# Multi-source remote sensing-based forest fire monitoring

Qinglie Yuan[a*]

[a] School of Civil and Architecture Engineering, Panzhihua University, Panzhihua 617000, China-[*]yuanqinglie@pzhu.edu.cn

**Keywords:** forest fire, remote sensing, GIS, spatial analysis.

## Abstract

Wildfires bring a significant threat to the ecological environment and the safety of human society. Therefore, a timely and accurate understanding of the situation in the fire area is crucial for reducing fire damage. This study takes the forest fire in Xichang City, China as a case, using multi-source remote sensing data to dynamically monitor and analyze forest fires, aiming to provide a scientific basis and technical support for fire prevention and firefighting. The study first uses temperature inversion technology based on multi-source remote sensing data to monitor the fire scene in real time and accurately extract fire points. In addition, the study extracts key factors affecting fire suppression, such as water resources, vegetation coverage, and terrain, and evaluates the safety factor of the burned area using spatial principal component analysis. To optimize rescue route planning, the study constructs a minimum resistance surface and uses GIS spatial analysis to extract the minimum cost path for rescue safety network construction. The results show that the burned area, dense vegetation, farther from water bodies, located in high-altitude and steep slope regions have a greater impact on the safety of the firefighting area. This study provides scientific and effective decision support for the prevention and firefighting of forest fires through multi-source remote sensing technology and GIS spatial analysis. The research findings not only improve the efficiency of fire emergency response but also offer new perspectives and methods for forest fire management.

## 1. Introduction

### 1.1 General Instructions

As global climate change intensifies and human productive activities expand into forest resources. Certain operations inherent to these areas carry a significant fire risk due to their nature(Koetz et al. 2008). This risk is further exacerbated by the increase in natural combustible materials that come with seasonal changes. Forest fires have occurred periodically in various countries, causing severe devastation to forest resources and the ecological environment (Hua et al. 2017). Moreover, they pose a threat to the property and lives of workers in the affected areas and residents within the vicinity (Maffei et al. 2021). With the rise in extreme weather events and rapid advancements in productivity, society has begun to place greater emphasis on the protection and utilization of forest resources. Consequently, the early prevention and timely management of forest fires have become critical factors affecting the safety and sustainability of these regions (Li et al. 2020).

Initially, forest fire monitoring relied primarily on ground patrols, observation towers, and aerial surveillance. In the early 1960s, with the development of aerial infrared detection technology, remote sensing began to be used for forest fire monitoring, mainly through the interpretation of color infrared aerial photographs (Sherstjuk et al. 2018). By the 1980s, as satellite remote sensing technology advanced comprehensively, the practice of using meteorological satellites for forest fire monitoring gained increasing attention. Remote sensing for forest fire monitoring has evolved from manual qualitative observation to automated quantitative calculations. Currently, research on remote sensing technology for forest fire monitoring focuses on methods for fire point extraction, estimation of burned area loss, and early warning systems (Chowdhury et al. 2015). Many scholars have tirelessly explored remote sensing detection methods for forest fires, developing numerous mature and advanced algorithms.

Multi-source remote sensing data offers extensive coverage, rapid updates, and rich information, providing comprehensive and real-time support for the dynamic monitoring of forest fires (Wei et al. 2021). By comparing and analyzing remote sensing data from different times and with varying spatial resolutions, we can capture the changes in the fire scene, providing a basis for predicting the spread of the fire and locating its source (Yuan et al. 2015). Moreover, multi-source remote sensing data can also be used to assess the surrounding environment of the fire scene, such as vegetation types and topographical conditions, which aids in devising targeted firefighting strategies (Bolton et al. 2017).

Given the differences in spatial resolution, temporal scale, and spectral characteristics among various types of remote sensing data, effectively integrating these data to enhance monitoring accuracy and efficiency is one of the key issues in this study. Research on the preprocessing, feature extraction, and classification algorithms of multi-source remote sensing data can provide more accurate and reliable results for the dynamic monitoring of forest fires.

The primary objective is to evaluate the effectiveness of multisource remote sensing in detecting and monitoring forest fires. This involves simulated fire scenarios to compare topographical data, understanding the impact of topographical, biological, and climatic factors on the optimal rescue routes, and constructing an intelligent rescue path network. This aids in optimizing rescue operations, enhancing efficiency, and increasing the success rate.

