Journal of Network Intelligence ©2025 ISSN 2414-8105
Taiwan Ubiquitous Information Volume **10**, Number **3**, August **2025**

An Empirical Study on Spatio-temporal Evaluation of Post-earthquake Landslide Risk with Hybrid Coupling Model

Cheng-Di Luo[1], De-Cheng Zhang[2,*], Ming-Yang Li[3]

[1]Administration Office, Sichuan Institute of Tourism, Chengdu 610299, China
luochengdi12392@163.com

[2]Capital Construction Department, Chengdu Sports University, Chengdu 610041, China
zdc19830813@163.com

[3]School of Civil Engineering and Architecture, Southwest University of Science and Technology, Mianyang 621010, China
bhjxsy0801@163.com

*Corresponding author: De-Cheng Zhang

Received June 21, 2024, revised November 15, 2024, accepted February 26, 2025.

Abstract. *Catastrophic earthquakes typically trigger landslides and can have long-term effects on subsequent landslide activity. Therefore, assessing long-term and spatial geological hazard risks after an earthquake is of utmost importance. This study uses the post-earthquake conditions in Jiuzhaigou in 2017 as a reference for assessing the spatiotemporal evolution patterns and changes in landslide risk in the area. By employing integrated "space–time–ground" monitoring technologies, this study develops a comprehensive multitemporal dataset of typical post-earthquake landslide disasters. Moreover, by building on the foundation, this study introduces typical influencing factors to develop a coupled model (i.e., CF + LR model) of post-earthquake landslide susceptibility that combines certainty factor and logistic regression methods. In addition, this study summarizes the spatiotemporal evolution patterns of landslides, and the results indicate that the coupled model demonstrates high accuracy and reliability in identifying high-risk areas. The prediction accuracy of the coupling model is increased by 5.99% and 8.92% respectively. Sensitive regions exhibit features such as low elevation, gentle slopes, windward slopes, and proximity to drainage channels. This study identifies significant implications for temporal segmentation, geographic zoning, and the long-term risk assessment and management of post-earthquake landslides.*
Keywords: Jiuzhaigou Earthquake; Landslide; Risk Assessment; Risk Management

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1. **Introduction.** When a catastrophic earthquake occurs, it will not only trigger numerous landslides but also significantly impact major infrastructure projects and people's lives and property [1, 2, 3]. As one of the most severe and destructive geological hazards, landslides triggered by earthquakes typically evolve into a complex chain reaction. The Jiuzhaigou earthquake that occurred on August 8, 2017, triggered several coseismic landslides. Studies showed that the earthquake caused the surrounding mountains to vibrate and crack. Under the combined effects of rainfall, seismic activity, and other factors, the cracked mountain slopes became highly susceptible to destabilization, which led to a series of secondary geological disasters [4, 5, 6]. Five years after the earthquake, the affected area experienced multiple rainfall events, which led to frequent secondary disasters, such as landslides. Therefore, assessing landslide risk is crucial to predict hazardous areas and

delineate prevention and control zones at different times and stages. Such an evaluation is of utmost importance to theoretical research and technical support.

Landslide risk assessment is a fundamental evaluation method based on the combined influence of multiple factors for predicting the likelihood of a landslide. The method can provide important scientific support for landslide management, ecological restoration, and optimal resource allocation [7]. Post-earthquake landslide susceptibility assessment models can be divided into qualitative and quantitative methods [8]. Qualitative models rely mainly on expert knowledge, whereas quantitative models depend on data collection and analysis. The models use single mathematical theories and conduct modeling to analyze and assess susceptibility to geological hazards [9, 10]. However, quantifying the complex relationships between post-earthquake landslide risk and its influencing factors, as well as determining the impact of different factors and the influence of the same factors with varying characteristic values, is challenging. Therefore, the multimodal coupling of various methods has emerged as a new research direction [11, 12].

Studies showed that compared with single models, multimodal coupling models demonstrate higher accuracy, rationality, and success rates in predicting landslide susceptibility [13]. Some studies explored the impact of different regions and influencing factors on landslide risk by analyzing post-earthquake landslide events. For example, some studies used coupling methods based on geographically weighted regression models and support vector machines, which have shown significant advantages in landslide prediction [14]. In addition, coupling methods that combine certainty factor (CF) and logistic regression (LR) models can not only address the variability in the impact of different influencing factors on landslide activity but also determine the weights of the factors in landslide disaster points at different time periods through LR analysis, which can enhance the accuracy and reliability of landslide risk assessment. The findings of this research can provide scientific and systematic methodological support for post-earthquake landslide risk assessment and contribute to the development of highly effective disaster prevention and mitigation measures.

