Susceptibility assessment of “2020.3.30” Xichang post-fire debris flow using a machine learning method

Tao Jin, Xiewen Hu, Chuanjie Xi, Kun He, Ying Yang, Xichao Cao
Faculty of Geosciences and Environmental Engineering, Southwest Jiaotong University, Sichuan Chengdu 610031, China
Corresponding author: huxiewen@swjtu.edu.cn ORCID: 0000-0002-7816-5601

Abstract In this study, a machine learning method, i.e., random forest (RF) model, was employed to assess post-fire debris flow (PFDF) susceptibility after the Xichang forest fire occurred on 30 March, 2020. First, we conducted a tracking survey in the rainy season, on-site tests, and remote sensing image interpretation and obtained 10 impacting factors, i.e., the basin area, relief ratio, basin shape coefficient, percentage of area with a slope greater than 50%, proportion of moderate or high severity burned areas, distribution of gravel in the basin, vegetation types and distribution in the basin, early cumulative erosion after fire, peak rainfall in a 1-h interval, and peak rainfall in a 24-h interval, after their correlation test to build a spatial database. Subsequently, a total of 181 PFDF events in the database were randomly divided into training (70%) and validation (30%) samples. Thereafter, the RF model was used to acquire the susceptibility of PFDF in the study area. Finally, receiver operating characteristic (ROC) curve, area under curve (AUC) value, sensitivity, specificity, and accuracy were utilized to validate the predictive performance of the model. Results show that the RF model has good predictive ability with AUC of 93.4%, sensitivity of 88.3%, specificity of 99.3%, and accuracy of 97.8%. This study provides a scientific basis for PFDF disaster prevention and risk management in Xichang City and its surrounding areas.

1 Introduction
Forest fire is a common natural disaster that not only causes damage to infrastructure and ecosystems but also induces severe environmental pollution and related secondary geological disasters. Post-fire debris flows (PFDF) are major fire-related hazards in burned areas [1]. They mobilize ash layers resulting from fires and rock-soil mixtures from hillslopes and stream channels, forming destructive mass movements often resulting in both loss of life and damage to infrastructure [2]. These events are predicted to increase further as the global climate warms [3]. In recent years, this type of debris flow has been sufficiently confirmed by the increasing occurrence of forest fires and subsequent post-fire...
debris flows in Ganzi and Liangshan Prefectures in the mountainous areas of southwestern Sichuan, China[4-7].

Wildfires increase the susceptibility of watersheds to runoff-induced debris flows in the steep terrain of mountainous areas [1]. The possibility of PFDF occurrence in burned areas around the world is approximately 60%, with the occurrence probability in the United States ranging 35%–40% [8,9], in Australia approximately 81% [9,10], and in China approximately 70% [4,5]. Early warning is a critical element for successfully mitigating the damage of PFDF. Over the past decade, many researchers have devoted themselves to developing models for predicting the occurrence of PFDF [1,11-13]. This includes prediction models for determining rainfall intensity-duration thresholds in a specific area and the possibility, rainfall thresholds, and potential intensities of PFDF [1,11,13,14]. Moreover, Kern et al. (2017) evaluated PFDF prediction with a variety of machine learning methods and suggested that advanced machine learning methods could significantly improve the performance of current PFDF prediction models [15]. Efthymios et al. (2018) also indicated that the prediction performance of the random forest (RF) model considerably outperformed the current debris flow prediction model in the western United States. The RF model has obvious advantages in the ability to successfully assimilate new information [14].

This study collected 10 factors affecting the susceptibility of PFDF through field investigation, on-site tests, and remote sensing image interpretation in 82 basins of the “2020.3.30” fire-burned area in Xichang, Sichuan Province. After the correlation test of impacting factors, an advanced machine learning method, the RF model, was adopted to develop a susceptibility prediction model for PFDF and to generate the susceptibility map. The research results can provide a scientific basis for the prevention and risk management of PFDF disasters in the study area and its vicinal burned areas.