The main research content includes extracting fire point areas, identifying safety indicator influencing factors, and analyzing regional safety conditions. By combining the distribution characteristics of regional elements and adverse factors, it provides reliable and accurate data support for optimizing rescue paths. This approach offers scientific solutions and decision support for the monitoring and management of forest fires.

The integration of remote sensing technology with advanced data analysis techniques not only enhances our ability to predict and respond to forest fires but also contributes to the development of more effective strategies for fire prevention and management (Chu et al. 2013). By leveraging the strengths of multi-source remote sensing data, we can better anticipate fire risks, allocate resources more efficiently, and safeguard both human life and natural ecosystems.

## 2. Method and Research Case

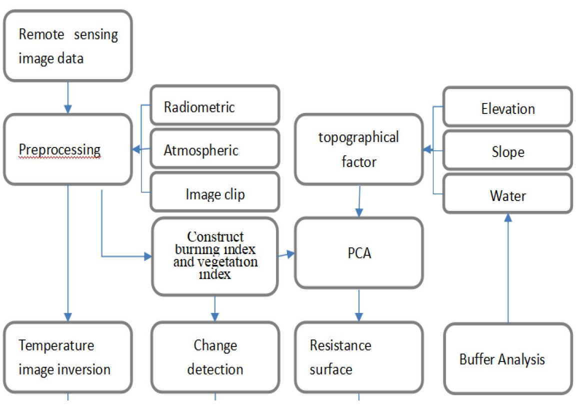
### 2.1 Research Case Background

The research background of the Muli forest fire disaster in Sichuan Province of China. Muli County, located in the western part of Liangshan Prefecture, Sichuan Province, sits at the juncture of the Qinghai-Tibet Plateau and the Yunnan-Guizhou Plateau. It is characterized by complex geological and topographical features, with rugged landscapes and deep valleys. The climate of Muli is marked by a long dry season from November to June of the following year, during which precipitation accounts for less than 10% of the annual total. This period is characterized by dry air and frequent windy days, with wind directions varying significantly depending on the terrain.

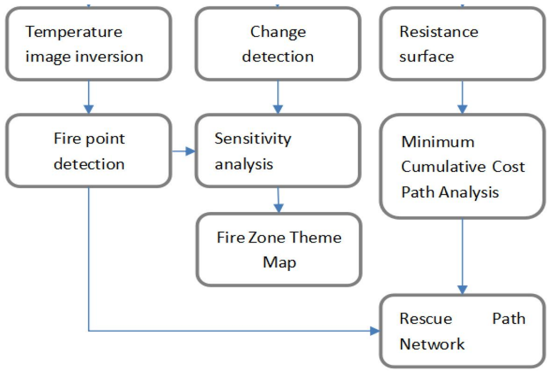
In recent years, Muli County has experienced several forest fires. For instance, fires occurred on May 16, 2018, February 10, 2019, March 30, 2019 (resulting in the tragic loss of 30 firefighting personnel), and March 28, 2020 (the focus of this study). These incidents have placed enormous pressure on forest fire prevention efforts in the county. Despite the adoption of various preventive measures by local governments and relevant departments, fires continue to occur.

### 2.2 Overall Technical Process

Figure 1 shows the overall technical process, including data preprocessing, fire point detection, thematic mapping of burnt areas, and modeling of rescue path networks based on Spatial Principal Component Analysis (SPCA). Firstly, data preprocessing includes radiometric correction, atmospheric correction, and image cropping to ensure the quality and usability of the data.




(a)




(b)

Figure 1. Technical flowchart. (a) is data preprocessing and evaluation factors; (b) is fire point detection and rescue network modeling.

Radiation correction aims to eliminate radiation errors caused by the sensor itself, while atmospheric correction aims to eliminate the influence of the atmosphere on remote sensing data. Then, surface temperature information is extracted from the preprocessed data to complete the detection of fire points and inference of fire intensity. Constructing a combustion index and vegetation index, creating thematic maps of burned areas, and combining sensitivity analysis and visual interpretation can help identify and evaluate the impact of fire on different areas. This can provide a basis for precise extraction of ignition points.

