

Article

Forest Fire Forecasting and Early Warning Model Based on Satellite FY-4 and Other Multi-Source Data

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Abstract

Forest fires pose a severe threat to ecosystems and human safety in the mountainous Liangshan Prefecture, China. To enhance early warning capabilities, this study constructs a fire risk prediction model by combining FY-4A satellite data, historical fire records, and terrain data. Through principal component analysis and multicollinearity diagnostics, critical factors including topography, vegetation indices (NDVI, NDII7), and a moisture index (TVDI) were selected for a logistic regression model. The model successfully identifies key risk drivers, with vegetation moisture content (NDII7) being the most influential. Validation shows the model achieves an AUC of 0.77 and a prediction accuracy of 71.5%, confirming its effectiveness. This work demonstrates the utility of China's FY-4 satellite for operational forest fire risk forecasting, providing a methodological basis for improved disaster prevention.

Keywords: forest fire in Liangshan Prefecture; FY-4A satellite; logistic regression; ROC curve

1. Introduction

A forest fire refers to uncontrolled wildfire behavior in forested land [1], posing severe threats to the ecological environment, air quality, and human safety. Liangshan Prefecture, a high-altitude region with abundant forests and a subtropical monsoon climate, experiences distinct dry seasons characterized by high temperatures, low humidity, and windy conditions, leading to highly combustible vegetation. Consequently, spring and winter are peak fire seasons, with devastating events like the 2019 Muli and 2020 Xichang fires causing significant losses [1]. This underscores the critical need for effective forest fire early warning.

Numerous studies have focused on forest fire warning technology. The most widely applied model is the Canadian Forest Fire Danger Rating System (CFDRS) [2], which integrates multi-source data. Similar systems developed in the United States also form a theoretical foundation for fire danger warning. To improve applicability and accuracy, recent models incorporate diverse factors (e.g., distance to infrastructure) and advanced algorithms, such as geographically weighted logistic regression [3] and the MARS-DFP model [4]. Furthermore, the rapid development of remote sensing and artificial intelligence has propelled the field forward. Research now encompasses multi-source data for all-weather monitoring [5], spatiotemporal analysis in specific regions [6], and monitoring of fire spread [7]. Advanced



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techniques include super-resolution for smoke segmentation [8], deep learning for fire detection [9], methods to reduce false alarms [10], spatiotemporal contextual models [11], deep learning frameworks for fire index forecasting [12], AI-based index fusion [13], deep neural networks for spread prediction [14], and machine learning for regional assessment [15], demonstrating increasing sophistication in predictive modeling.

Extensive research has been conducted on forest fire warning in China. Early studies primarily focused on meteorological factors, such as the average maximum temperature, consecutive dry days, and dryness index [16], as well as models incorporating wind speed, humidity, and comprehensive ignition sources [17]. Subsequent work established regional warning systems using factors like precipitation, brightness temperature, and road density [18], or seasonal patterns of temperature and humidity [19], with logistic regression also being applied to pre-fire meteorological conditions [20]. Specific research on Liangshan Prefecture has analyzed spatiotemporal fire characteristics [21], developed real-time monitoring algorithms [22], and calculated fire risk probabilities using logistic models based on terrain, vegetation, and socio-economic data [23]. Satellite-based monitoring in the region has also been advanced using GF-4 geostationary imagery [1]. Concurrently, the application of China's self-developed satellite data, including FY-3D with genetic algorithms [24] and the Transformer-XGBoost model [25], has progressed. Research in other key regions, such as Yunnan, employs methods like convolutional neural networks [26], spatial-scale predictive models [27], and all-weather monitoring systems [5]. Additional contributions, including the use of international geostationary satellites [28], statistical and weighted modeling [29], lightning-based prediction [30], nationwide machine learning predictions [31], and GIS-based risk modeling [32], collectively enrich the methodological spectrum of forest fire research in China.

Compared to conventional monitoring methods, satellite remote sensing technology offers significant advantages for forest fire monitoring, such as wide coverage, high spatiotemporal resolution, and timeliness. It enables quicker and more timely monitoring of forest fire occurrences and progression. The FY-4 satellite, China's new generation of geostationary meteorological satellites, is equipped with an advanced optical imager. This instrument can continuously capture high-frequency, high-quality data with full coverage of the monitored areas. Such capabilities provide valuable information for forest fire suppression efforts and open a new phase for forest fire early warning system research in China. While most previous studies have relied on MODIS data from NASA satellites, this study utilizes data from China's independently developed FY-4 satellite. We integrated FY-4 remote sensing imagery with geographic information, wildfire records from 2018 to 2021 in the Liangshan area, and Digital Elevation Model (DEM) data obtained from the "Geospatial Data Cloud" of the Chinese Academy of Sciences. Using principal component analysis, multicollinearity diagnostics, and a logistic regression model, we constructed a forest fire warning model for Liangshan Prefecture based on terrain, vegetation, and meteorological factors. The resulting model can provide theoretical support for forest fire warning in the region.

2. Data and Methods

2.1. The Study Area

Liangshan Prefecture is located between 100°26'–103°56' E and 26°03'–29°15' N in the southwestern part of Sichuan Province (Figure 1). The region exhibits complex physical geographical characteristics, which are fundamental to understanding its forest fire regime.

Liangshan Prefecture experiences a subtropical monsoon climate characterized by distinct dry and wet seasons. The annual average temperature ranges from 14 °C to 17 °C. The wet season (June to October) receives the majority of the annual precipitation. Conversely, the dry season (November to May) is marked by high temperatures, low

precipitation, low relative humidity, and frequent windy conditions, particularly in the valleys [30].

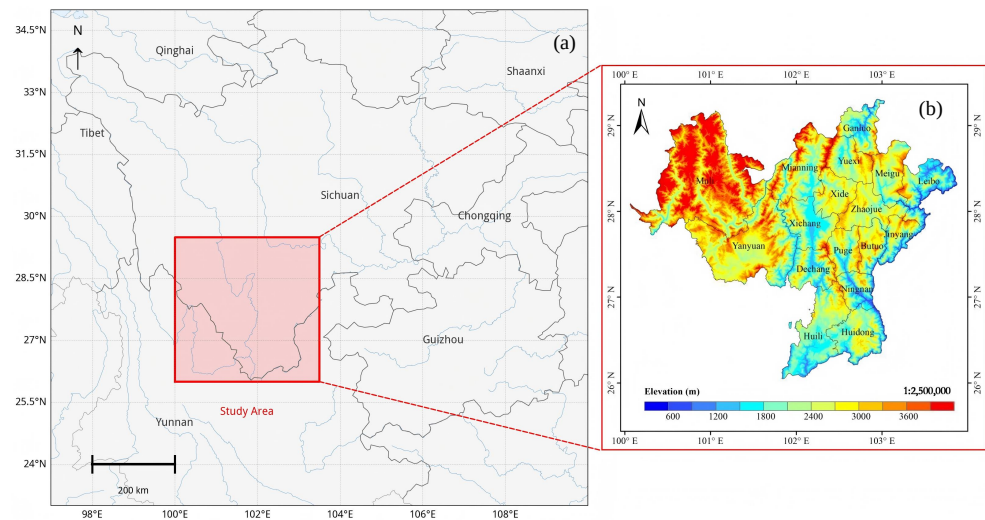


Figure 1. Location of the study area. (a) General location of Liangshan Prefecture within Sichuan Province and China. (b) Detailed map of Liangshan Prefecture showing its topography.

The terrain is dominated by high mountains and deep valleys with intermontane basins, forming a landscape that slopes from northwest to southeast. Elevation ranges dramatically from approximately 256 m in the southern river valleys to 5898 m at the peak of Mount Gongga in the north [33].

The region is dissected by several major river systems, including the Yalong, Anning, and Jinsha rivers, which have carved deep gorges [33]. These rivers, along with their tributaries, create a dense drainage network that influences local microclimates and vegetation distribution.

The pronounced vertical relief results in distinct vegetation zonation. Coniferous forests cover extensive areas across the mid-elevation slopes and represent the dominant combustible fuel type [30]. Other vegetation types include mixed coniferous-broadleaf forests, broadleaf forests, shrublands, grasslands, meadows, and cultivated vegetation. As will be shown in Section Land Cover Types, coniferous forests accounted for the highest proportion (50.79%) of recorded fire occurrences from 2018 to 2021.

2.2. Datasets

The forest fire and meteorological data for the period 2018–2021 were obtained from the Liangshan Prefecture Forestry and Grassland Bureau and the Liangshan Prefecture Meteorological Bureau, respectively. The dataset comprises a total of 64 fire records.

FY-4A remote sensing data were obtained from the National Meteorological Satellite Center. The satellite's Advanced Geosynchronous Radiation Imager (AGRI) provides 14 optical channels (Table 1), with bands B7, B8, and B12 offering the optimal combination for fire detection. Although AGRI channels have spatial resolutions ranging from 0.5 km to 4 km (Table 1), all FY-4A-derived products used in this study—including reflectances for index calculation and land surface temperature—were resampled to a uniform 4 km resolution using bilinear interpolation. This common resolution aligns with the coarsest bands required for fire detection and surface temperature retrieval and is suitable for regional-scale risk assessment.