This study employs a comprehensive "space–air–ground" monitoring approach to create a multisource, multitemporal, and multiscale landslide dataset covering the five-year period after the Jiuzhaigou earthquake. This study incorporates typical influencing factors and comprehensively considers landslide risk variability and combines the CF model with the LR model to create a landslide risk assessment model to accurately determine the mutual weights of the factors that can influence landslide risk. This model can deepen our understanding of the spatiotemporal evolution patterns of landslide risk, and the accurate calculation of the relative weights of the factors that can influence landslide risk will deepen our understanding of landslide spatiotemporal evolution. The findings are crucial for predicting post-earthquake landslides, defining disaster prevention zones, and informing recovery strategies after an earthquake.

2. **Study Area Overview.** On August 8, 2017, a 7.0-magnitude earthquake hit Jiuzhaigou, with the epicenter located at 33.20°N latitude and 103.82°E longitude and a focal depth of 20 km. The earthquake resulted in numerous casualties and substantial property damage, with hundreds of people sustaining injuries, approximately 25 fatalities, severe damage to buildings, and varying degrees of infrastructure destruction [15, 16]. The earthquake triggered several secondary geological disasters, such as landslides and collapses, which significantly impacted Jiuzhaigou's natural landscape and ecological environment.

This study selects 20 debris flow catchments along the core scenic areas of Jiuzhaigou National Park, which cover a total area of 171.3 km^2. The study area is located in a deeply cut high mountain canyon region characterized primarily by tectonic and erosional mountain landscapes. The valleys within each debris flow catchment are deeply incised, and the tributary valleys are well developed. The area exhibits significant relative elevation differences, with altitudes ranging from 2,150 m to 4,502 m. The complex terrain and topographic features can increase the frequency and exacerbate the severity of geological hazards, such as landslides.