The research synthesizes various influencing factors to create a comprehensive safety grading map for areas affected by disasters. Subsequently, the computation of the minimum cumulative resistance surface offers a scientific foundation for the strategic planning of rescue routes. Integrating Geographic Information System (GIS) spatial analysis tools, the most efficient rescue path is meticulously chosen from a multitude of potential routes.

### 2.3 Land Surface Temperature Retrieval

The commonly used methods for surface temperature inversion include atmospheric correction (radiative transfer equation), single window algorithm, and split window algorithm (split window). These methods require at least knowledge of atmospheric profile parameters (mainly atmospheric transmittance) and surface emissivity. In the process of surface temperature inversion, the goal is to separate the radiation L caused by temperature from the total radiation energy (Lobs) through atmospheric correction methods, to calculate the actual temperature of the target object. Based on the assumption that the total energy received by the sensor (Lobs) minus the upward radiation (Lu) and downward radiation (Ld) of the atmosphere, the remaining energy is the radiation of the target object itself. The blackbody radiance (LT) at the same temperature can be obtained, as defined in Equation 1.

$$Lobs=(LT\epsilon+(1-\epsilon)Ld)\tau+Lu \tag{1}$$

where $\epsilon$ represents emissivity
Ld represents atmospheric downward radiation
$\tau$ represents atmospheric transmittance
Lu represents atmospheric upward radiation

### 2.4 Spatial Principal Component Analysis

Principal Component Analysis (PCA) transforms multiple spatial data with varying degrees of correlation into a few almost unrelated composite indicators by rotating the initial spatial coordinate axis and objectively determining the weight of each indicator. The SPCA combines the principles of GIS and statistics. Each spatial variable corresponds to a corresponding matrix, and the impact of relevant spatial variables on the dependent variable is assigned to the corresponding principal component factors. The results of principal component factor analysis can be accurately and clearly implemented on each pixel corresponding to the space, allowing the original principal component analysis results to be intuitively extended to two-dimensional space.

Minimum Cumulative Resistance (MCR) can be generated using SPCA and multiple environmental impact factors. The MCR can analyze and find the channels for humans or other organisms to overcome the minimum cumulative landscape element resistance during the process from the starting point to the endpoint. It is a cost model for studying the movement process of species from the source point to the destination and is currently widely used in the study of natural ecology and social and cultural processes. The calculation process is as shown in Equation 2.

$$MCR = f\,\min\left(\sum\nolimits_{i=n}^{i=1} D_{ij} \times R_i\right) \qquad (2)$$

where MCR is the minimum cumulative resistance value

$D_{ij}$ is the spatial distance from the source point to the destination

$R_i$ is the resistance coefficient of motion from the source point

$f$ is the positive correlation function between the minimum cumulative resistance and ecological processes

## 3. Experiment and Discussion

Type text single-spaced, with one blank line between paragraphs and following headings. Start paragraphs flush with the left margin.

### 3.1 Data Description and preprocessing

The experimental data consists of Landsat 8 satellite imagery and digital elevation models (DEM). The Landsat 8 series satellites are equipped with two types of sensors, the Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), which have higher spatial imaging resolution than previous satellite series. Landsat 8 has similar spectral characteristics and resolution to the previous series in obtaining images. It contains a total of 11 bands, with band 8 being the panchromatic band and a spatial resolution of 15 meters for the image; The remaining bands are all spectral bands, and the image resolution obtained is 30 meters. DEM is sampled to the same spatial resolution. The preprocessed result is shown in Figure 2.

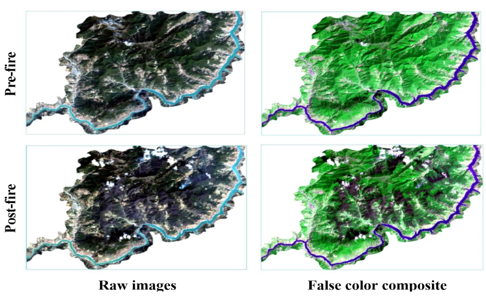



Figure 2. Preprocessed results on the study area.

Geographically, the study area belongs to the tropical plateau monsoon climate zone, with strong solar radiation during the day and large temperature differences between day and night. The altitude of the entire area is above 1500 meters. The terrain is dominated by Zhongshan. This chapter's data preprocessing includes radiometric calibration, atmospheric correction, and image cropping.