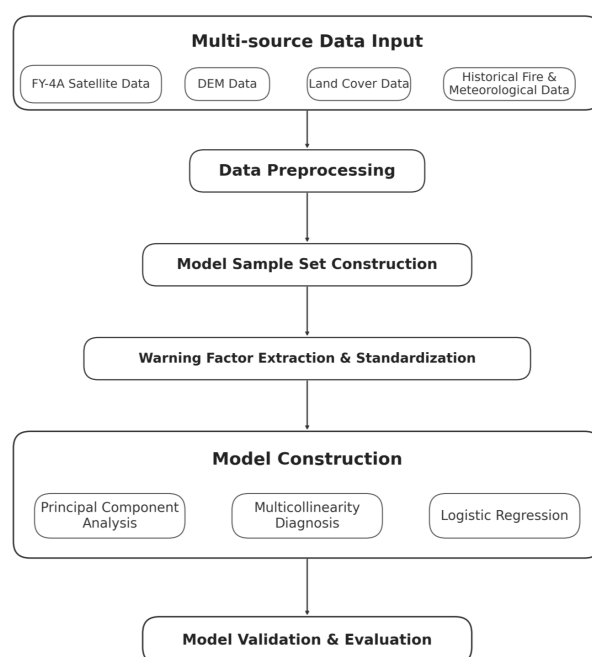
Spatial data for Liangshan Prefecture, including 30-m resolution elevation data, were sourced from the “Geospatial Data Cloud” of the Chinese Academy of Sciences.

Table 1. The information of bands of FY-4.

Band Number	Wavelength Ranges (μm)	Central Wavelengths (μm)	Resolution (km)	Main Applications
B1	0.45~0.49	0.47	1.0	Small particle aerosols, True color composite
B2	0.55~0.75	0.65	0.5	Vegetation, Stellar observation, image positioning
B3	0.75~0.90	0.83	1.0	Vegetation, Aerosols over the water surface
B4	1.36~1.39	1.37	2.0	Cirrus cloud
B5	1.58~1.64	1.61	2.0	Low clouds, Snow detection, Water cloud identification
B6	2.1~2.35	2.22	2.0	Cirrus clouds, Aerosols, Particle size
B7	3.5~4.0	3.72	2.0	Cloud and other high albedo targets, Fire points
B8	3.5~4.0	3.72	4.0	Daily surface albedo, Surface
B9	5.8~6.7	6.25	4.0	High-level Water vapor
B10	6.9~7.3	7.10	4.0	Mid-level Water vapor
B11	8.0~9.0	8.50	4.0	Total water vapor, Cloud
B12	10.3~11.3	10.8	4.0	Surface temperature
B13	11.5~12.5	12.0	4.0	Total water vapor content, Surface temperature
B14	13.2~13.8	13.5	4.0	Cloud, Water vapor

2.3. Methods

The methodological framework for developing the forest fire early warning model is depicted in Figure 2. The process is structured into four consecutive phases: (1) multi-source data preprocessing, involving the harmonization of FY-4A satellite imagery, DEM, and land cover data; (2) model sample set construction, creating a balanced dataset of fire and non-fire points; (3) model establishment, featuring factor screening via principal component analysis and multicollinearity diagnostics, followed by logistic regression fitting; and (4) model testing and evaluation, utilizing ROC curve analysis and accuracy metrics to validate predictive performance.

**Figure 2.** Methodological workflow of the forest fire early warning model construction.

2.3.1. Principal Component Analysis

Principal Component Analysis (PCA) is a multivariate statistical method for dimensionality reduction. It transforms the original data through linear transformation into a set of linearly independent variables, known as principal components, which retain as much information from the original data as possible.

2.3.2. Multicollinearity Diagnostic Analysis

Multicollinearity diagnostic analysis is used to detect and assess collinearity among independent variables in a multiple regression model. Collinearity refers to a high correlation between independent variables, which can lead to unstable model estimates and unreliable regression coefficients. Consequently, this affects the prediction and interpretation of the dependent variable. Addressing multicollinearity can improve the model's stability and predictive performance.

2.3.3. Analytic Hierarchy Process

The analytic hierarchy process (AHP) is a quantitative analysis method for multi-criteria decision-making, adaptable to various real-world situations. It structures complex decision problems into a hierarchy. By employing pairwise comparisons and weight calculations, it helps decision-makers systematically evaluate and choose between alternatives to arrive at a final decision. The fundamental idea behind AHP is to break down the decision problem into hierarchical levels, such as goals, criteria, and alternative options. Through pairwise comparisons and priority derivation (often involving eigenvalue calculations), a final decision can be obtained.

2.3.4. Fire Occurrence Frequency

Fire occurrence frequency (f) refers to the frequency of forest fire under different conditions in Liangshan Prefecture.

$$f = \frac{k}{n} \times 100 \quad (1)$$

where n represents the total number of fire occurrences during 2018–2021, and k is the number of fire occurrences under certain statistical conditions.

2.3.5. Harmonization of Multi-Resolution Data and Processing Flow

Given the multi-resolution nature of the FY-4A AGRI bands, a specific processing workflow was adopted to calculate vegetation and moisture indices while preserving data integrity. For indices requiring bands of different native resolutions (e.g., NDVI using B2 at 0.5 km and B3 at 1 km), the higher-resolution band was first resampled to match the resolution of the lower-resolution band using bilinear interpolation. The index was then calculated at this intermediate resolution. Subsequently, all derived index rasters (NDVI, NDII7) and the land surface temperature product were resampled to a final, common analysis resolution of 4 km. This 'calculate-then-resample' approach minimizes information loss compared to resampling raw bands to the coarsest resolution prior to calculation. The choice of 4 km as the final grid size represents a balance suitable for regional-scale modeling and aligns with the spatial scale of the dominant forest fire spread and risk patterns in Liangshan Prefecture.

2.4. Risk Warning Factors for Forest Fires

Referring to the construction of domestic and international forest fire warning models, the preliminary selection of risk factors was conducted using expert scoring combined with the AHP to weigh and prioritize potential variables. For topographic factors (elevation, slope, aspect), refs. [30,33] justify the importance of terrain characteristics in fire behavior. For vegetation factors (NDVI, land cover), refs. [30,33–35] support the role of vegetation structure and fuel characteristics. For moisture indices (NDII7, TVDI), refs. [35,36] validate these as critical moisture indicators. The factors of Table 2 were subsequently chosen for building the forest fire warning model.

Table 2. The factors for forest fire risk warning.

Types of Factors	Factors
Types of combustible materials	Vegetation index (NDVI) Land cover type (LC) Fuel type (FT)
Humidity	Temperature vegetation drought index (TDVI) Normalized difference infrared index (NDII7)
Topography	Elevation (ELE) Slope (SLP) Aspect (ASP)

2.4.1. Topography

Elevation

Elevation has an impact on plant growth and local climate. Generally, at lower elevations, relative humidity is higher, which leads to increased moisture content in forest vegetation and thus reduces the probability of fires. As elevation increases, wind speed also tends to increase. Should a fire occur at higher elevations, the stronger winds can accelerate its spread. The topography of Liangshan Prefecture and the distribution of fire points from 2018 to 2021 are shown in Figure 3, while the number and frequency of forest fires across different altitudes are presented in Table 3. The elevation in Liangshan ranges from 256 to 5898 m, being higher in the northwest than in the southeast. Forest fires occur mainly in the northwest, such as in Muli and Mianning, whereas fewer fires are recorded in areas like Zhaojue and Meigu. The highest altitude at which a forest fire was recorded is 3103 m, and the lowest is 1438 m. To statistically analyze the relationship between fire occurrence and elevation, the actual elevation range of all recorded fire points (from the lowest at 1438 m to the highest at 3103 m) was divided. Using the equal interval classification method, which is common in geographic and environmental studies, the entire range was partitioned into six intervals of approximately 280 m each. The number and frequency of fires within these elevation intervals are presented in Table 3. Most fires occurred at altitudes between 1438 and 1718 m, with 17 incidents, accounting for 26.5% of the total.

The spatial distribution of fire points (Figure 3) reveals a pronounced concentration in the northwestern part of Liangshan Prefecture, notably in Muli and Mianning counties. This pattern is closely linked to the region's topography. These areas are characterized by higher elevations and complex mountainous terrain. The concentration of fires at elevations between 1438 and 1718 m (accounting for 26.5% of occurrences, Table 3) may represent an optimal risk zone. At these mid-elevations, vegetation is often sufficient to provide continuous fuel loads, while the climatic conditions—particularly during the dry season—combine lower humidity and higher temperatures than in the deep valleys, yet are not as persistently wet as the highest peaks. This creates a recurrent environment where fuels dry out effectively, elevating fire risk. The lower fire frequency at the highest elevations (>2800 m) is likely due to lower temperatures, higher humidity, and more fragmented vegetation cover.

Table 3. The number and frequency of forest fire occurrences at different altitudes during 2018–2021 in Liangshan Prefecture.