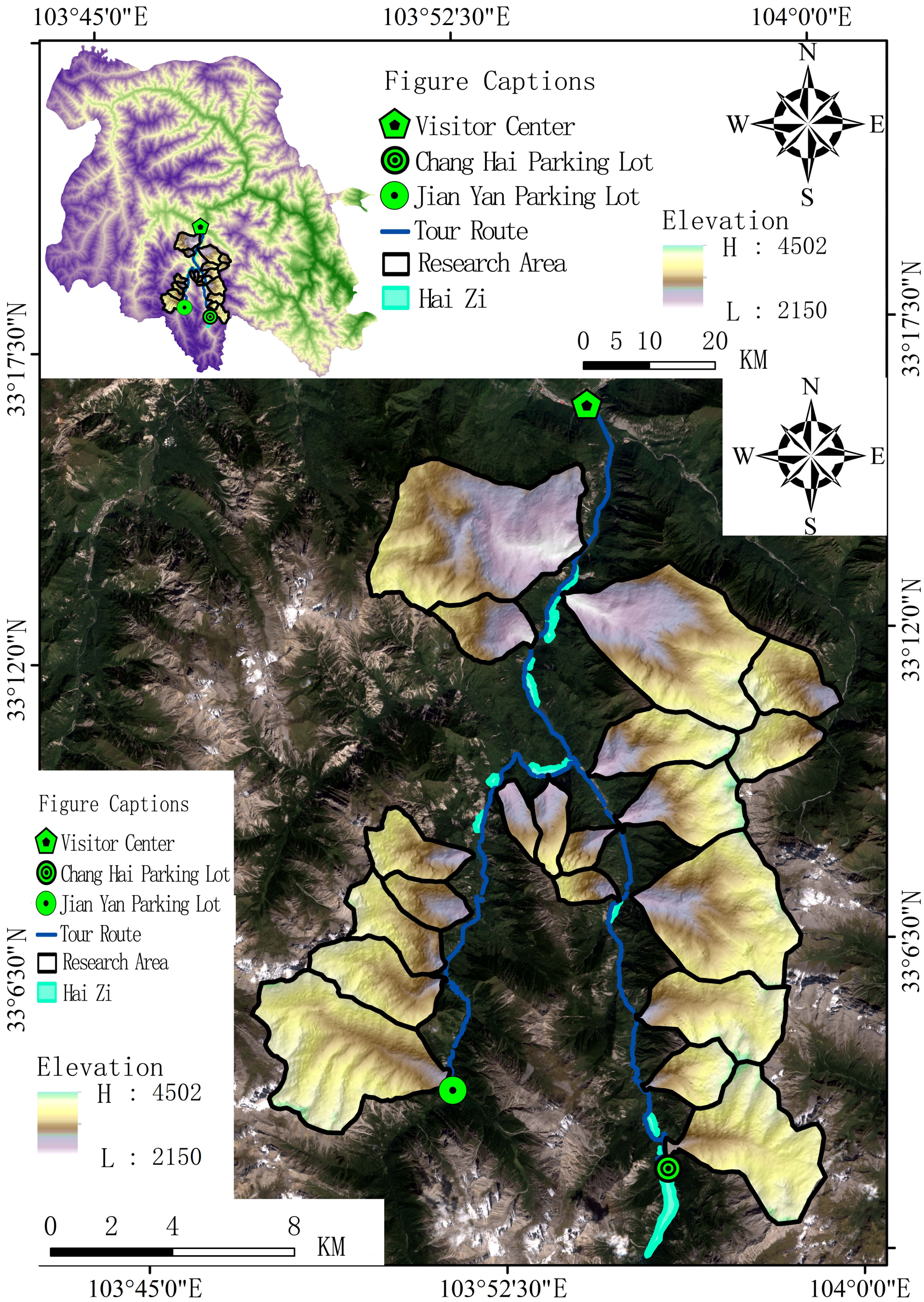


Figure 1. Study Area

The research area is located in the region that was most severely affected by the earthquake, which demonstrated high seismic intensity and triggered significant geological hazards. After the earthquake, the 20 debris flow catchments remained in a state of high activity for an extended period. The landslide bodies within the catchments exhibited severe instability and deformation, which manifested primarily as localized collapses on exposed surfaces and partial sliding at the rear edges. Under the influence of subsequent heavy rainfall, the landslide bodies became highly susceptible to further instability, thereby posing a direct threat to the residents and tourists. Therefore, assessing the risk of secondary disasters, such as landslides, is of utmost importance to post-disaster reconstruction and safety management in scenic areas.

3. **Research Methods.** This study employed ArcGIS spatial statistical analysis tools to vectorize the spatiotemporal distribution of landslides in various periods after the earthquake to determine the quantity and scale of subsequent landslides. The spatial statistical analysis tools in ArcGIS comprise a robust set of functional modules capable of conducting in-depth analyses and interpretations of geospatial data. These tools facilitate the exploration of spatial distribution patterns within the data, such as clustering and dispersion. Additionally, they enable hotspot analysis to identify areas of high or low value concentration, thereby providing critical insights for decision-making. Supported by raster processing, surface analysis, and proximity analysis tools, this study conducted a multifactor evaluation to analyze the spatiotemporal risk and landslide patterns. The evaluation considered indicators such as the slope gradient, aspect, elevation, and distance to channels.

The basic dataset of the interpreted results was divided into 70% training data and 30% testing data. The spatiotemporal risk assessment of landslides was conducted by using the CF, LR, and coupled models [17, 18]. The optimal model was determined based on the area under the curve (AUC) value of the receiver operating characteristic (ROC) curve, then assessed to determine its predictive effectiveness for post-earthquake landslide risk. The post-earthquake risk assessment process and landslide interpretation results are shown in Figures 2 and 3.

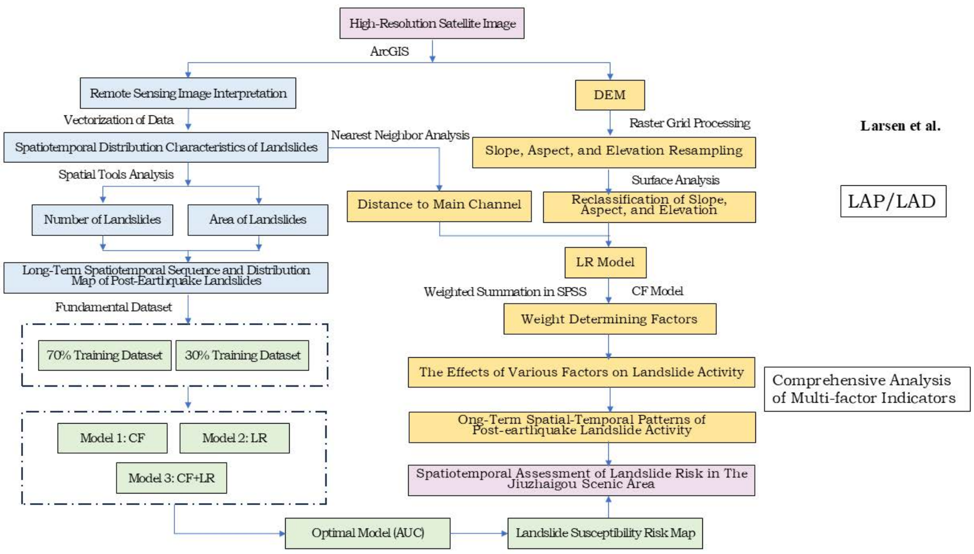
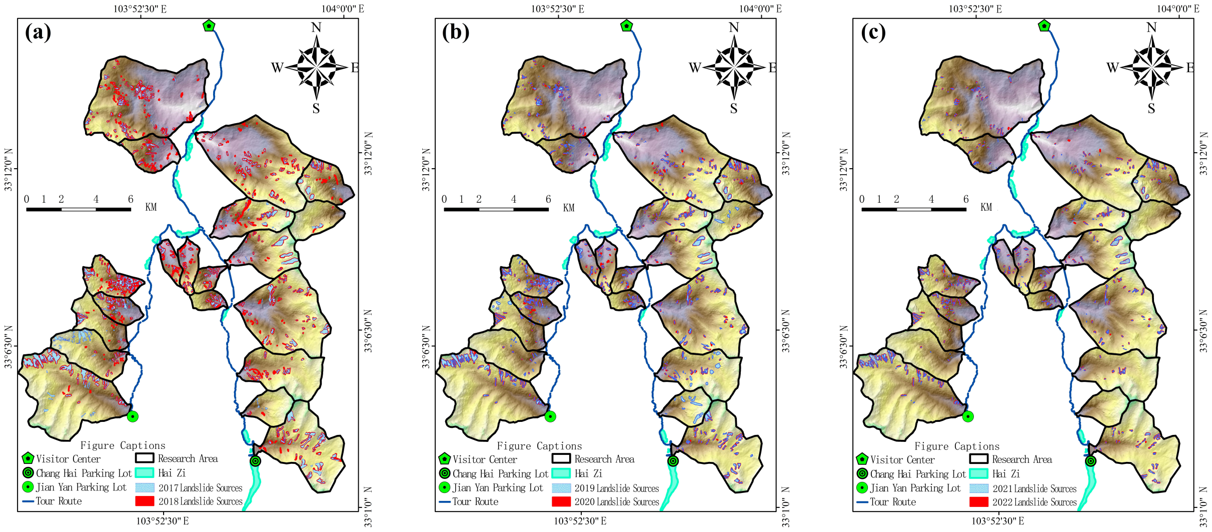