For the convenience of visual selection of disaster areas, the preprocessed images are subjected to band transformation, selecting the red band (0.6546 um), near-infrared band (0.8646 um), and green band (0.5613 um). By utilizing the display features of these three bands, the contrast between vegetation biological characteristics and bare land can be significantly improved.

### 3.2 Fire point detection

Focus extraction is performed on the temperature data that has already been converted. This aims to identify and extract the maximum value of the grid data within the analysis window as the focus and determine the center point of the grid to be calculated. Based on the spatial resolution of the data source, detailed focus extraction can be performed on the converted temperature data to determine the grid point with the highest temperature in the analysis window. After focus analysis, points with temperatures exceeding 40 degrees Celsius are considered warning ignition points.

By converting high-temperature dense areas into point feature set data, a point-dense area map can be obtained, where these points represent locations within a specific area where temperature changes are relatively small and the average temperature is higher than the surrounding area. This method is very effective for initially identifying areas of concentrated fire points, as it can reveal patterns and ranges of temperature anomalies. Figure 3 presents the results of fire point detection.

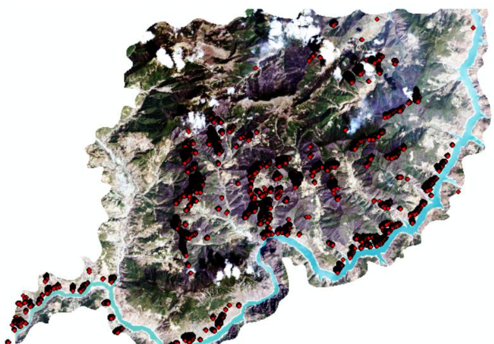
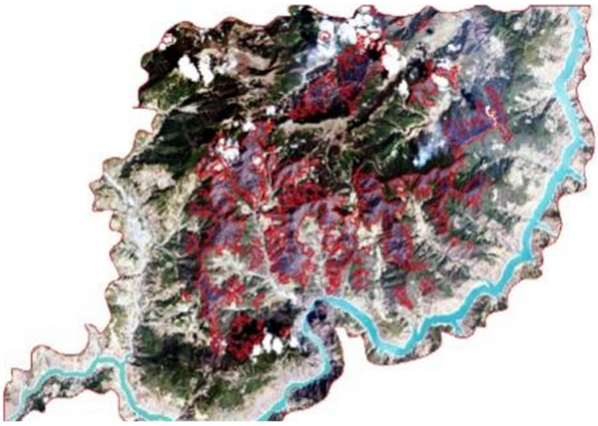


Figure 3. The results of fire point detection.

### 3.3 Overfire Area Detection

Figure 4 are thematic map derived from the detection results of wildfire-affected areas. These maps can fully and intuitively represent the extent of the affected areas from different detection perspectives. They primarily consist of Normalized Burn Ratio (NBR) and NDVI. These are used to calculate the difference to identify the boundary of fire. By combining the high-temperature areas of interest obtained from temperature inversion, the highest temperature points in several burned areas were compared with various detection results. The verification results showed that although there were certain discrepancies in the detection boundaries and cloud coverage pollution areas in each detection area, the detection of central high-temperature areas was largely consistent. This was verified by comparing with temperature data, and the deviations in the fire areas presented in the false color images after band combination under visual interpretation were within a reasonable range. From the thematic maps, it can be seen that the affected areas are concentrated in dense vegetation-covered areas with relatively high elevations, surrounded by rivers in various continuous regions.

(a)



(b)

Figure 4. Thematic map of burnt areas. (a) NBR difference detection; (b) NDVI difference detection

### 3.4 Rescue Safety Network Modeling

#### 3.4.1 Safety Evaluation Factors

Considering the actual situation of the study area, elevation, slope, vegetation coverage, and water bodies can represent the natural appearance of the study area. Among them, elevation and slope are related to the terrain composition of the study area and will directly affect the difficulty and feasibility of rescue route design. Grading and scoring are carried out based on the basic principle that as elevation height and slope increase, rescue difficulty decreases. Vegetation coverage has a positive correlation with fire hazards and is also one of the main factors constituting safety evaluation indicators. However, the actual division of fire-affected areas requires comparison within the same area before and after the disaster based on the post-disaster fire range. Therefore, it needs to be combined with the combustion index analysis image for comprehensive scoring.