2 Study area

The study area is located in Lushan District, Xichang City, Liangshan Yi Autonomous Prefecture, Sichuan Province, between longitudes 102°12′–102°18′E and latitudes 27°48′–27°52′N (Fig. 1). The study area is mainly mountainous, with altitudes ranging from 1500 to 2510 m. The climate of the study area is typical subtropical southwest monsoon and plateau climate. Based on local meteorological organizations, the average annual temperature is approximately 17°C, average annual rainfall 1013.5 mm, and daily maximum rainfall 199.5 mm. The rainy season is from May to October, and the rainfall is mainly in the form of rainstorm at night, which contributes to approximately 90% of the total annual rainfall [5]. The study area is originally a forest, with vegetation coverage of approximately 90%, mainly Yunnan pine and Eucalyptus. Various lithological formations outcrop in the study area, including the mudstone, shale, and siltstone of the Cretaceous, and the Quaternary Holocene eluvium is mainly silty clay with gravel. On March 30, 2020, a large-scale forest fire occurred in the study area, which lasted for three days and affected an area of more than 30 km². From May to October 2020, PFDFs had occurred in several basins (50 in total) in the study area, which posed a significant threat to life and property around the study area.
3 Materials and methods

To prepare a susceptibility map of PFDF in the study area, we adopted the following steps: (1) data preparation involving the preparation of a PFDF inventory and its spatial database of impacting factors, (2) multicollinearity test and the RF importance analysis of impacting factors, (3) PFDF susceptibility modeling using the RF model, and (4) the validation of PFDF susceptibility maps produced using the RF model.

3.1 Data preparation

3.1.1 Post-fire debris flow inventory

In this study, a PFDF inventory was produced based on field tracking surveys and aerial images during the rainy season (from May to October 2020). A total of 1312 hydrological response events were counted, including 181 (~13.8%) debris flow events and 1131 flood events.

3.1.2 Post-fire debris flow impacting factors

Based on previous studies and the availability of data in the study area [1,5,15], this study selected 10 impact factors of post-fire debris flow, as shown in Table 1, from the aspects of the basin morphology, fire severity, vegetation coverage, distribution of dynamic material sources in the basin, and rainfall intensity. The methods for obtaining each impact factor were as follows:

(1) Basin morphology: The steepness of the topography and shape of the basin directly affect the erosion rate and sediment stability of the slope and channel and contribute to the transition from surface runoff to debris flow in the burned area [9,13]. Four widely used basin morphological factors, i.e., the basin area (Area), relief ratio (RR), basin shape coefficient (BS), and percentage of the basin area with slope greater than or equal to 50% (Slope ≥ 50% (%)) were calculated using the ArcGIS spatial analysis tool based on digital elevation models with a 12.5-m resolution [1,15].

(2) Fire severity: The intensity and duration of a forest fire directly relates to reductions in protective cover and changes in the physical and chemical properties of soils, thereby elevating runoff response during rainfall and increasing the susceptibility of surface to erosion processes [13]. A high-intensity forest fire has a more significant impact on the surge of peak discharge in the burned basin [10].

According to the normalized burn ratio calculated using the Landsat Thematic Mapper data and
combined with the verification of the field investigation results of fire severity (Fig. 2), the fire severity of the basins was divided into four grades: high, moderate, low, and unburned (Fig. 3)[16]. The percentage of the basin burned at moderate or high severity was then calculated using the ArcGIS spatial analysis tool; this factor is commonly used to quantify the impact of fire behavior conditions on PFDF [1,13,15].

(3) Distribution of dynamic material sources: Through field measurements (immediately after the fire) and by referring to the investigation standards in the Specification of Geological Investigation for Debris Flow Stabilization (DZ/T 0220-2006) [17], the distribution of gravel in each basin was recorded. This factor is a descriptive variable that can be divided into four categories in the database. Numbers 1–4, respectively, represent the ratio of the supply length of the gravel along the main channel in the basin and are divided into <10%, 10%–30%, 30%–60%, and >60%.

(4) Vegetation coverage: Forest fires induce the production or enhancement of soil water repellency. This reduces soil permeability and increases slope runoff to increase the sensitivity of post-fire debris flow. Compared with other forest vegetation, the water repellency of the soil under a pine forest increases more significantly after forest fires [18]. Therefore, through aerial images and field surveys, the distribution of vegetation coverage in each basin was recorded. This factor is divided into five categories in the database, and the numbers 1–5 represent the proportion of the original pine tree coverage area in the basin as <20%, 20%–40%, 40%–60%, 60%–80%, and 80%–100%, respectively.