Figure 2. Spatiotemporal Assessment of Post-earthquake Landslide Risk in Jiuzhaigou Scenic Area

3.1. **CF model.** The CF model is a probabilistic function first proposed by Shortliffe and Buchanan (1975) [19]. By utilizing the ArcGIS platform for the landslide hazard interpretation, this study calculated the conditional probability of a landslide occurrence under



(a) Distribution of landslide sources in 2017 and 2018

(b) Distribution of landslide sources in 2019 and 2020

(c) Distribution of landslide sources in 2021 and 2022

Figure 3. Spatiotemporal Evolution of Post-earthquake Landslide Sources

various influencing factors and proposes relevant prevention and mitigation strategies. The expression of the calculation is as follows:

$$\mathrm{CF} = \begin{cases} \frac{P_a - P_s}{P_s(1-P_a)}, & P_a < P_s \\ \frac{P_a - P_s}{P_a(1-P_s)}, & P_a \geq P_s \end{cases} \tag{1}$$

where P_a is the conditional probability of a landslide occurring at each factor level (the ratio of the landslide area under each factor to the factor level area), and P_s is the conditional probability of a landslide occurring within the entire study area (the ratio of the total landslide area under each factor to the total area of the study region).

Positive values indicate increased conditional probability of a landslide occurrence, which means that landslides will likely occur under the factor condition. Conversely, negative values indicate decreased conditional probability, which means that landslides will less likely occur under the factor condition. A CF value close to 0 suggests that the factor condition will not clearly determine whether a landslide will occur, which will indicate the factor's minimal impact on the landslide activity.

3.2. **Spatial LR model.** The LR model is a widely used standard regression technique for solving binary classification problems. The model can accommodate discrete and continuous variables and does not require the assumption of normal distribution. The primary objective of the LR model is to establish a regression relationship between the probability of a landslide occurrence (where 0 denotes no landslide, and 1 denotes a landslide occurrence) and the various influencing factors $(x_1, x_2, \ldots, x_n)$ [20].

In the context of earthquake disaster remote sensing interpretation and landslide spatiotemporal distribution patterns, the LR model can serve as an effective multivariate statistical method for addressing the interdependence of the influencing factors. The model is well suited for evaluating spatial susceptibility to geological hazards. The LR function is expressed as follows:

$$P(Y=1|x) = \frac{1}{1+\exp\left(-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)\right)} \tag{2}$$

where $P(Y = 1|x)$ is the probability of a landslide occurrence given the influencing factors $x_1, x_2, \ldots, x_n$; $\beta_1, \beta_2, \ldots, \beta_n$ represents the regression coefficients of the model; and $x = (x_1, x_2, \ldots, x_n)$ is the vector of the influencing factors.