Altitude (m)	Number of Forest Fires	Frequency of Forest Fires
1438–1718	17	26.5
1718–1998	14	21.8
1998–2278	10	15.6
2278–2558	13	20.3
2558–2838	8	12.5
2838–3103	2	3.12

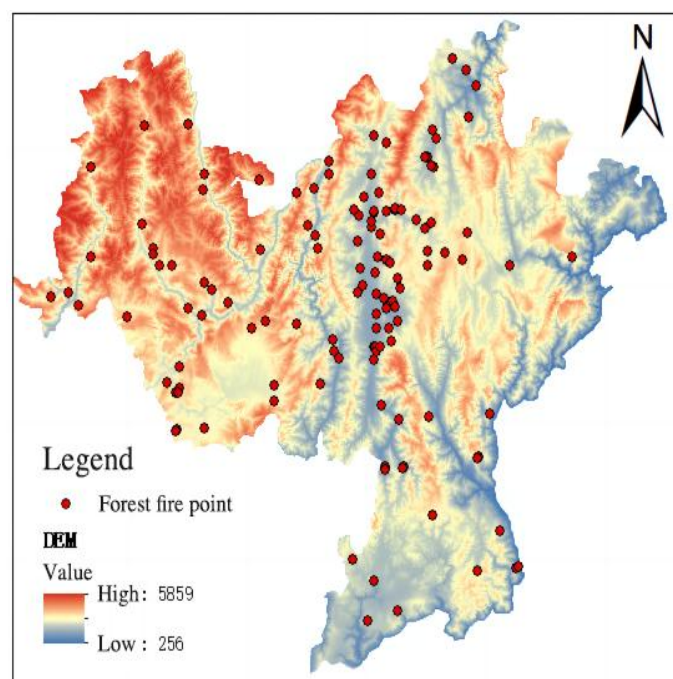


Figure 3. The topography and the distribution of forest fire points in Liangshan Prefecture.

Slope

The water storage capacity of the ground is negatively correlated with slope steepness. On steeper slopes, surface moisture loss is more severe, leading to lower moisture content in forest fuels and consequently a higher probability of fire ignition and spread. The spread rate of a forest fire is also influenced by slope, with steeper slopes accelerating the fire's progression. It is generally observed that for every 5-degree decrease in slope angle, the rate of fire spread is reduced by half. The slope distribution and the locations of fire points from 2018 to 2021 in Liangshan Prefecture are shown in Figure 4, while the number and frequency of fires across different slope ranges are presented in Table 4. Forest fires occurred mainly in areas with slopes between 0° and 54° ; no fires were detected on slopes exceeding 54° . The strong predominance of fires on slopes between 18° and 36° (53.84%) underscores the critical role of terrain steepness in fire initiation and behavior. Steeper slopes promote faster drainage of surface water and soil moisture, leading to drier and more combustible fuels. Furthermore, from a fire physics perspective, slope directly accelerates upslope fire spread. Radiative and convective heat transfer is oriented preponderantly uphill, preheating fuels ahead of the flame front.

Table 4. The number and frequency of forest fire occurrences at different slopes during 2018–2021 in Liangshan Prefecture.

Slope ($^{\circ}$)	Number of Forest Fires	Frequency of Forest Fires
0–18	17	26.5
18–36	36	53.84
36–54	12	19.66
54–72	0	0
>72	0	0

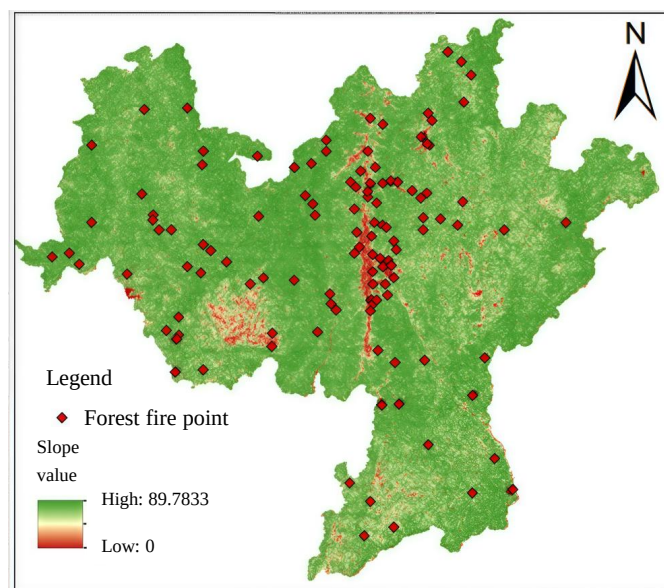


Figure 4. The slope and the distribution of forest fire points.

Aspect

Aspect was classified into nine categories for analyzing its relationship with forest fire frequency. As shown in Table 5, which presents the number and frequency of forest fires across different aspects in Liangshan Prefecture from 2018 to 2021, fires occurred most frequently on west- and southwest-facing slopes. These aspects recorded 15 and 11 fires, accounting for 23.43% and 17.18% of the total, respectively. In contrast, flat areas and east-facing slopes experienced the fewest fires, with only 2 and 3 occurrences (3.12% and 4.68%, respectively). North and southeast aspects showed moderate fire activity, each recording 8 fires, which corresponds to a frequency of 12.5%.

Table 5. The number and frequency of forest fire occurrences at different aspects during 2018–2021 in Liangshan Prefecture.

Aspect	Flat	North	Northeast	East	Southeast	South	Southwest	West	Northwet
Number of forest fires	2	8	6	3	8	5	11	15	6
Frequency of forest fires	3.12	12.5	9.37	4.68	12.5	7.81	17.18	23.43	9.37

2.4.2. Types of Combustible Materials

Land Cover Types

Different vegetation types exhibit varying susceptibility to ignition and fire intensity. Therefore, vegetation type is a critical factor in forest fire prediction models. Figure 5 displays the land cover types and the distribution of forest fire points in Liangshan Prefecture. Correspondingly, Table 6 presents the number and frequency of forest fires across different vegetation types from 2018 to 2021. Liangshan Prefecture features a diverse range of vegetation types. Among these, coniferous forests not only cover the largest area but also experienced the highest number of fires, with 32 occurrences, accounting for 50.79% of the total.

The finding that coniferous forests account for 50.79% of all fire occurrences (Table 6, Figure 5) aligns with well-documented fuel characteristics of these ecosystems. Coniferous species, particularly pines and firs common in Liangshan, often contain volatile resins and terpenes that lower ignition thresholds. Their canopy structure allows for higher solar radiation penetration and wind flow within the stand, aiding fuel drying. Additionally, the needle litter they produce forms a continuous, porous, and highly flammable surface

fuel bed that facilitates fire ignition and spread. In contrast, broadleaf forests typically have higher fuel moisture content and less flammable litter, while shrublands and grasslands, though flammable, may have lower fuel biomass or be subject to different ignition and management pressures. This makes coniferous forests the landscape’s primary “fire carrier” vegetation type.

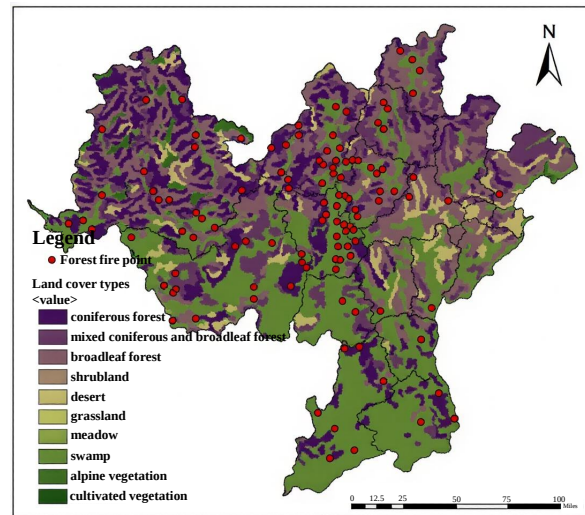


Figure 5. The land cover types and distribution of forest fire points in Liangshan Prefecture.

Table 6. The number of occurrences and frequency of forest fire with different vegetation types in Liangshan Prefecture during 2018–2021.

Vegetation Type	Number of Occurrences	Frequency
Coniferous Forest	32	50.79
Mixed Coniferous and Broadleaf Forests	1	1.58
Broadleaf Forests	4	6.34
Shrubland	9	14.28
Desert	0	0
Grassland	3	4.76
Meadow	1	1.58
Swamp	0	0
Alpine Vegetation	0	0
Vultivated Vegetation	13	20.63

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) [34] reflects the degree of vegetation cover on the land surface. Sufficient ground vegetation coverage, as indicated by a higher NDVI, is necessary to provide the fuel required to sustain a forest fire [35]. The NDVI is calculated using the surface reflectance from FY-4A bands B2 and B3. The formula is:

$$NDVI = \frac{\rho_{NIR} - \rho_R}{\rho_{NIR} + \rho_R} \quad (2)$$

where ρ_{NIR} (0.75~0.90 μm) and ρ_R (0.55~0.75 μm) represent the surface reflectance of B2 and B3 in the geometrically corrected FY-4A satellite imagery data, NDVI ranges from -1 to 1 .

(1) When $NDVI < 0$, the ground cover is water, cloud, or snow; when $NDVI = 0$, the ground cover is rock or bare soil. This means the forest fires can not occur when $NDVI \leq 0$.

(2) When $NDVI > 0$, NDVI index is directly proportional to the ground vegetation coverage.

(3) When $0 < NDVI \leq 0.1$, the vegetation coverage is extremely low, when $0.1 < NDVI \leq 0.3$, the vegetation coverage is low, when $0.3 < NDVI \leq 0.5$, the vegetation

coverage is moderate, when $0.5 < \text{NDVI} \leq 0.7$, the vegetation coverage is moderately high, when $0.7 < \text{NDVI} \leq 1$, the vegetation coverage is high. The larger the NDVI value, the higher the vegetation coverage.

When calculating the NDVI using FY-4A satellite data (bands B2 and B3), issues such as data gaps and cloud cover can arise. Since vegetation coverage does not change significantly over short periods, a monthly composite NDVI can be used to ensure data accuracy for model construction.