(5) Slope soil erosion: The high-temperature burning caused by forest fires degrades the slope-surface soil properties, resulting in material that is loose, fragile, and easily eroded. As shown in Fig. 4, with the increase in rainfall events after fire, the average of the early accumulated erosion (ECE) gradually increased, whereas the PFDF outbreak frequency showed a gradually decreasing trend, i.e., ECE was negatively correlated with PFDF susceptibility. ECE was derived from the on-site testing of burned areas. We selected seven typical burned basins in the study area and performed erosion needle monitoring plots in different fire severity areas, slopes, and slope lengths, with a total of 1600 erosion needles (Figs. 5 and 6). The erosion depth was measured after each effective rainfall, and a total of 12 sets of effective monitoring data were obtained through field tracking tests during the whole rainy season (May to October 2020). Based on the cumulative rainfall, slope, and slope length factors, the calculation models of soil erosion under different fire severities (Eq.1–4) were obtained using nonlinear fitting methods, and these quantitatively describe the cumulative soil erosion of the different basins in the study area.

(6) Rainfall intensity: Short-term heavy rainfall is often described as a trigger for PFDF [13]. Cannon et al. (2010) also believes that it is best to define thresholds for rainfall intensity measured over a short duration of rainfall (<20 h) [1]. Therefore, two rainfall factors with different durations (Peak 1 h and Peak 24 h) were collected from 11 radar rainfall monitors located within a maximum radius of 2 km in each basin.

\[
D_U = 0.06691 \ln I - 3.0457L^{0.12405}R^2 = 0.55795, n = 204, P < 0.0001 \quad (1)
\]

\[
D_L = 0.09887 \ln I - 3.3933L^{0.22916}R^2 = 0.50569, n = 204, P < 0.0001 \quad (2)
\]

\[
D_M = 0.19621 \ln I - 3.2425L^{0.28474}R^2 = 0.75184, n = 204, P < 0.0001 \quad (3)
\]

\[
D_H = 0.41717 \ln I - 5.12284L^{0.1637}R^2 = 0.55142, n = 355, P < 0.0001. \quad (4)
\]

Where \(D_U, D_L, D_M, \) and \(D_H\) denote the slope soil erosion depth in the unburned, slight severity,
moderate severity, and high severity burned zones, respectively, in millimeters; $I$ represents the cumulative rainfall in millimeters; $S$ denotes the slope in degrees; and $L$ represents the slope length in meters. (Note: Experimental data, fitting process, and the application effect of Eq.1–4 are presented in another paper: “Characteristics and calculation of the dynamic reserves of slope erosion materials in burned areas in Xichang, China, on March 30, 2020,” which is currently under review at Journal Catena.)

Figure 2. Typical photos of different fire severity areas in the study area [5]: a. high severity burned; b. moderate severity burned; c. slight severity burned; and d. unburned.

Figure 3. Characteristics and spatial distribution of fire severity in the study area.
3.2 Methodology

3.2.1 Data preprocessing

Variance inflation factor (VIF) and tolerance (TOL) methods are two common methods used to analyze the multicollinearity of the impacting factors of debris flow and landslides [15,19]. VIF > 5 or tolerance < 0.1 indicates potentially severe multicollinearity [19]. The results of the current study show that the highest VIF value of the 10 PFDF impacting factors is 3.508, and the lowest TOL value is 0.285, indicating that there is no multicollinearity relationship among the PFDF impacting factors (Table 1).

Table 1. Multicollinearity analysis and description for the PFDF impacting factors

| Factors                  | Description               | VIF   | TOL   |
|--------------------------|---------------------------|-------|-------|
| Area (km²)               | Basin area                | 1.550 | 0.645 |
| RR (‰)                   | Relief ratio              | 2.613 | 0.383 |
| BS                       | Basin shape coefficient   | 1.809 | 0.553 |
| Slope ≥ 50% (%)          | Percentage of area with slope greater than 50% | 2.649 | 0.378 |
### 3.2.2 Model

