeastern direction, indicating a significant increase in forest fire occurrences in the northeastern part of Southwestern China. From 2010 to 2015, there was a slight movement of 82.3 km in a northwestern direction, and from 2015 to 2019, it moved 117.5 km in a southwestern direction. The centroid of forest fire occurrences from 2001 to 2019 was mainly distributed in Puer City, Yuxi City, and Kunming City, before eventually moving to Yuxi City. The azimuth fluctuated significantly from 2001 to 2019, without obvious directional characteristics. The minor axis mainly fluctuated in the range of 440–550 km, with slight expansions in 2001 and 2015. The major axis showed an overall increasing trend, increasing from 490.32 km to 886.96 km from 2010 to 2015 and then slightly reducing from 2015 to 2019. The changes in the minor and major axes indicate a continuous east–west expansion trend of forest fire occurrences in Southwestern China, while the north–south direction is relatively stable. After a significant expansion from 2001 to 2005, the flattening ratio remained relatively stable from 2005 to 2019. Considering the changes in the major and minor axes, it is clear that Southwestern China experienced significant expansion in forest fire occurrences from 2010 to 2015, with the east–west expansion trend stronger than that moving in the north–south direction, resulting in relatively small fluctuations in the flattening ratio. Based on the distribution and changes in the standard deviation ellipse from 2001 to 2019, it can be concluded that the spread direction of forest fire occurrences in Southwestern China is variable, lacking a clear trend. Yunnan Province has been the most affected by forest fires overall, but as forest fire occurrences expand in the east–west direction, the impacts on Guizhou Province, the southwestern part of Sichuan Province, western Chongqing, and eastern Tibet gradually increase (Table 2).

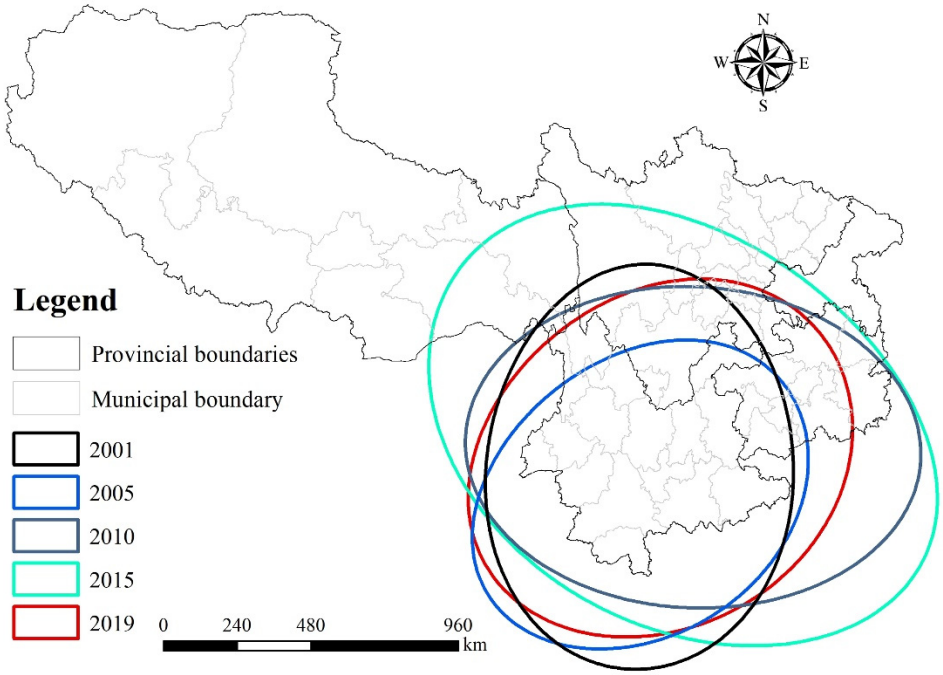

Figure 4. The result of the standard deviation ellipse in Southwestern China.

Table 2. Standard deviation of the oval-shaped parameters of forest fire occurrence in Southwestern China, 2001–2019.