The spatial distribution of the NDVI and forest fire points in March for Liangshan Prefecture is shown in Figure 6, and the corresponding fire frequency across different NDVI ranges from 2018 to 2021 is presented in Table 7. No fires were recorded in areas with $\text{NDVI} < 0.2$. The highest number of fires occurred in the NDVI ranges of 0.2–0.4 and 0.4–0.6, with 27 fires (42.2%) in each range. Combined, these two ranges ($0.2 < \text{NDVI} \leq 0.6$) accounted for 85% of all forest fires.

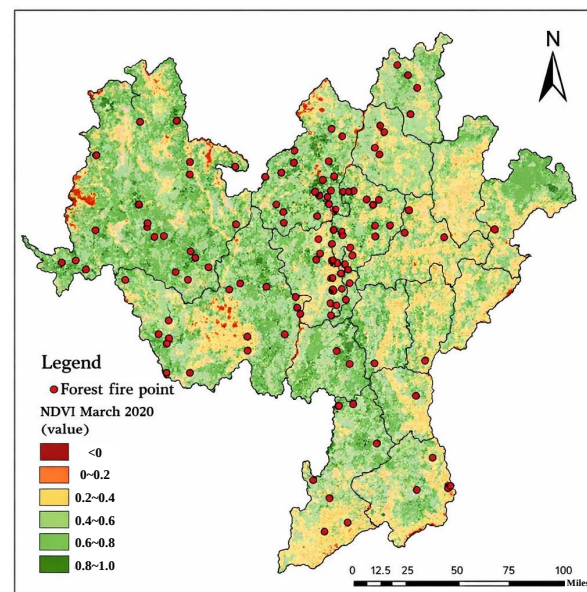


Figure 6. The NDVI index and forest fire points in March in Liangshan Prefecture.

The concentration of 84.36% of fires within the NDVI range of 0.2 to 0.6 (Table 7, Figure 6) reveals a non-linear relationship between vegetation greenness and fire risk. Very high NDVI values (>0.7) indicate dense, vigorous vegetation typically associated with higher fuel moisture and less flammable conditions. Conversely, very low NDVI values (<0.2) often represent sparse vegetation with insufficient fuel continuity to sustain a spreading fire. The intermediate range (0.2–0.6) represents a critical “Goldilocks zone” for fire risk: vegetation is abundant enough to provide a continuous fuel load (e.g., forests, dense shrubs), yet dry enough (due to seasonal drought or water stress) to become highly combustible. This range likely includes both healthy but water-stressed forests and drier shrubland/grassland complexes, both key contributors to the regional fire regime.

Table 7. The number and frequency of fire occurrences at different NDVI indices in Liangshan Prefecture during 2018–2021.

NDVI	Number of Forest Fires	Frequency of Forest Fires
<0	0	0
0–0.2	0	0
0.2–0.4	27	42.18
0.4–0.6	27	42.18
0.6–0.8	9	14.06
0.8–1	1	1.56

2.4.3. Humidity

Normalized Difference Infrared Index

The moisture content of forest fuels is a critical factor in determining the ease of ignition and spread of forest fires. Consequently, it serves as an essential indicator for assessing forest fire risk. Asam et al. [35] demonstrated the water absorption curve in plants, which can serve as an indicator of moisture content in combustible materials. Normalized Difference Infrared Index (NDII7), which significantly affects forest fire ignition, can be calculated using bands B3 and B6 from FY-4A. The formula is as follows:

$$\text{NDII7} = \frac{\rho_3 - \rho_6}{\rho_3 + \rho_6} \quad (3)$$

where ρ_3 and ρ_6 are the reflectance of FY-4A B3 (0.75~0.90 μm) and B6 (2.1~2.35 μm). Lower NDII7 values indicate drier vegetation conditions, which are associated with higher fire risk.

Figure 7 shows the spatial distribution of the NDII7 index calculated from FY-4A data for Liangshan Prefecture on May 30, 2020. The frequency of forest fires across different NDII7 ranges from 2018 to 2021 is presented in Table 8. The data indicate that no fires occurred within the NDII7 ranges of $0 < \text{NDII7} < 0.1$ and $0.5 < \text{NDII7} < 1$. The highest number of fires (24 occurrences, accounting for 36.92% of the total) was concentrated in the range of $0.2 < \text{NDII7} < 0.3$. Overall, forest fires were most likely to occur within the broader NDII7 range of $0.1 < \text{NDII7} < 0.5$.

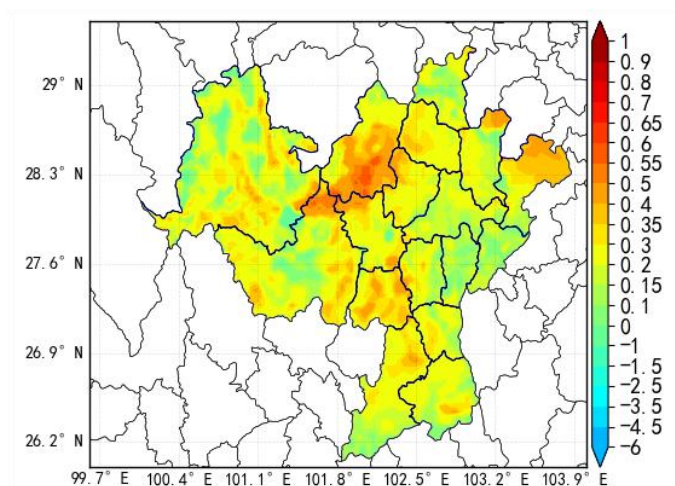


Figure 7. The distribution of NDII7 on March 30, 2020 in Liangshan Prefecture.

Table 8. The number and frequency of fire occurrences at different NDII7 indices in Liangshan Prefecture during 2018–2021.

NDVII7	Number of Forest Fires	Frequency of Forest Fires
0–0.1	0	0
0.1–0.2	14	21.53
0.2–0.3	24	36.92
0.3–0.4	21	32.81
0.4–0.5	5	7.69
0.5–1	0	0

NDII7 is a sensitive indicator of canopy water content, with lower values signifying drier vegetation. The distribution of fire points (Figure 7) shows that over 91% of fires occurred when NDII7 was below 0.5, and none occurred when NDII7 exceeded 0.5 (Table 8).

This establishes a clear moisture threshold for fire occurrence in this region. The peak fire frequency within the 0.2–0.3 range suggests that this interval represents a critical level of fuel desiccation where live and dead fuels have lost significant moisture, drastically reducing the energy required for ignition. This finding operationally validates NDII7 derived from FY-4A as a key real-time variable for assessing the “ignition readiness” of vegetation, complementing the structural information provided by NDVI.

Temperature Vegetation Drought Index

The Temperature Vegetation Drought Index (TVDI) [36] is a method for assessing surface moisture conditions by utilizing optical and thermal infrared remote sensing data. A higher TVDI value indicates a greater probability of forest fire occurrence. The calculation formula for TVDI is as follows:

$$\text{TVDI} = \frac{T_s - T_{\min}}{T_{\max} - T_{\min}} \quad (4)$$

where T_s represents the land surface temperature ($^{\circ}\text{C}$), $T_{\min}$ and $T_{\max}$ are the minimum and maximum land surface temperature corresponding to the given NDVI, respectively.

$$T_{\max} = a + b \times \text{NDVI} \quad (5)$$

$$T_{\min} = c + d \times \text{NDVI} \quad (6)$$

Here, a , b , c , and d are the regression coefficients for the dry- and wet-edge equations. For a given vegetation index, as the land surface temperature (T_s) approaches the maximum temperature ($T_{\max}$), the TVDI increases, indicating lower vegetation moisture. The TVDI is scaled between 0 and 1.

Land surface temperature (LST) was obtained from the FY-4A Level 2 product, while the NDVI was calculated using B2 and B3 bands from the FY-4A Level 1 data. The TVDI calculation requires the determination of the theoretical maximum (dry edge) and minimum (wet edge) land surface temperatures for each NDVI value within the study area. This is achieved by analyzing the feature space formed by plotting NDVI against LST. Figure 8 shows this characteristic LST-NDVI scatter plot for Liangshan Prefecture on a representative date (30 March 2020). The data points form a triangular distribution, where the upper envelope represents the dry edge (conditions of maximum water stress and heating), and the lower envelope represents the wet edge (conditions of maximum moisture and evaporative cooling).

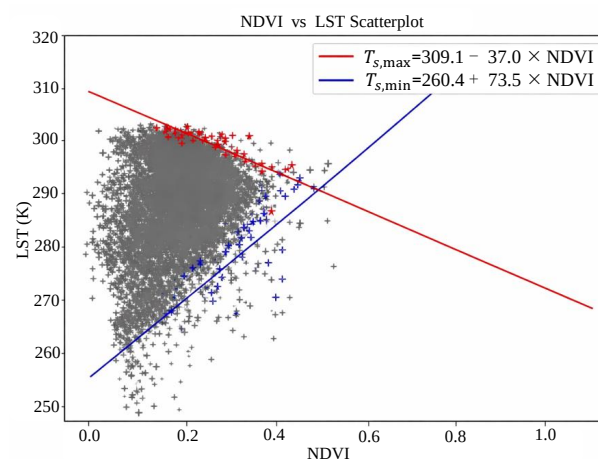


Figure 8. The scatter plot of T_s and NDVI (the data is derived from FY-4A on 30 March 2020).