3.3. **Coupled analysis of CF and LR methods.** To precisely evaluate the spatiotemporal evolution and risk characteristics of post-earthquake landslide activity, this study integrated the CF and LR methods [21] to address the variability in the impact of the different factors on landslide activity. LR analysis can provide insights into the weights of each influencing factor across different periods and estimate the probability of a landslide occurrence based on the factors. The CF method complements the LR method by applying the conditional probability of each factor under specific variables and using CFs for the weighted summation. The combination of the methods will generate the landslide-triggering index G which is defined as follows:

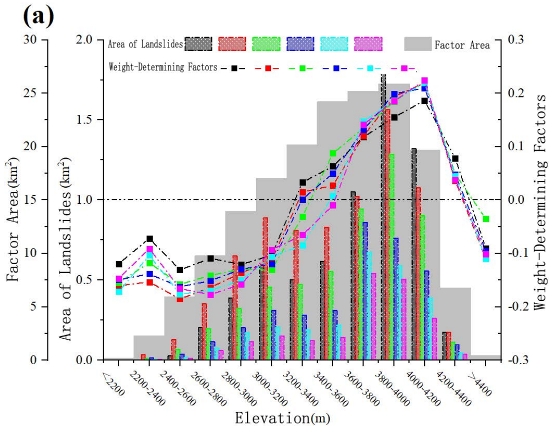
$$G = \sum_{i=1}^{n} P_i \, \mathrm{CF}_i \quad (i = 1, 2, \ldots, n) \tag{3}$$

where G is the landslide-triggering index, P_i is the probability of a landslide occurrence influenced by each factor, and CF_i is the weight factor associated with each influencing variable.

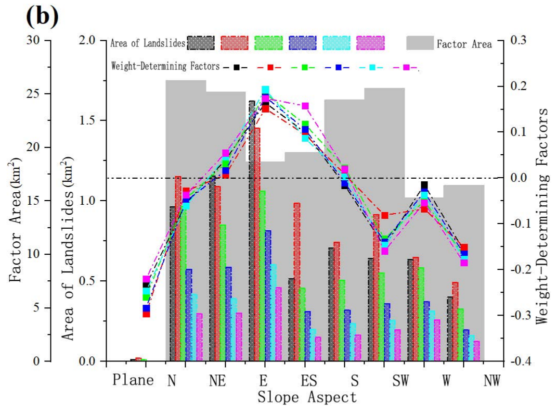
4. **Long-term Spatiotemporal Distribution of Post-earthquake Landslide Activity in Jiuzhaigou.** This section describes the method of the combined CF and LR models and integrates the multitemporal survey data and triggering factors (i.e., slope gradient, elevation, slope aspect, and distance to drainage channels) to explore the long-term spatiotemporal evolution patterns and landslide activity trends under the influence of the factors. The CF values of the factor conditions in the CF model and the corresponding weight values in the LR model are substituted into Equation (3) to obtain the weighted landslide susceptibility index, which is the weighted CF value. As the value of the weight-determining factor increases, the probability of a landslide occurrence rises.

5. **Spatiotemporal Assessment of Landslide Risk in Jiuzhaigou after the Earthquake as the Primary Objective of the Research.** To ensure that the classification results accurately reflect the inherent distribution characteristics of the data, the Jenks natural breaks optimization method was used in this study to classify the landslide risk in Jiuzhaigou under five categories: very low, low, moderate, high, and very high. The Jenks natural breaks optimization classification method is a data classification method. It aims to find natural groupings in data based on the characteristics of the data itself, maximizing the differences between categories and minimizing the differences within a category. This method determines natural breakpoints by analyzing the distribution of data, thus dividing continuous data into different categories.

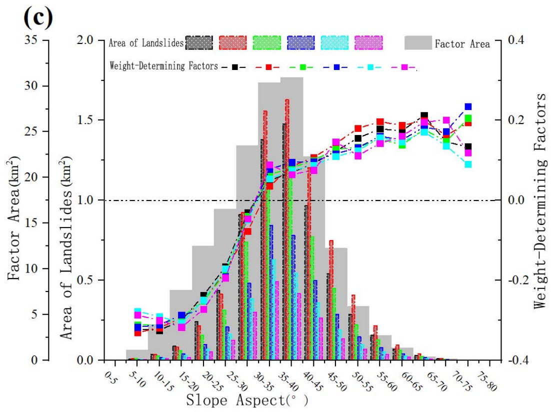
This study employed the ROC curve to quantitatively evaluate the accuracy of the spatiotemporal model for landslide risk in Jiuzhaigou after the earthquake. The ROC curve is a comprehensive index curve reflecting continuous variables of sensitivity and specificity. The ROC curve takes the true positive rate (sensitivity) as the ordinate and the false positive rate (specificity) as the abscissa. By drawing ROC curves under different diagnostic criteria, the accuracy of different diagnostic methods can be intuitively compared. The area under the curve (AUC) can be used to evaluate the performance of diagnostic methods. The closer the AUC is to 1, the higher the accuracy of the diagnostic method. *Dai Lanxin et al.* confirmed the validity of the classification system and demonstrated its applicability across diverse data types [22]. Table 1 shows the range of the AUC values and the corresponding predictive performance.