Year	CenterX/°	CenterY/°	XStdDist/m	YStdDist/m	Rotation/°	Oblateness
2001	101.36	24.32	490.32	666.61	4.27	0.74
2005	101.48	23.51	591.86	446.99	51.09	1.32
2010	103.05	24.95	736.07	528.21	92.61	1.39
2015	102.55	25.54	886.96	641.08	123.62	1.38
2019	102.09	24.6	666.32	534.97	52.46	1.25

3.3. The Result of Nuclear Density

The kernel density results of forest fire occurrences in Southwestern China show that high-density areas are concentrated in regions such as Xishuangbanna Dai Autonomous Prefecture, Puer City, Dali Bai Autonomous Prefecture, Liangshan Yi Autonomous Prefecture, and Panzhihua City. The occurrence of forest fires in Southwestern China is influenced by multiple factors, including climate conditions, human activities, natural factors, and fire prevention and control capabilities. These high-density areas may have drier and hotter climate characteristics, which promote the occurrence and spread of fires. Additionally, these regions may have complex terrain, dense mountains, insufficient fire prevention facilities, obstructed fire roads, and lax supervision, leading to difficulties in terms of timely controlling and extinguishing fires (Figure 5).

3.4. Accuracy Assessment

The specific performance metrics of the model, including accuracy, precision, recall, F1 score, and AUC, are shown in Figure 6. For the training dataset, the accuracy is 83.089%, precision is 81.27%, recall is 88.76%, F1 score is 84.85%, and AUC is 91.32%. For the testing dataset, the accuracy is 79.99%, precision is 78.54%, recall is 85.98%, F1 score is 82.09%, and AUC is 87.98%. The performance metrics used for the entire dataset are as follows: the accuracy is 82.16%, precision is 80.45%, recall is 87.93%, F1 score is 84.02%, and AUC is 90.32%.

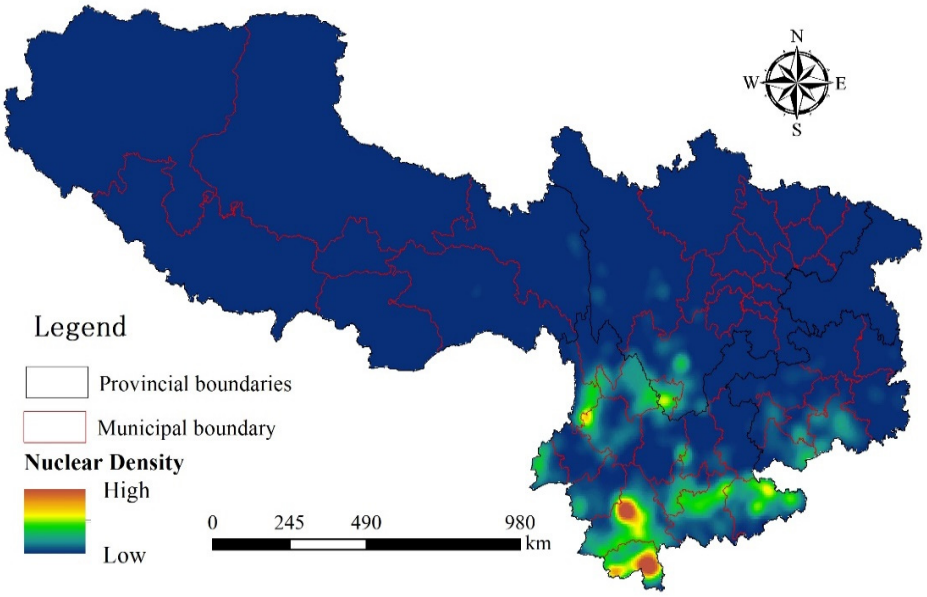

Figure 5. Nuclear density of forest fire occurrence in Southwestern China.