Through fitting boundary of scatter plot, the dry-wet edge equation can be derived:

$$T_{\max} = 309.1 - 37.0 \times \text{NDVI} \quad (7)$$

$$T_{\min} = 260.4 + 73.5 \times \text{NDVI} \quad (8)$$

where the parameters of dry and wet edge equations are as follows:

$$a = 309.1, b = -37.0, c = 260.4, d = 73.5.$$

The linear regression lines fitted to these boundaries (shown conceptually in Figure 8) provide the coefficients (a, b, c, d) necessary to calculate $T_{\max}$ and $T_{\min}$ in Equations (5) and (6) for any given NDVI. Subsequently, the TVDI for each pixel can be computed using Equation (4). A TVDI value closer to 1 indicates drier surface conditions and, consequently, a higher potential fire risk.

The corresponding minimum and maximum surface temperature for a given NDVI can be calculated by the above equations. Then the TVDI can also be calculated (Figure 9). Spatially, higher TVDI values (drier conditions) are evident in the river valleys and lower elevations during the dry season, which correlates well with the observed distribution of historical fire points.

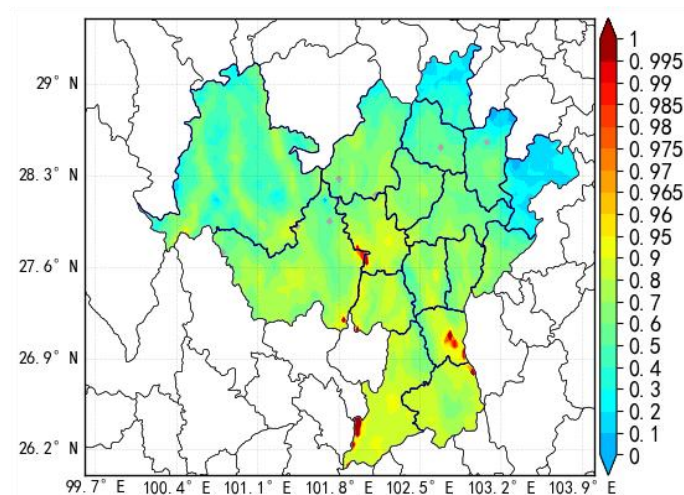


Figure 9. The distribution of TVDI in Liangshan Prefecture (the data derived from FY-4A on 30 March 2020).

2.5. Model Formulation and Structure

Based on the prepared dataset and the validated set of independent predictors, a logistic regression model was fitted to quantify the relationship between the warning factors and the probability of forest fire occurrence. The model was structurally designed to consist of two additive components: a fixed part and a dynamic part. This design is grounded in both physical understanding and operational practicality.

The fixed part ($z_1 = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4$) incorporates static factors: elevation (x_1), slope (x_2), aspect (x_3), and land cover type (x_4). These topographic and land cover characteristics are invariant over short timescales and represent the inherent, long-term susceptibility of the landscape to fire. This component can be pre-calculated once using Digital Elevation Model (DEM) and land cover data to generate a baseline static risk layer.

The dynamic part ($z_2 = \alpha_5 x_5 + \alpha_6 x_6 + \alpha_7 x_7$) integrates near-real-time satellite-derived indices: NDVI (x_5), NDII7 (x_6), and TVDI (x_7). These indices, calculated from the FY-4A imagery, reflect the instantaneous conditions of vegetation vigor, canopy water content, and surface moisture, which fluctuate daily with weather and seasonal changes.

This separation offers key operational advantages for an early warning system. The static risk layer (z_1) serves as a permanent backdrop. Upon the arrival of new FY-4A data (every 15 min for full-disk scans), only the dynamic indices need to be processed and combined with z_1 through the logistic function to compute the updated fire probability P .

Based on the design principle of integrating static landscape susceptibility and dynamic environmental conditions, the logistic regression model for forest fire early warning is formulated as follows:

$$P(Y = 1) = \frac{e^z}{1 + e^z} = \frac{e^{\alpha_0 + z_1 + z_2}}{1 + e^{\alpha_0 + z_1 + z_2}} \quad (9)$$

$$P(Y = 0) = \frac{e^z}{1 + e^z} = \frac{1}{1 + e^{\alpha_0 + z_1 + z_2}} \quad (10)$$

where z_0 is the constant term of the logistic regression model. z_1 and z_2 are the linear functions of the independent variables.

$$z_1 = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_3 x_3 + \alpha_4 x_4 \quad (11)$$

$$z_2 = \alpha_5 x_5 + \alpha_6 x_6 + \alpha_7 x_7 \quad (12)$$

where x_1, x_2, x_3 , and x_4 represent ELE, SLP, ASP, and LC, respectively. These four are static factors that remain constant over time. In contrast, x_5, x_6 , and x_7 represent the NDII7, TVDI, and NDVI indices, respectively. These three are dynamic factors, derived in near real-time from FY-4 satellite data. The terms $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_7$ are the regression coefficients for the corresponding independent variables.

3. Forest Fire Prediction Mode

The development and validation of the forest fire early warning model proceeded through a sequence of logical steps, presented in this section. First, the composition of the modeling dataset is described. Subsequently, the relative importance and statistical independence of the candidate warning factors are analyzed. These analyses then inform the fitting of the logistic regression model, whose final form, interpretation, and predictive accuracy are presented in sequence.

3.1. The Composition of the Datasets for Forest Fire Prediction Model

In this paper, a logistic regression method was used to construct the forest fire prediction model. The construction of such a model requires a set of non-fire point samples. Since the generation of non-fire points can affect model accuracy, a conventional approach is to create non-fire points at 1.5 times the number of fire points. These non-fire points must satisfy specific conditions: they must exhibit no spatial autocorrelation [37] (i.e., the distance between any two points should be ≥ 1 km), be evenly distributed across the study area, and possess temporal randomness in their occurrence dates [38]. Following this method, the final sample dataset for forest fire warning was constructed, comprising 97 historical fire points and 116 randomly generated non-fire points, resulting in a total of 213 sample points. Figure 10 shows the spatial distribution of both fire and non-fire points in Liangshan Prefecture.

Based on historical forest fire data from Liangshan Prefecture, warning factors were extracted according to the time and location of fire occurrences. To ensure consistent value ranges during model fitting, all warning factors were normalized. Among these factors, the NDVI, NDII7, and TVDI indices are real-time variables derived from FY-4A Level 1 data, and their values naturally fall within the $[0, 1]$ range. Other factors, such as ELE, SLP, ASP, and LC, are static. These were uniformly mapped to the $[0, 1]$ interval through a linear transformation of the raw data.

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (13)$$

where x is the raw data, x_{max} and x_{min} are the maximum and minimum of datasets, respectively. Figure 11 shows the elevation (left) and the normalized elevation (right) in Liangshan Prefecture.

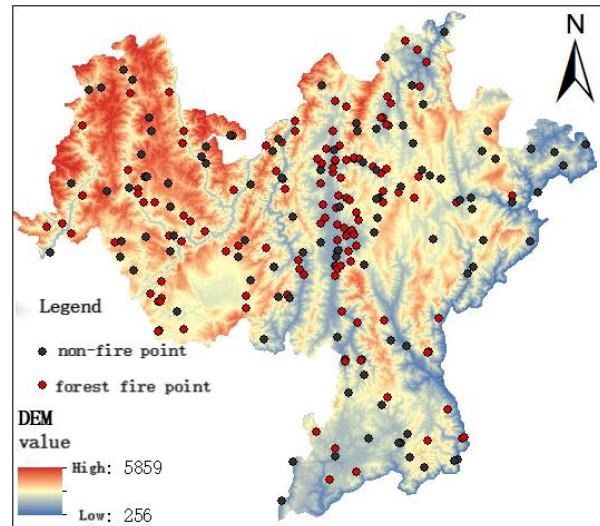


Figure 10. The distribution of sample of risk warning model.

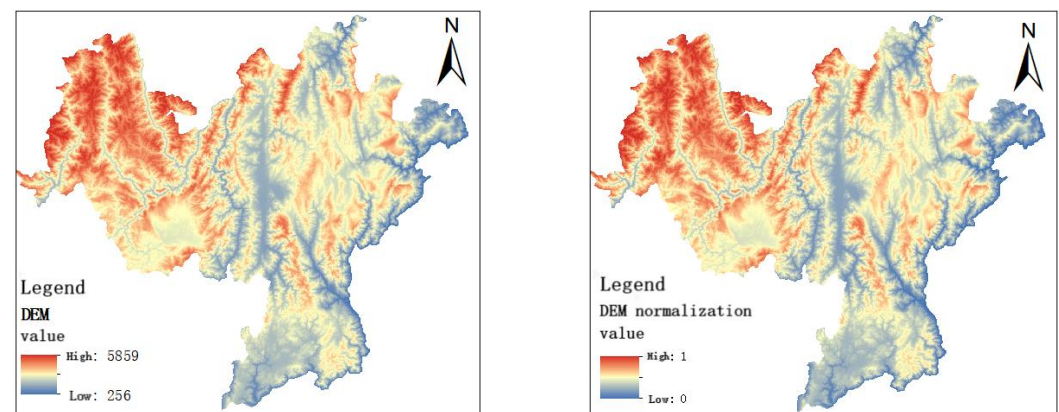


Figure 11. The elevation (left) and the normalized elevation (right) in Liangshan Prefecture.