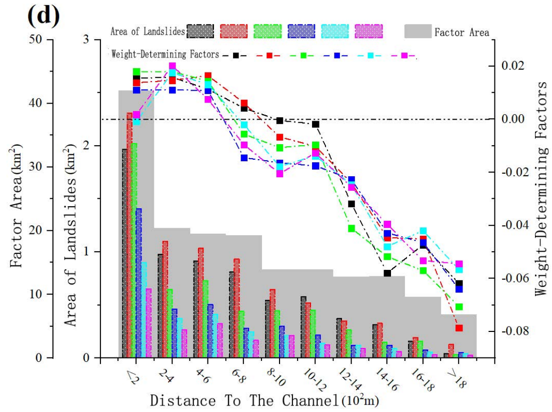
(a) Relationship between post-earthquake landslide activity and elevation



(b) Relationship between post-earthquake landslide activity and slope orientation



(c) Relationship between post-earthquake landslide activity and slope gradient



(d) Relationship between post-earthquake landslide activity and distance to channel

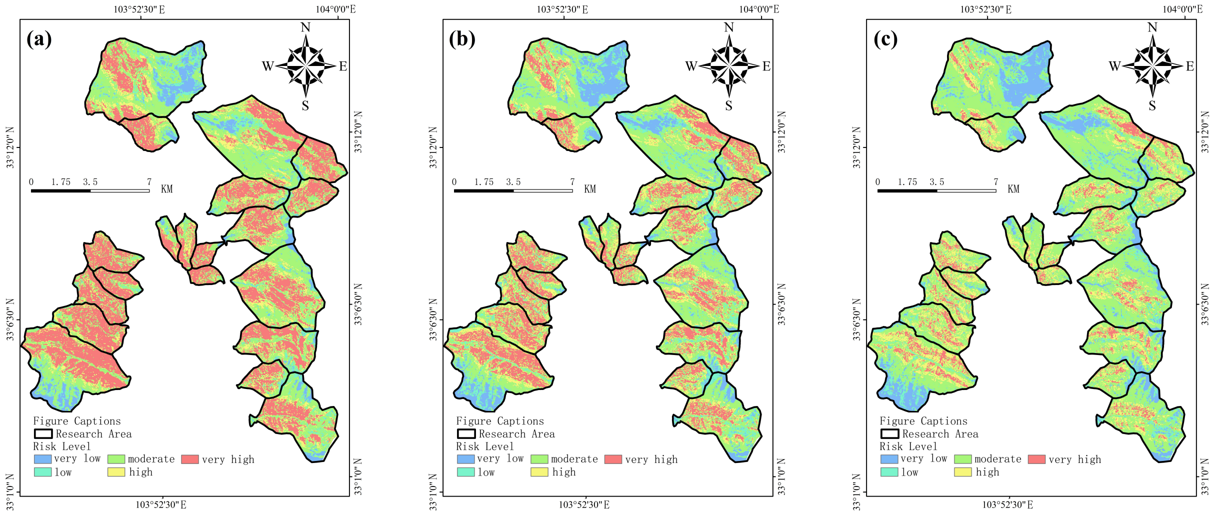
Figure 4. Influence of Various Factors on Spatiotemporal Evolution of Landslides. In the figure, black, red, green, blue, cyan, and purple represent 2017, 2018, 2019, 2020, 2021, and 2022 respectively.

Table 1. Range of AUC Values and Predictive Performance

AUC	< 0.5	0.5–0.7	0.7–0.9	>0.9
Predictive performance	Low performance	Suboptimal performance	High performance	Excellent performance