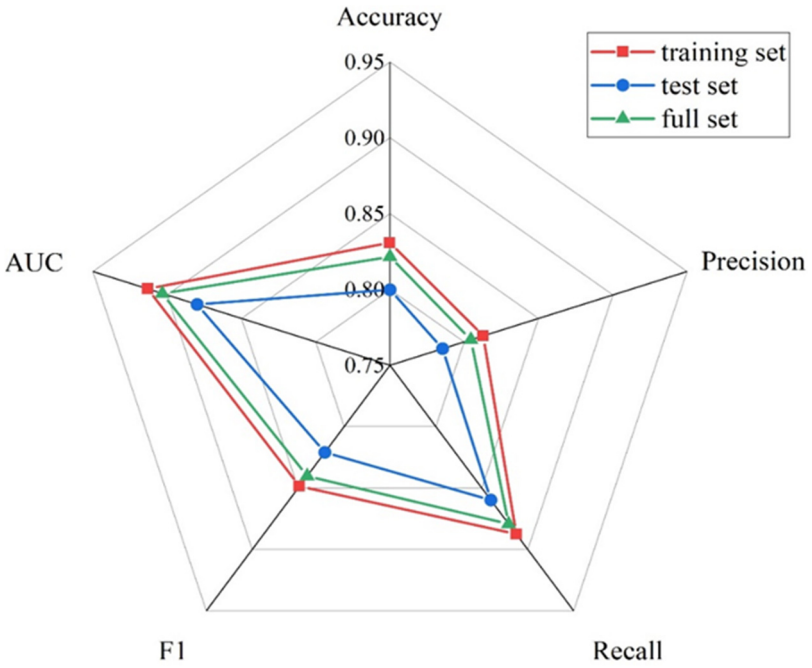

Figure 6. Accuracy evaluation of the Light Gradient Boosting Machine Model.

3.5. Results of Fire Zone Mapping

In this study, the prediction and spatial zoning were performed using the LightGBM model, as illustrated in Figure 7; the forest fire occurrences for each season are as follows: Across the year, elevated forest fire risks are concentrated in specific regions: Yunnan Province (comprising Pu'er City, Xishuangbanna Dai Autonomous Prefecture, and Wenshan Zhuang and Miao Autonomous Prefecture), Sichuan Province (encompassing Liangshan Yi Autonomous Prefecture and Panzhihua City), Guizhou Province (including Qiannan Buyei and Miao Autonomous Prefecture), and select areas of Chongqing Municipality. The most frequent forest fire occurrences align with spring and winter, followed by autumn and summer. During spring, Yunnan Province (including Honghe Hani and Yi Autonomous Prefecture, Lijiang City, and Chuxiong Yi Autonomous Prefecture), Sichuan Province (encompassing Liangshan Yi Autonomous Prefecture, Suining City, and

Panzhihua City), Guizhou Province (covering Tongren City, Qiannan Buyei, and Miao Autonomous Prefecture), and specific areas of Chongqing Municipality experience heightened forest fire risk. The areas at highest risk in summer include Pu'er City in Yunnan Province, Panzhihua City in Sichuan Province, and certain areas of Chongqing Municipality. Autumn elevates the risk in Panzhihua City in Sichuan Province, Wenshan Zhuang and Miao Autonomous Prefecture of Yunnan Province, Yuxi City in Yunnan Province, and specific areas of Chongqing Municipality. Areas at the highest risk in winter include Yunnan Province (including Nujiang Lisu Autonomous Prefecture, Dali Bai Autonomous Prefecture, Lijiang City, and Wenshan Zhuang and Miao Autonomous Prefecture), Sichuan Province (covering Liangshan Yi Autonomous Prefecture and Panzhihua City), Guizhou Province (encompassing Qiannan Buyei and Miao Autonomous Prefecture, Tongren City), and specific areas of Chongqing Municipality. During winter, areas at the highest risk of forest fires include Yunnan Province (including Nujiang Lisu Autonomous Prefecture, Dali Bai Autonomous Prefecture, Lijiang City, and Wenshan Zhuang and Miao Autonomous Prefecture), Sichuan Province (encompassing Liangshan Yi Autonomous Prefecture and Panzhihua City), Guizhou Province (including Qiannan Buyei and Miao Autonomous Prefecture and Tongren City), and specific areas of Chongqing Municipality. The climate conditions of Southwestern China include high temperatures, dryness, and strong winds. These climatic conditions make vegetation more susceptible to drying out and catching fire, thus increasing the risk of forest fires [67].