Water sources are an important factor that cannot be ignored during the rescue process. When it comes to fire fighting in mountainous areas, water sources are derived from natural water bodies such as rivers and lakes. The closer the fire point is to the water body, the higher the priority of the score, making it the most influential factor in the environment. According to Table 1, each factor is divided into levels 1-4. The smaller the value, the lower the difficulty of rescue in the area and the higher the safety level. As shown in Table 1, each factor is divided into levels 1-4. The smaller the value, the lower the difficulty of rescue in the area and the higher the safety level. Figure 5 presents the visualization results of different factors using a graded coloring method.

Table 1. Safety Indicators

| Evaluation factors | Factor grading | Security level |
|---|---|---|
| elevation | ＜2336 | 1 |
| | 2336-2847 | 2 |
| | 2847-3359 | 3 |
| | ＞3359 | 4 |
| Slope | ＜20 | 1 |
| | 20—40 | 2 |
| | 40—60 | 3 |
| | ＞60 | 4 |
| Temperature | ＜18 | 1 |
| | 18—25 | 2 |
| | 25—33 | 3 |
| | ＞33 | 4 |
| Distance to water | ＜500 | 1 |
| | 500—1500 | 2 |
| | 1500—3000 | 3 |
| | ＞3000 | 4 |
| NDVI | ＜0.25 | 1 |
| | 0.25—0.55 | 2 |
| | 0.55—0.8 | 3 |
| | ＞0.8 | 4 |
| NBR | ＞0.37 | 1 |
| | 0.14—0.37 | 2 |
| | -0.14—0.14 | 3 |
| | -0.14＜ | 4 |

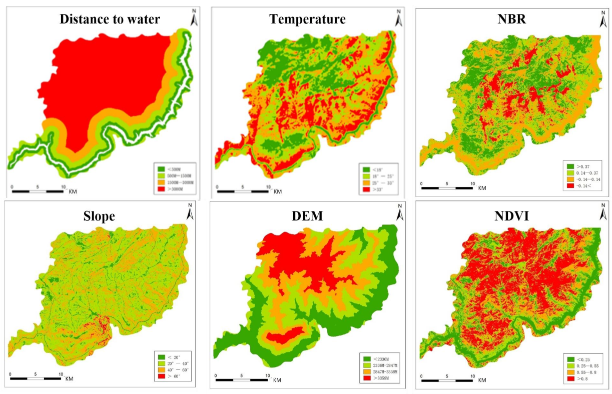



Figure 5. Safety indicators visualization.

#### 3.4.2 Safety Network Modeling

Based on the comprehensive index of ecological security, combined with the correlation matrix of each principal component, the cumulative contribution rate of the first five principal components of spatial principal component analysis is calculated, and the weights of each influencing factor are obtained, as shown in Table 2.

Table 2. The contribution rate and weight coefficients of the influencing factors.

| Factors | Score coefficient | Weights |
|---|---|---|
| DEM | 0.3294 | 0.33 |
| Slope | 0.0519 | 0.05 |
| temperature | 0.0688 | 0.07 |
| water | 0.3060 | 0.30 |
| NBR | 0.0900 | 0.09 |
| NDVI | 0.3417 | 0.34 |

The highest load in the disaster-stricken area includes elevation, slope, distance from water bodies, vegetation coverage index, and combustion index. This indicates that the above ecological resistance indicators have a significant impact on the ecological resistance surface of the study area. Using the raster calculator in ArcGIS software for overlay analysis, six impact indicators were overlapped and added together according to their weights. Then, using a reclassification tool, the raster layers obtained from the overlay analysis were divided into four levels: low, low, medium, and high. The final distribution map of safety levels in the study area was generated as shown in Figure 6.

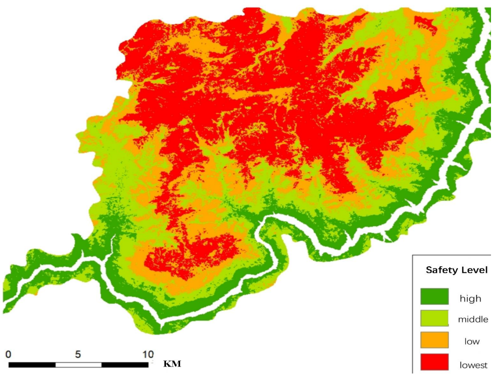



Figure 6. Safety levels in the study area.