In this paper, the initial set of predictor variables includes meteorological indices (TVDI, NDII7), topographic factors (ELE, SLP, ASP), and vegetation factors (NDVI, LC). These variables are all treated as continuous numerical types for modeling purposes.

The sample dataset was split into training and validation subsets at an 8:2 ratio. Using the training data, the PCA was applied to evaluate the contributions of the warning factors and to conduct multicollinearity diagnostics. This analysis helps determine the suitability of these factors for inclusion in a logistic regression model. Subsequently, the validation data are used to test the accuracy of the forest fire early warning model and to evaluate its effectiveness for providing warnings in Liangshan Prefecture.

This curated and balanced sample dataset forms the essential foundation for the subsequent statistical analyses aimed at identifying key risk drivers and building a predictive model.

3.2. Analysis of Early Warning Factors Weights

To understand the relative influence of the seven selected warning factors on fire occurrence, PCA was performed on the training dataset. Therefore, before constructing the logistic regression model for forest fire warning, it is essential to analyze the influence of the selected predictors on fire occurrence, assess the contribution of each factor, and determine whether any redundant factors are present. If multicollinearity exists among the selected factors, highly influential ones may be incorrectly excluded from the model. This can increase the variance and standard deviation of parameter estimates and reduce the accuracy of predictions. Therefore, conducting multicollinearity diagnostics is an essential prerequisite for building a reliable logistic regression model for forest fire early warning.

High correlation between factors indicates that they exert similar influences on forest fires. This collinearity can increase the variance and standard deviation of the coefficients in the fitted logistic regression model, thereby reducing prediction accuracy. Therefore, before model construction, a correlation analysis is essential. The procedure involves: (1) preparing the sample dataset of forest fires, (2) calculating the raster values for all early warning factors, (3) extracting these factors for the training samples, and (4) computing their relative weights via PCA. Table 9 presents the correlation coefficients among the warning factors. With the exception of the TVDI-NDII7 pair, all factor pairs show positive correlations. The strongest correlation is observed between NDII7 and NDVI, reaching 0.646. In contrast, correlations among other factor pairs generally range between 0.2 and 0.3.

Table 9. The correlation coefficient between the early warning factors.

	ELE	SLP	ASP	LC	NDVI	TVDI	NDII7
ELE	1.000	/	/	/	/	/	/
SLP	0.566	1.000	/	/	/	/	/
ASP	0.229	0.211	1.000	/	/	/	/
LC	0.174	0.429	0.136	1.000	/	/	/
NDVI	0.353	0.089	0.232	0.041	1.000	/	/
TVDI	0.543	0.450	0.273	0.132	0.209	1.000	/
NDII7	0.327	0.231	−0.093	0.047	0.646	−0.054	1.000

Table 10 summarizes the weights assigned to each early warning factor. These weights were derived through a PCA performed on the seven factors (ELE, SLP, ASP, LC, NDVI, TVDI, NDII7) extracted from the training samples. The weight of each factor was calculated according to its contribution to the principal components, which was determined by combining the factor loadings with the variance explained by each component. The resulting weight percentages thus reflect the relative importance of each factor in explaining the overall variance within the dataset. The weight of each factor is as follows: 16.20%, 15.78%, 15.39%, 14.67%, 14.04%, 12.76%, and 11.16%. NDII7 has the highest weight (16.20%), indicating that moisture content is the most influential factor for forest fire occurrence. The second most important factor is NDVI, accounting for 15.78%. The cumulative contribution of the top five factors reaches approximately 76%. Elevation (ELE) has the lowest weight at 11.16%. These results confirm that all selected factors contribute to forest fire ignition.

Table 10. The weights of early warning factors.

Early Warning Factors	Weight (%)
NDII7	16.20
NDVI	15.78
SLP	15.39
TVDI	14.67
LC	14.04
ASP	12.76
ELE	11.16

While PCA indicates the relative importance of each factor, a reliable regression model requires that these predictors be statistically independent. Therefore, a multicollinearity diagnostic was conducted as the next step.

3.3. Multicollinearity Diagnostic Results

First, the values of the early warning factors were extracted from the sample point data. Subsequently, multicollinearity diagnostics were performed on the forest fire sample dataset for Liangshan Prefecture. Table 11 presents the characteristics of these early warning factors for the period 2018 to 2021.

Table 11. The statistical characteristics of forest fire early warning factors in Liangshan Prefecture during 2018–2021.

	Example	Max	Min	Mean	Std Dev
ELE	213	0.758	0.047	0.371	0.129
SLP	213	0.971	0.195	0.789	0.195
ASP	213	0.997	0.002	0.561	0.279
LC	213	0.594	0.012	0.108	0.135
NDVI	213	0.899	0.195	0.472	0.146
NDII7	213	0.454	−0.639	0.169	0.153
TVDI	213	0.981	0.0001	0.379	0.340

Table 12 presents the variance inflation factor (VIF) diagnostics for the forest fire early warning factors. The VIF values for NDII7 and TVDI are 4.090 and 6.138, respectively, while the VIF for each of the other factors ranges from 1 to 2. All VIF values are below 10, which indicates that there is no significant multicollinearity among the factors, thereby satisfying the key assumption for fitting a logistic regression model.

The VIF diagnostics in Table 12 indicate that all variables have VIF values below 10, the common threshold for indicating severe multicollinearity that would require remedial action. The TVDI variable shows a VIF of 6.138 (Tolerance = 0.163), which, while the highest among the predictors, remains within acceptable limits according to this standard. It is noted that more conservative guidelines suggest caution when VIF exceeds 5. After careful consideration, TVDI was retained in the model for two key reasons. First, from a statistical perspective, its VIF is still substantially below the critical level of 10. Second, and more importantly, TVDI quantifies surface moisture drought stress—a physically distinct and crucial mechanism influencing fuel flammability that is not redundant with the information provided by the vegetation moisture index (NDII7) or the greenness index (NDVI). Removing TVDI would result in the loss of this important drought dimension, thereby reducing the model’s comprehensiveness and physical grounding. The model’s subsequent validation performance confirms that its inclusion does not detract from predictive accuracy.

Table 12. The variance inflation factor (VIF) for forest fire early warning factors.

Early Warning Factors	Unstandardized Coefficients		Standardized Coefficients	t	Collinearity	
	B	Standard Error	Beta		Tolerance	VIF
Constant	0.010	0.218		0.047		
ELE	−0.019	0.260	−0.005	−0.074	0.725	1.379
SLP	−0.029	0.210	−0.012	−0.140	0.487	2.054
ASP	0.012	0.103	0.007	0.119	0.982	1.018
LC	0.040	0.226	0.011	0.179	0.876	1.142
NDVI	0.030	0.222	0.009	0.133	0.775	1.290
NDII7	0.109	0.378	0.034	0.287	0.245	4.090
TVDI	0.928	0.209	0.649	4.436	0.163	6.138

With the assumption of low multicollinearity among predictors being satisfied, all seven factors were retained for inclusion in the logistic regression model.

3.4. Model Building

The logistic regression model was fitted using the training samples (65 fire points and 98 non-fire points), with each sample point characterized by values for the seven early warning factors. The fitting results are presented in Table 13.

Table 13. The result of fitting the logistic regression model using the sample data.

Variables	Correlation	Sign
Constant	0.010	+
ELE	−0.019	−
SLP	−0.029	−
ASP	0.012	+
LC	0.040	+
NDVI	0.430	+
NDII7	1.109	+
TVDI	0.328	+

Table 13 presents the results of the logistic regression model fitted to the sample data. The values in the table are the regression coefficients obtained from the training sample data. The model results indicate that ASP, LC, NDVI, and NDII7 are positively associated with forest fire occurrence, meaning that higher values of these factors correspond to an increased probability of fire. In contrast, ELE and SLP show a negative association, where lower values of these factors are linked to a decreased fire probability.

The final step in the model development process was to rigorously evaluate its predictive performance and establish operational classification thresholds using an independent validation dataset.

3.5. The Analysis for Accuracy

Model accuracy was evaluated using the sensitivity and specificity derived from the ROC curve coordinates. The optimal probability threshold for classifying forest fire occurrences was determined by maximizing Youden's index, which is calculated as (Sensitivity + Specificity − 1).

Table 14 presents the prediction accuracy of the model. The area under the ROC curve (AUC) is greater than 0.7 for both the training and testing samples. For the training samples, the AUC reaches 0.904.

Table 14. The accuracy of model.

Sample	AUC	Optimal Threshold	Prediction Accuracy
Training sample	0.904	0.441	82.9%
Validation sample	0.77	0.45	71.5%

Figure 12 shows the ROC curve of the forest fire early warning model for Liangshan Prefecture. The area under the curve (AUC) for the model is 0.77. Using an optimal probability threshold of 0.441 (determined from the training samples), the logistic regression model achieved a prediction accuracy of approximately 82.9% on the training set. When applied to the independent validation sample, the model maintained an accuracy of 71.5%. These results demonstrate that the model has good predictive performance and can effectively forecast forest fire occurrences in the region.