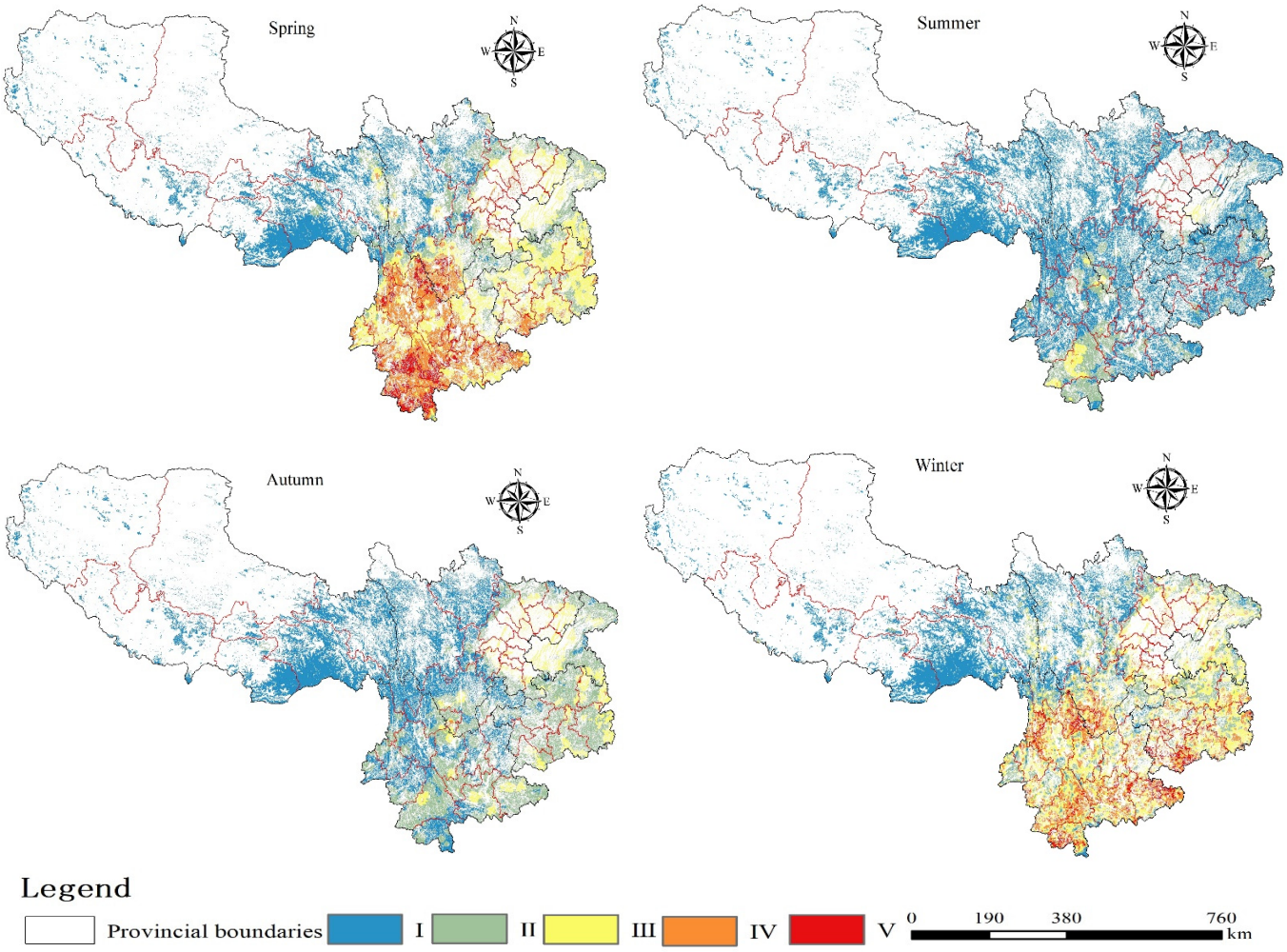

Figure 7. Forest fire zoning in Southwestern China (Classes I, II, III, IV, and V indicate very low, low, medium, high, and very high risk, respectively).

Southwestern China possesses dense forests and abundant vegetation. When the vegetation becomes excessively dense, wildfires can easily rapidly spread. Moreover, forests in this region are mainly composed of coniferous tree species, which contain resin and bark rich in combustible materials, making them susceptible to fire outbreaks. Human activities are one of the major factors contributing to forest fires. Improper practices, such as illegal logging, burning during field clearing, and open burning of grass in agricultural and forestry management, can lead to fire incidents. Additionally, human-related fire sources, fireworks, and firecrackers used during peak fire seasons increase the risk of wildfires. These factors collectively contribute to the frequent occurrence of forest fires in Southwestern China [66,68].

Spring is typically a high-risk season for wildfires, as it is characterized by rising temperatures and reduced precipitation. Autumn, on the other hand, experiences increased rainfall compared to summer, leading to greater accumulation of dry leaves and higher probabilities of forest fires. Despite relatively low temperatures, winter may still pose a risk for wildfires due to possible drought and the lack of precipitation. Extended dry periods during winter can result in dry and inflammable vegetation and forest areas, thereby increasing the risk of forest fires. Additionally, certain human activities may trigger wildfires, such as field burning, illegal logging, and uncontrolled burning practices. Winter also coincides with traditional festivals and the use of fireworks and firecrackers, which can further elevate the risk of fire incidents. Therefore, it is essential to establish effective forest fire monitoring and early warning systems, which may include satellite monitoring, meteorological data analysis, fire risk assessment, and early warning systems. These measures aim to promptly detect and respond to potential fire hazards. Strengthening public awareness of and education about forest fires is