The RF method is a nonparametric statistical technique based on a decision tree ensemble (i.e., forest) producer for regression or classification \[20\]. The samples and factors of RF are selected randomly, and this randomness leads to an increase in the deviation. However, because of the averaging of the results, the variance of RF decreases, and because this is more than the increase in the deviation, the overfitting can be effectively reduced. The RF model can also be used to rank the importance of variables in regression or classification problems and can measure the importance of impacting factors by calculating the Gini coefficient \[21\]. The calculation equation of the RF probability value is as follows:

\[
P_c = \max \left\{ p_i = \frac{\sum_{j=1}^{m} p_{ij}}{m} \mid i \in I \right\} \quad (5)
\]

Where \( I \) denotes the set of all classifications; \( m \) represents the number of decision trees; \( p_i \) denotes the probability of the occurrence or existence of an event; \( p_{ij} \) represents the probability of the existence or occurrence of the \( j \)-th decision tree; and \( p_c \) denotes the probability value of the final classification.

#### 3.2.3 Model training and validation

In this study, the RF model was employed to model the susceptibility of PFDF. The main model parameters “ \( n \text{\_estimators} \)”, “ \( \text{max\_depth} \)”, and “ \( \text{max\_features} \)” were set to “500,” “10,” and “10,” respectively, and the output “feature\_importances” was obtained to determine the importance of each PFDF impact factor. The data set was first divided into two subsets, i.e., the training set containing 70% of the instances and the validation set containing the remaining 30% of the instances, and stratified random sampling was used to explain the unbalanced binary results. Subsequently, through 10 iterations of random (fixed random seed) model training, the optimal prediction model (the final prediction model) of debris flow occurrence probability was obtained with the maximization of AUC as the evaluation standard. Finally, the susceptibility map of post-fire debris flow was generated and its accuracy verified. All data preprocessing and model development were conducted in the Python 3.6.5 environment.

In this study, the evaluation metrics used were sensitivity, specificity, accuracy, and AUC, which have been widely used in previous studies on PFDF prediction models \[13-15\] and are defined as follows:

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FP} \quad (6)
\]

\[
\text{Sensitivity} = \frac{TP}{TP + FN} \quad (7)
\]

\[
\text{Specificity} = \frac{TN}{TN + FP} \quad (8)
\]
Where FP (false positive) corresponds to the number of debris flow samples falsely classified, and FN (false negative) indicates the number of the misclassified samples of non-debris flow. TP (true positive) is the number of correctly classified debris flow samples, and TN (true negative) corresponds to the non-debris flow samples correctly classified. The true positive rate (TPR) is the “sensitivity” of the model, and the false positive rate (FPR) is the “1-specificity.” AUC is the area under the ROC curve, which is usually used to measure the performance of debris flow prediction model [13-15]. The larger the value, the better the prediction ability, which is generally divided into five categories: poor (0.5–0.6), average (0.6–0.7), good (0.7–0.8), very good (0.8–0.9), and excellent (0.9–1).

3.2.4 Susceptibility mapping and validation

Based on the final prediction model, this study substituted all debris flow impacting factors into the final prediction model to obtain the probability (P) of PFDF in the first rainstorm event immediately after the fire in each basin of the study area. The dynamic values of the influencing factors are defined as follows: the ECE is equal to 0 mm, and the rainfall factor is taken as the average value of the maximum 1 and 24 h rainfall intensity in the first month of the nearly 10 rainy seasons in the research area. Further, based on the natural breakpoint method in the ArcGIS software, the probability (P) is classified into four intervals: 0–0.178, 0.178–0.455, 0.455–0.737, and 0.737–1, corresponding to four susceptibility levels: low, moderate, high, and very high, and the susceptibility map of PFDF is generated. Finally, the accuracy of the susceptibility map of PFDF is validated by the ROC curve and field investigation results of the actual outbreak of PFDF.

4. Results

4.1. Model prediction results

Figure 7 shows the importance of each impacting factor of PFDF based on the RF method. Among them, Peak 1 h (0.2216) is the most important factor affecting the formation of PFDF, followed by ECE (0.2087), Peak 24 h (0.1844), Gd (0.0894), M/HS (%) (0.0685), slope ≥ 50% (%) (0.0545), BS (0.0524), VD (0.0493), RR (0.0381), and Area (0.0331). Therefore, ECE, Gd, and M/HS (%) are the controlling factors that affect the formation of PFDF except for rainfall factors, whereas Area and RR have little influence.