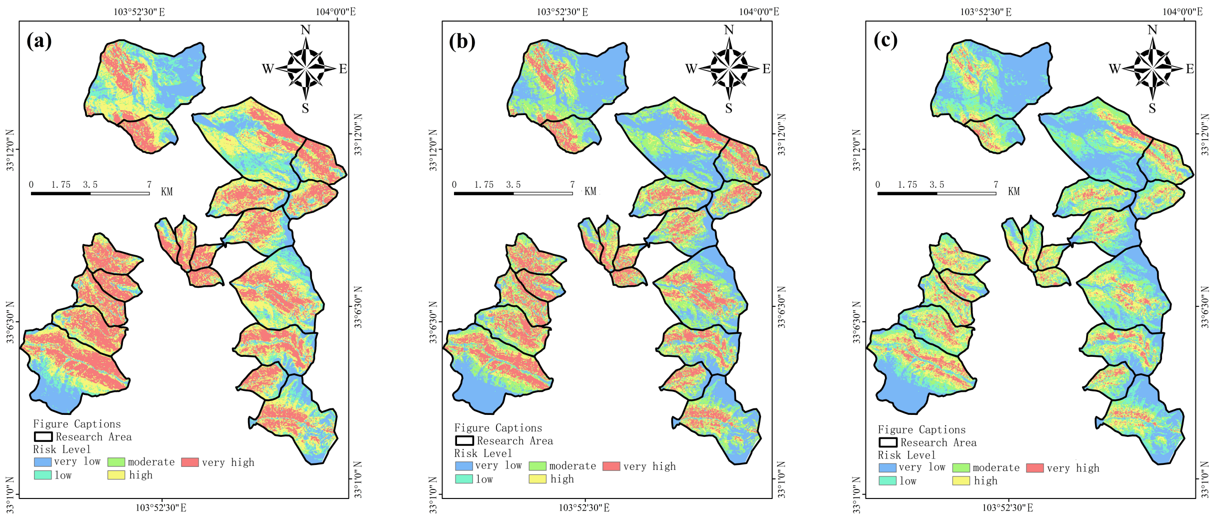
By comparing the landslide risk assessment results presented in Figures 5–7 with the ROC curves, this study drew the following conclusion: although the coupled model and the single model revealed similar trends in the spatiotemporal distribution of landslide risk in Jiuzhaigou after the earthquake, the coupled model demonstrated a significant advantage in accurately identifying the high- and very high-risk areas.

The AUC value of the coupled model immediately after the earthquake in 2017 was 0.792, which is notably higher than the 0.763 and 0.745 values of the LR model and CF model, respectively. By the fifth year after the earthquake, that is, in 2022, the AUC value of the coupled model increased to 0.852, whereas the AUC value of the LR and CF models was 0.801 and 0.776, respectively. The comparison of the AUC values demonstrated that the coupled model offers superior accuracy and practicality in predicting the spatial distribution of landslide risk.



(a) CF model (b) LR model (c) Coupled model

Figure 5. Landslide Risk Assessment Results of Different Models in 2017



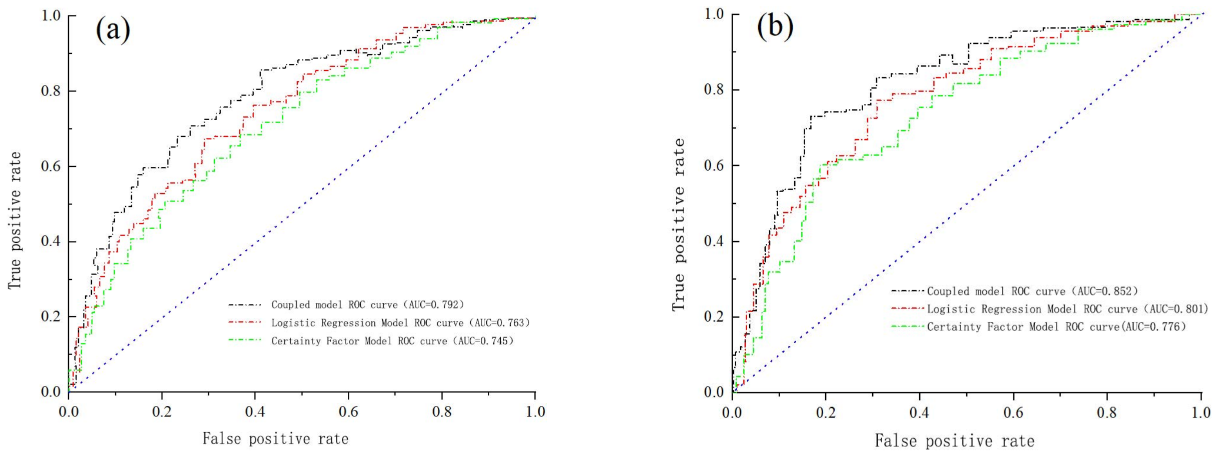
(a) CF model (b) LR model (c) Coupled model

Figure 6. Landslide Risk Assessment Results of Different Models in 2022

In summary, the coupled model not only more accurately identified the high- and very high-risk areas in the spatiotemporal distribution of landslide risk but also consistently exhibited superior predictive performance compared with the individual models at various time points. The advantages can enhance the coupled model's practical advantages in real-world applications.

By using the landslide risk trends after the 2017 Jiuzhaigou earthquake, this study calculated the proportion of landslides at different risk levels at the time of the earthquake and within five years after the event (Table 2). The results indicated that, immediately after the earthquake, owing to the loosening of slope structures and the influence of seasonal heavy rainfall, the proportion of the areas classified as "moderate" or "high risk," calculated by the three models, exceeded 70%.