crucial to enhance fire prevention awareness. Developing and implementing relevant forest fire prevention laws and regulations, as well as rigorously enforcing them, will help to combat illegal wildfires, logging, and other unlawful practices, reducing the number of human-induced fires. Regulating and monitoring the use of outdoor fire sources, especially during dry and high-risk periods, is also essential. Prohibiting the use of flammable items, such as fireworks and firecrackers, and enhancing the management and supervision of burning activities will ensure the safe use of fire sources. Investing in the construction of firebreaks and access roads is essential to ensure smooth traffic within forest areas, enabling firefighting personnel and equipment to reach the locations swiftly when needed [69]. Conducting regular forest management activities, including pruning and thinning overly dense vegetation, is crucial to reduce the accumulation of combustible materials and the spread of fires. Additionally, strengthening patrols and inspections in forest areas will help to identify and address potential fire hazards in a timely manner.

4. Discussion and Conclusions

The LightGBM forest fire prediction model demonstrated a good forecasting performance. NDVI (normalized difference vegetation index) is an index calculated based on the reflectance of vegetation in remote sensing images. It is commonly used as an indicator to assess vegetation greenness and growth conditions. In this research, NDVI is used to represent the fuel load, but the amount of fuel load, particularly the amount of litter (dry grass/dead vegetation), provides a more accurate reflection of the fuel condition than NDVI [70]. At a large regional scale, the complexity of vegetation types results in diverse spectral characteristics and spatial variability. This complexity makes it challenging to directly infer the amount of litter from remote sensing images. Different vegetation types exhibit significant differences in spectral reflectance, and the contribution of litter varies based on the vegetation type. Therefore, establishing an accurate correspondence between actual reflectance and remote sensing image reflectance becomes challenging [71].