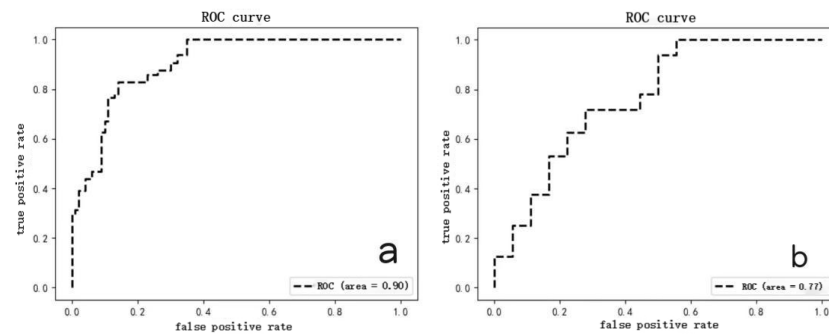


Figure 12. The ROC curves of training sample (a) and validation sample (b).

Based on the ROC curve, forest fire risk levels in Liangshan Prefecture were classified using two thresholds: the default threshold of 0.5 and the optimal cutoff value derived from Youden's index. Areas with predicted probabilities greater than the optimal cutoff were classified as high-risk; those with probabilities below the default threshold (0.5) were classified as low-risk; and areas with probabilities between these two thresholds were classified as medium-risk.

The accuracy analysis indicates that the early warning model for Liangshan Prefecture achieves a high overall forecasting performance. Using the fitted parameters, the final logistic regression model for forest fire prediction in the region is constructed as follows:

$$P = \frac{1}{1 + e^{-(0.010 - 0.019x_1 - 0.029x_2 + 0.012x_3 + 0.04x_4 + 0.43x_5 + 1.109x_6 + 0.328x_7)}} \quad (14)$$

where P is the probability of forest fire occurrences, $x_1, x_2, x_3, x_4, x_5, x_6, x_7$ are the ELE, SLP, ASP, LC, NDVI, NDII7 and TVDI in Liangshan Prefecture, respectively. To provide a more intuitive representation of the model's overall architecture, input variables, and computational flow, a corresponding schematic diagram is presented in Figure 13. This figure complements Equation (14), and together they offer a complete depiction of the early warning model.

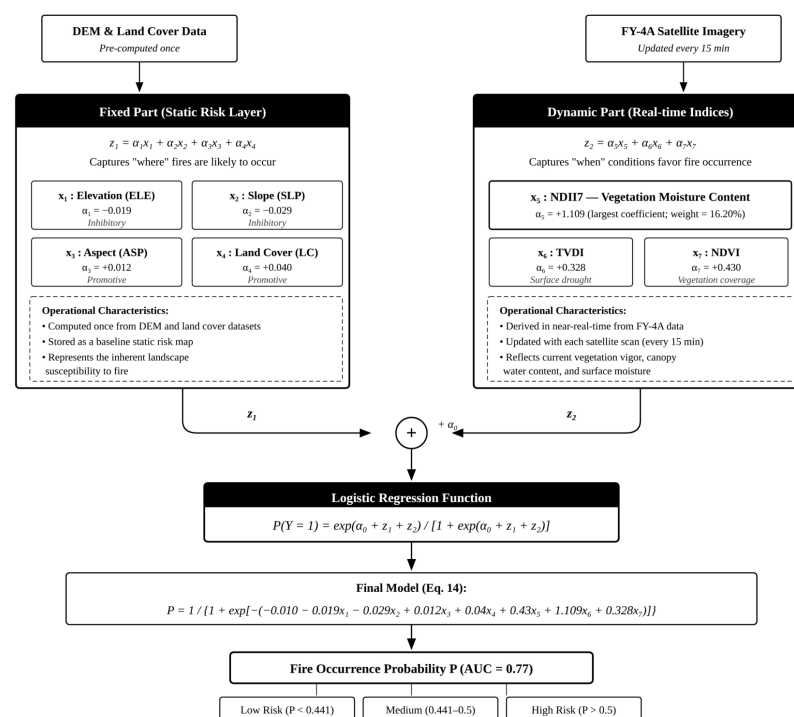


Figure 13. Schematic flowchart of the forest fire early warning logistic regression model.

4. Discussion

The findings of this study are contextualized within existing forest fire risk research, revealing both alignment with established knowledge and distinct methodological contributions. The prominence of moisture-sensitive indices (NDII7 and TVDI) among the warning factors corroborates the well-documented primacy of fuel moisture content in determining ignition potential [35,36]. This contrasts with some earlier regional models that primarily emphasized meteorological variables [16,17], highlighting the added value of direct, satellite-based vegetation water status monitoring. Furthermore, the identification of an intermediate NDVI range (0.2–0.6) associated with peak fire occurrence refines the conventional assumption of a linear positive relationship between vegetation density and fire risk, suggesting a more nuanced “fuel-availability-versus-moisture” interplay that aligns with recent complex models [3,23]. In terms of predictive performance, the logistic regression model’s area under the curve (AUC = 0.77) is consistent with the accuracy range reported for comparable regional-scale, factor-driven models [29,32], affirming its operational viability. The principal methodological advancement lies in the operational integration of China’s FY-4A geostationary satellite data into the warning framework. While most previous studies in China and the Liangshan region have relied on polar-orbiting sensors like MODIS [1,24], the use of FY-4A leverages its high temporal resolution to better capture diurnal variations in dynamic risk factors, such as surface heating and moisture loss. This addresses a key temporal limitation in composite-based approaches [5] and establishes a more responsive, near-real-time assessment paradigm. Consequently, this work advances beyond earlier spatial-pattern analyses for Liangshan [21,23] by providing a dynamically updatable, integrated model that balances physical interpretability with the observational frequency required for proactive forest management.

The proposed model exhibits several limitations that warrant consideration. First, its development relied on a regional, four-year fire record (2018–2021), which may not fully capture long-term climate-driven fire regimes and limits direct transferability to other regions without recalibration. Second, the model focuses on biophysical drivers and does not explicitly incorporate anthropogenic ignition factors (e.g., distance to roads or population density), which could improve its explanatory power. Third, operational use depends on FY-4A data, whose high temporal resolution comes at the cost of spatial resolution (1–4 km) and susceptibility to cloud cover; thus, the model is best suited for regional-scale, fair-weather risk assessment rather than precise fire detection. Finally, while within accepted thresholds, the moderate multicollinearity associated with the TVDI variable suggests caution when interpreting individual coefficient magnitudes. Acknowledging these constraints clarifies the model’s current scope as a regionally tailored monitoring tool and highlights pathways for future enhancement, such as integrating longer time series, human-activity variables, and multi-source data fusion.

5. Conclusions

In this paper, forest fire data and FY-4A satellite data from Liangshan Prefecture (2018–2021) were used to construct a logistic regression model. The model incorporated terrain, vegetation, and meteorological factors as predictors for forest fire risk warning, facilitated by principal component analysis and multicollinearity diagnostics.

(1) The early warning factors selected for the model were ELE, SLP, ASP, LC, NDVI, and NDII7. The elevation of forest fires ranged from 1438 m to 3103 m, with the highest frequency (26.5%; 17 occurrences) observed between 1438 m and 1718 m. The slope range of 18°–36° had the highest fire frequency (53.84%; 36 occurrences). West- and southwest-facing slopes were most susceptible, accounting for 23.43% (15) and 17.18% (11) of fires, respectively. For NDVI, the highest fire frequency (42%; 27 occurrences) was recorded when

$NDVI \leq 0.4$ and $0.4 < NDVI \leq 0.6$. The highest number of fires (36.92%; 24 occurrences) occurred when NDII7 was between 0.2 and 0.3.

(2) All selected warning factors had a weight exceeding 10%. Their respective weights were NDII7 (16.20%), NDVI (15.78%), SLP (15.39%), TVDI (14.67%), LC (14.04%), ASP (12.76%), and ELE (11.16%). Multicollinearity diagnostics showed that the VIF for all factors was below 10, indicating no significant collinearity. The VIF values for NDII7 and TVDI were 4.090 and 6.138, respectively, while the VIF for other factors ranged between 1 and 2.

(3) Non-fire points were generated at a ratio of 1.5 times the number of fire points, resulting in a final dataset of 97 fire points and 116 non-fire points (213 total samples). This dataset was split into training and validation subsets at an 8:2 ratio for model construction. In the fitted logistic regression model, elevation and slope had negative coefficients (-0.019 and -0.029 , respectively), indicating an inhibitory effect on fire occurrence. All other factors had positive coefficients, suggesting a promoting effect. NDII7 had the largest coefficient (1.109), implying the strongest influence, while aspect had the smallest absolute coefficient (0.012), indicating a minimal effect.

(4) Model accuracy was assessed using the ROC curve, which yielded an AUC curve of 0.77, indicating relatively high predictive accuracy. For risk classification, two thresholds were used: the default logistic regression threshold of 0.5 and the optimal cutoff of 0.441 derived from the ROC curve. Areas with a predicted probability below 0.441 were classified as low-risk, those between 0.441 and 0.5 as medium-risk, and those above 0.5 as high-risk.

It should be noted that the limited sample size (64 fire records) used in this study may affect the representativeness of the results and the generalizability of the model to other regions. Future studies should incorporate longer time series data and consider expanding the dataset as more fire records become available. Additionally, validation of the model in other fire-prone regions with similar environmental conditions would strengthen its applicability.