The prediction results of PFDF susceptibility are shown in Fig. 8 and Table 2. The very high susceptibility class has the largest percentage (47.6%) of basins, followed by low susceptibility (23.20%), moderate susceptibility (21.90%), and high susceptibility (7.3%).

4.2 Validation of model results

The validation results of the prediction performance of the RF model using the validation dataset and receiver operating characteristic (ROC) curve are shown in Fig. 9 and Table 3. The results suggest that the RF model has a good predictive performance of which the AUC is 93.4%, sensitivity 88.3%, specificity 99.3%, and accuracy 97.8%.

According to the field investigation results of the actual occurrence of PFDF, the prediction accuracy of the susceptibility of PFDF is shown in Table 2. Evidently, the actual number of PFDF events is proportional to the susceptibility level: the ratios of the actual occurrence of PFDFs in each
susceptibility level are 0.55% (low susceptibility), 2.21% (moderate susceptibility), 7.18% (high susceptibility), and 90.06% (very high susceptibility). In other words, the actual number of PFDF events increases with the increase in the susceptibility level, which is consistent with the field investigation results. Therefore, the RF prediction model in this study can accurately classify the susceptibility of PFDF.

Figure 7. Importance of each impacting factor of PFDF based on the RF method.

Figure 8. Susceptibility map of PFDF in the study area.

Figure 9. ROC curves and prediction rate for the RF model.

Table 2. Prediction results and accuracy validation of PFDF susceptibility

| Susceptibility level | Low | Moderate | High | Very high |
|----------------------|-----|----------|------|-----------|
| Predicted number of basins | 19  | 18       | 6    | 39        |
| Predicted percentage of basins (%) | 23.2 | 21.9     | 7.3  | 47.6      |
| Actual number of PFDF disasters | 1   | 4        | 13   | 163       |
| Ratio of actual occurrence of PFDF disasters (%) | 0.55 | 2.21     | 7.18 | 90.06     |

Table 3. Validation results of the RF model’s prediction performance

| Metrics | AUC   | Sensitivity | Specificity | Accuracy |
|---------|-------|-------------|-------------|----------|
| Result  | 93.4% | 88.3%       | 99.3%       | 97.8%    |
5. Conclusion
The present study modeled the PFDF susceptibility spatially in the Xichang “2020.3.30” fire-burned area using an advanced machine learning method, i.e., the RF model. We first conducted a tracking survey on the rainy season, on-site tests, and remote sensing image interpretation and obtained 10 PFDF susceptibility factors, i.e., Area, RR, BS, Slope ≥ 50% (%), M/HS (%), GD, VD, ECE, Peak 1 h, and Peak 24 h. After multicollinearity and importance analyses, the RF model was used for susceptibility modeling. The main conclusions are as follows:
(1) The result of the multicollinearity analysis shows no collinearity among the 10 spatial impacting factors of PFDF selected herein. The importance of the debris flow impacting factors analysis results show that Peak 1 h is the most important factor affecting the initiation of PFDF and that ECE, GD, and M/HS (%) are the three main factors that affect the formation of PFDF besides rainfall, whereas Area and RR have little influence.
(2) The ROC curve verified the predictive performance of the RF model. The results show that the RF model has good predictive ability with AUC of 93.4%, sensitivity of 88.3%, specificity of 99.3%, and accuracy of 97.8%.
(3) The prediction results of PFDF susceptibility based on an RF model show that among the 82 basins in the study area, there are 19 basins with low susceptibility, 18 basins with moderate susceptibility, 6 basins with high susceptibility, and 39 basins with high susceptibility, accounting for 23.2%, 21.9%, 7.3%, and 47.6%, respectively. The actual number of PFDF events is proportional to the susceptibility level: the ratios of the actual occurrence of PFDFs in each susceptibility level are 0.55% (low susceptibility), 2.21% (moderate susceptibility), 7.18% (high susceptibility), and 90.06% (very high susceptibility), which is consistent with the field investigation results. Thus, the RF prediction model used in this study can accurately classify the susceptibility of post-fire debris flow.

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