In the future, ground surveys and sampling will be conducted to obtain more accurate data regarding litter loads. These data will be used to validate and invert the remote sensing images, allowing a more precise estimation of litter loads. By integrating ground-based

measurements into remote sensing technology, researchers can enhance the reliability and accuracy of assessments of litter loads in various vegetation types and improve the overall understanding of forest fire risks and dynamics [72]. By taking this approach, a specific relationship model can be established for a particular region or vegetation type, thereby more accurately inferring litter loads. This model will be based on ground-based data collected through surveys and sampling, which will serve as the ground truth. In addition, future research will incorporate the study of extreme weather events' impacts on forest fire occurrences in Southwestern China [73]. In addition to the temporal scale, future studies should consider different spatial scales. The research area can be divided into various regions, plots, or geographical units to analyze the occurrences of forest fires among them. Establishing a multi-scale forest fire dataset and conducting spatiotemporal analysis will contribute to a more comprehensive understanding and assessment of the spatiotemporal distribution characteristics of forest fires.

The main objective of this study was to investigate the occurrence of forest fires in Southwestern China and utilize the LightGBM model to perform prediction and spatial zoning. We acknowledged the significance of ignition factors in fire prediction; however, in this particular study, our primary focus was on understanding the combined effects of various factors on fire probability, aiming to provide a holistic predictive framework. Due to the limitations in data availability and quality, we chose to incorporate representative factors, such as residential areas and road networks, into our model to capture the influence of human activities. While we did not include detailed information about lightning activity and ignition sources in the current study, we recognized the potential importance of these factors in terms of influencing fire occurrences. In future research, our main objective will be to adjust and optimize the forest fire risk prediction model by collecting more data, aiming to improve the accuracy and reliability of the predictions. To achieve this goal, we plan to consider new factors, such as spatiotemporal elements [74], government policy [75], lightning strike [76], and soil moisture [77], in the analysis. To comprehensively predict the occurrence risk of forest fires in the region, we will consider joint monitoring of forest fire occurrence and suppression using multi-source remote sensing data. In addition to predicting forest fire incidents, this approach will enhance our ability to effectively monitor and respond to fire emergencies [78,79]. We also plan to establish a feedback mechanism to evaluate and optimize our predictive results by comparing them to actual fire events. This feedback loop is crucial in terms of achieving continuous improvement of the model and indicators. To achieve these objectives, we will actively collect more data. We will seek diverse data sources and ensure data integrity and accuracy. Real-time data acquisition will be a focus to enable timely monitoring and assessment of fire risks. Additionally, we will consider seasonal variations, regional characteristics, and other relevant factors that more accurately reflect the occurrence risk of forest fires in Southwestern China.

In conclusion, this study has extensively leveraged a diverse range of datasets encompassing historical fire records, meteorological observations, topographic information, vegetation indices, population demographics, economic indicators, and geographical data spanning two decades in Southwestern China. Through the application of mathematical techniques and kernel density analysis, a comprehensive exploration of the spatial and temporal distribution patterns of forest fires in this region was conducted. Furthermore, this study has meticulously identified driving factors intricately linked to forest fire occurrences, categorizing them into climate parameters, topographic characteristics, vegetation variations, and human activities. The amalgamation of these crucial factors facilitated the development of a robust forest fire prediction model using LightGBM. This predictive model demonstrated its effectiveness in forecasting and visually representing the risk of forest fire incidents across the entirety of Southwestern China. The findings of this investigation have revealed prominent patterns in the occurrence of forest fires within Southwestern China. The concentration of these incidents within specific geographic areas, most notably provinces such as Sichuan, Guizhou, and Yunnan, as well as certain parts of Chongqing, has been accentuated. In summary, this study has not only shed light on the

intricate dynamics of forest fires within Southwestern China, but also paved the way for the creation of a reliable predictive tool to assess and map the likelihood of such incidents. This knowledge holds the potential to inform proactive fire management strategies and resource allocation in the mitigation of forest fire risks.

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