On the basis of the resistance surface model, the study used 7 fire points as target points, 2 water source areas, and 1 urban area as starting points for path analysis. The connection path tool was used to generate the minimum cost path between ecological sources, where the water source point served as both the starting point and the target water intake point, requiring multiple path links. The feasible rescue routes in the study area were determined by stacking and eliminating duplicate paths. After removing duplicate paths, 27 potential rescue routes were finally obtained in the study area. The final result is shown in Figure 7.

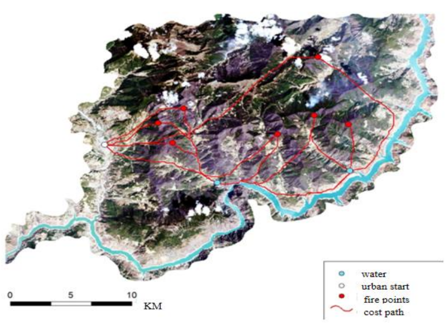



Figure 7. Potential rescue routes.

## 4. Conclusion

This study uses multi-source remote sensing data and GIS spatial analysis technology to monitor and manage forest fires. Taking the Liangshan Prefecture wildfire as an example, the various steps from pre-processing Landsat 8 satellite images and DEM data to fire point extraction, impact factor analysis, and rescue path planning are described in detail. The proposed method and experimental results provide feasible solutions for improving the efficiency of emergency response to fires, offering new perspectives and methods for preventing and extinguishing forest fires, helping to reduce losses caused by fires, protecting the ecological environment, and ensuring human safety.

## References

Koetz, B., Morsdorf, F., Van der Linden, S., Curt, T., Allgöwer, B., 2008. Multi-source land cover classification for forest fire management based on imaging spectrometry and LiDAR data. *Forest Ecology and Management*, 256(3), 263-271.

Hua, L., Shao, G., 2017. The progress of operational forest fire monitoring with infrared remote sensing. *Journal of forestry research*, 28(2), 215-229.

Maffei, C., Lindenbergh, R., Menenti, M., 2021. Combining multi-spectral and thermal remote sensing to predict forest fire characteristics. *ISPRS Journal of Photogrammetry and Remote Sensing*, 181, 400-412.

Li, Q., Cui, J., Jiang, W., Jiao, Q., Gong, L., Zhang, J., Shen, X., 2021. Monitoring of the Fire in Muli County on March 28, 2020, based on high temporal-spatial resolution remote sensing techniques. *Natural Hazards Research*, 1(1), 20-31.

Sherstjuk, V., Zharikova, M., Sokol, I., 2018, August. Forest fire monitoring system based on UAV team, remote sensing, and image processing. In 2018 IEEE second international conference on data stream mining processing (DSMP), 590-594.

Chowdhury, E. H., Hassan, Q. K., 2015. Operational perspective of remote sensing-based forest fire danger forecasting systems. *ISPRS Journal of Photogrammetry and Remote Sensing*, 104, 224-236.

Wei, X., Bai, K., Chang, N. B., Gao, W., 2021. Multi-source hierarchical data fusion for high-resolution AOD mapping in a forest fire event. *International Journal of Applied Earth Observation and Geoinformation*, 102, 102366.

Bolton, D. K., Coops, N. C., Hermosilla, T., Wulder, M. A., White, J. C. (2017). Assessing variability in post-fire forest structure along gradients of productivity in the Canadian boreal using multi-source remote sensing. *Journal of biogeography*, 44(6), 1294-1305.

Chu, T., Guo, X., 2013. Remote sensing techniques in monitoring post-fire effects and patterns of forest recovery in boreal forest regions: A review. *Remote Sensing*, 6(1), 470-520.

Yuan, C., Zhang, Y., Liu, Z., 2015. A survey on technologies for automatic forest fire monitoring, detection, and fighting using unmanned aerial vehicles and remote sensing techniques. *Canadian journal of forest research*, 45(7), 783-792.