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

References

- Lu, Q.-H.; Wang, X.-Q.; Cao, H.; Li, W.; Wang, B.-P. Remote sensing monitoring of forest fire in Liangshan Prefecture, Sichuan province. *Surv. Mapp. Geol. Miner. Resour.* **2020**, *36*, 9–12.
- Tian, X.-R.; Douglas, J.-M.; Zhang, Y.-H. Assessment of forest fire danger rating systems. *World For. Res.* **2006**, *19*, 39–46.
- Rodrigues, M.; Alcasena, F.; Vega-Garcia, C. Modeling initial attack success of wildfire suppression in Catalonia, Spain. *Sci. Total Environ.* **2019**, *666*, 915–927. [\[CrossRef\]](#)
- Dieu, T.B.; Nhat-Duc, H.; Samui, P. Spatial pattern analysis and prediction of forest fire using new machine learning approach of Multivariate Adaptive Regression Splines and Differential Flower Pollination optimization: A case study at Lao Cai province (Viet Nam). *J. Environ. Manag.* **2019**, *237*, 476–487. [\[CrossRef\]](#)
- Gao, B.; Jia, W.; Wang, Q.; Yang, G. All-Weather Forest Fire Automatic Monitoring and Early Warning Application Based on Multi-Source Remote Sensing Data: Case Study of Yunnan. *Fire* **2025**, *8*, 344. [\[CrossRef\]](#)
- Zhang, Z.; Wang, L.; Xue, N.; Du, Z. Spatiotemporal Analysis of Active Fires in the Arctic Region during 2001–2019 and a Fire Risk Assessment Model. *Fire* **2021**, *4*, 57. [\[CrossRef\]](#)
- Tian, Y.; Wu, Z.; Li, M.; Wang, B.; Zhang, X. Forest Fire Spread Monitoring and Vegetation Dynamics Detection Based on Multi-Source Remote Sensing Images. *Remote Sens.* **2022**, *14*, 4431. [\[CrossRef\]](#)
- Liang, H.; Zheng, C.; Liu, X.; Tian, Y.; Zhang, J.; Cui, W. Super-Resolution Reconstruction of Remote Sensing Data Based on Multiple Satellite Sources for Forest Fire Smoke Segmentation. *Remote Sens.* **2023**, *15*, 4180. [\[CrossRef\]](#)
- Rostami, A.; Shah-Hosseini, R.; Asgari, S.; Zarei, A.; Aghdami-Nia, M.; Homayouni, S. Active Fire Detection from Landsat-8 Imagery Using Deep Multiple Kernel Learning. *Remote Sens.* **2022**, *14*, 992. [\[CrossRef\]](#)
- Wang, H.; Zhang, G.; Yang, Z.; Xu, H.; Liu, F.; Xie, S. Satellite Remote Sensing False Forest Fire Hotspot Excavating Based on Time-Series Features. *Remote Sens.* **2024**, *16*, 2488. [\[CrossRef\]](#)
- Xie, Z.; Song, W.; Ba, R.; Li, X.; Xia, L. A Spatiotemporal Contextual Model for Forest Fire Detection Using Himawari-8 Satellite Data. *Remote Sens.* **2018**, *10*, 1992. [\[CrossRef\]](#)
- Shahriar, S.A.; Choi, Y.; Islam, R. Advanced Deep Learning Approaches for Forecasting High-Resolution Fire Weather Index (FWI) over CONUS: Integration of GNN-LSTM, GNN-TCNN, and GNN-DeepAR. *Remote Sens.* **2025**, *17*, 515. [\[CrossRef\]](#)
- Ntinopoulos, N.; Sakellariou, S.; Christopoulou, O.; Sfougaris, A. Fusion of Remotely-Sensed Fire-Related Indices for Wildfire Prediction through the Contribution of Artificial Intelligence. *Sustainability* **2023**, *15*, 11527. [\[CrossRef\]](#)
- Shadrin, D.; Illarionova, S.; Gubanov, F.; Evteeva, K.; Mironenko, M.; Levchunets, I.; Belousov, B.; Burnaev, E. Wildfire spreading prediction using multimodal data and deep neural network approach. *Sci. Rep.* **2024**, *14*, 2606. [\[CrossRef\]](#)
- Moghim, S.; Mehrabi, M. Wildfire assessment using machine learning algorithms in different regions. *Fire Ecol.* **2024**, *20*, 104. [\[CrossRef\]](#)
- Wang, W.-J.; Qian, C.; Zhang, Y.; Feng, X.; Zhang, J. Multi-time scale features of fire weather in two major forests in China during 1961–2020. *Clim. Environ. Res.* **2022**, *27*, 559–577.
- Zhang, X.-Y.; Li, F.-X. Study on forecasting danger weather grades of forest fire in Ningxia Autonomous region. *J. Wildland Sci.* **2006**, *2*, 28–30.
- Wang, J.-L. Study on the forest fire danger class division of Yong'an city. *J. Fujian For. Sci. Technol.* **2001**, *28*, 63–64.
- Wen, H.; Guo, Q.; Zeng, Y.; Wu, Z.; Sun, Z. Study on forest fire risk in Conghua District of Guangzhou City based on multi-source data. *Nat. Hazards* **2022**, *114*, 3163–3183. [\[CrossRef\]](#)
- Chen, F. The response of forest fires to climate change and fire trend prediction in Yunnan province. *J. Beijing For. Univ.* **2015**, *32*, 3–10.
- Zhang, X. Research on prediction model and risk zoning of forest fire in Liangshan Prefecture. *J. Chengdu Univ. Technol.* **2020**, *32*, 2–5.
- Parto, F.; Saradjian, M.; Homayouni, S. MODIS brightness temperature change-based forest fire monitoring. *J. Indian Soc. Remote Sens.* **2020**, *48*, 163–169. [\[CrossRef\]](#)
- Li, H.-P.; Long, Z.-H.; Yang, Z.-H.; Xu, Z.Q.; Li, Y.Z. Analysis of forest fire risk in Sichuan Liangshan based on logistic model. *J. Saf. Environ.* **2021**, *21*, 498–505.
- Dong, Z.; Yu, J.; An, S.; Zhang, J.; Li, J.; Xu, D. Forest Fire Detection of FY-3D Using Genetic Algorithm and Brightness Temperature Change. *Forests* **2022**, *13*, 963. [\[CrossRef\]](#)
- Dong, L.; Wang, Y.; Li, C.; Zhu, W.; Yu, H.; Tian, H. A Joint Transformer–XGBoost Model for Satellite Fire Detection in Yunnan. *Fire* **2025**, *8*, 376. [\[CrossRef\]](#)
- Zhang, G.; Wang, M.; Liu, K. Forest Fire Susceptibility Modeling Using a Convolutional Neural Network for Yunnan Province of China. *Int. J. Disaster Risk Sci.* **2019**, *10*, 386–403. [\[CrossRef\]](#)
- Li, W.; Xu, Q.; Yi, J.; Liu, J. Predictive model of spatial scale of forest fire driving factors: A case study of Yunnan Province, China. *Sci. Rep.* **2022**, *12*, 19029. [\[CrossRef\]](#) [\[PubMed\]](#)

28. Jang, E.; Kang, Y.; Im, J.; Lee, D.-W.; Yoon, J.; Kim, S.-K. Detection and Monitoring of Forest Fires Using Himawari-8 Geostationary Satellite Data in South Korea. *Remote Sens.* **2019**, *11*, 271. [[CrossRef](#)]
29. Das, J.; Mahato, S.; Joshi, P.K.; Liou, Y.-A. Forest Fire Susceptibility Zonation in Eastern India Using Statistical and Weighted Modelling Approaches. *Remote Sens.* **2023**, *15*, 1340. [[CrossRef](#)]
30. Zhang, Z.; Tian, Y.; Wang, G.; Zheng, C.; Zhao, F. A forest fire prediction method for lightning stroke based on remote sensing data. *Forests* **2024**, *15*, 647. [[CrossRef](#)]
31. Pang, Y.; Li, Y.; Feng, Z.; Feng, Z.; Zhao, Z.; Chen, S.; Zhang, H. Forest Fire Occurrence Prediction in China Based on Machine Learning Methods. *Remote Sens.* **2022**, *14*, 5546. [[CrossRef](#)]
32. Zhao, P.; Zhang, F.; Lin, H.; Xu, S. GIS-Based Forest Fire Risk Model: A Case Study in Laoshan National Forest Park, Nanjing. *Remote Sens.* **2021**, *13*, 3704. [[CrossRef](#)]
33. 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. [[CrossRef](#)]
34. Turner, M.G.; Romme, W.H. Landscape dynamics in crown fire ecosystems. *Landsc. Ecol.* **1994**, *9*, 59–77. [[CrossRef](#)]
35. Asam, S.; Eisfelder, C.; Hirner, A.; Reiners, P.; Holzwarth, S.; Bachmann, M. AVHRR NDVI Compositing Method Comparison and Generation of Multi-Decadal Time Series—A Timeline Thematic Processor. *Remote Sens.* **2023**, *15*, 1631. [[CrossRef](#)]
36. Wang, C.-Y.; Qi, S.-H.; Niu, Z.; Wang, J. Evaluating soil moisture status in China using the temperature–vegetation dryness index (TVDI). *Can. J. Remote Sens.* **2014**, *30*, 671–679. [[CrossRef](#)]
37. Hendrik, S.; Tani, H.; Hirano, T. Detection of fire impact and vegetation recovery over tropical peat swamp forest by satellite data and ground-based NDVI instrument. *Int. J. Remote Sens.* **2010**, *31*, 5297–5314.
38. Gabban, A.; San-Miguel-Ayanz, J.; Viegas, D. A comparative analysis of the use of NOAA-AVHRR NDVI and FWI data for forest fire risk assessment. *Int. J. Remote Sens.* **2008**, *4*, 5677–5687. [[CrossRef](#)]

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