Over the five-year period after the earthquake, the proportion of the moderate- or high-risk areas decreased significantly. Specifically, the coupled model assessed the proportion of the moderate- or high-risk areas, which decreased sharply from 70.79% to 22.81%.



(a) 2017 (b) 2022

Figure 7. ROC Curves and AUC Values of Each Model

Meanwhile, the proportion of the low-risk areas increased from 22.21% to 77.19%. The trend suggested a general transition in landslide risk, from high to low, with a corresponding shift in the regional proportion, from low- to high-risk areas.

In addition, the spatiotemporal landslide risk evolution trends calculated by the single models are consistent with those obtained by the coupled model, which demonstrated the reliability and consistency of the different models. Further analysis indicated that the slope-loosening effect was most pronounced in the early post-earthquake stages, which led to a substantial increase in landslide risk. However, over time and as natural recovery occurred, the geological conditions stabilized, which resulted in a clear reduction in landslide risk. Notably, the implementation of various disaster prevention and mitigation measures, such as vegetation restoration, slope reinforcement, and drainage system construction, has significantly enhanced the stability of landslide risk areas.

Table 2. Proportion of Landslides at Different Risk Levels After the Earthquake

Model	Year	Landslide risk levels				
		Very low	Low	Moderate	High	Very high
Coupled model	2017	9.85%	19.36%	30.78%	22.23%	17.78%
	2022	59.67%	17.52%	9.66%	8.23%	4.92%
LR model	2017	11.57%	13.62%	34.56%	18.39%	21.86%
	2022	52.55%	17.34%	10.06%	8.32%	11.73%
CF model	2017	15.56%	11.99%	10.35%	19.58%	42.52%
	2022	46.88%	15.68%	5.25%	5.33%	26.86%

The coupled model for landslide risk proposed in this study served as an effective and robust quantitative tool for regional disaster assessment. As indicated by the ROC curve results (Figure 7), the coupled model achieved a prediction accuracy improvement of 5.99% and 8.92% compared with that of the LR model and the CF model, respectively, in the five-year period after the earthquake. The enhancement can be attributed to several key factors.

First, the coupled model thoroughly incorporated the spatiotemporal characteristics of landslides and used a comprehensive analytical approach, which increased its prediction accuracy. Second, the model integrated the strengths of various landslide risk assessment models to create a holistic and detailed evaluation system. Last, by identifying and selecting the relevant influencing factors, the coupled model effectively eliminated extraneous assessment information, which resulted in reliable and precise predictions.

Moreover, the combined methods enhanced not only the model's landslide risk assessment accuracy but also its effectiveness in practical applications. The integration of multiple models and data sources enabled the coupled model to provide a highly accurate representation of the spatial distribution and temporal evolution of post-earthquake landslide risk and thus offer a scientific basis for regional disaster prevention and mitigation. The model's improved performance in long-term post-earthquake prediction underscored its significant advantages in assessing landslide risk within complex geological environments.

In conclusion, through its development and application, the coupled model can serve as a high-precision and practical tool for regional disaster assessment and facilitate the formulation of effective disaster prevention strategies for mitigating landslide disaster impact and ensuring regional safety and stability.

6. **Conclusion.** This study established a comprehensive dataset of post-earthquake landslides in Jiuzhaigou by using multisource and multitemporal data on the ArcGIS platform. The analysis revealed the spatiotemporal distribution patterns and evolution of landslide activity in the area after the earthquake. This study also provided a systematic evaluation of landslide risk in Jiuzhaigou. The key findings are presented below.

(1) By using a post-earthquake landslide risk assessment coupled model (CF + LR model), this study conducted an in-depth analysis of the landslide evolution. Over time, post-earthquake landslide activity shifted progressively to the areas with low elevations (3,200–3,400 m) and gentle slopes (30°–35°). Furthermore, owing to the influence of the monsoon climate and precipitation, landslide activity was concentrated predominantly on the northeast-facing slopes (0–180°).

(2) This study conducted ROC curve analysis to evaluate the prediction accuracy of the coupled model based on the spatiotemporal distribution characteristics of post-earthquake landslide hazards. The results demonstrated that the coupled model exhibited high prediction accuracy for high and very high-risk zones. The prediction accuracy of the coupling model is increased by 5.99% and 8.92% respectively compared with the LR model and CF model.

(3) Effective strategies for post-earthquake landslide prevention should focus on mitigating the expansion of existing landslide-prone areas, particularly that triggered by rainfall. The findings can offer a scientific basis for long-term risk assessment and disaster prevention and contribute to the development of effective post-earthquake geological disaster management strategies.

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