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Spatial distribution patterns and hazard assessment of co-seismic landslides triggered by the 2022 Luding earthquake (M_S 6.8): An RF-AdaBoost model approach

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ABSTRACT

On September 5, 2022, a magnitude 6.8 earthquake struck Luding County, Sichuan Province, China, at a depth of 16 km, triggering numerous co-seismic landslides. Using multi-temporal satellite imagery, the authors identified 7463 co-seismic landslides with varying spatial distributions. Focusing on the differences between the western and eastern sections of the Xianshuihe fault zone, the influences of elevation, slope, aspect, topographic wetness index (TWI), stream power index (SPI), distance to river, distance to seismogenic fault, seismic intensity, lithology, and land surface temperature (LST) on the co-seismic landslide distribution were analyzed. Random Forest-Adaptive Boosting (RF-AdaBoost), Support Vector Machine (SVM) and Back Propagation Neural Network (BP) models were used to assess landslide hazards in the region. The RF-AdaBoost model performed the best, achieving an Area Under the Curve (AUC) of 0.954. The zones of high co-seismic landslide hazard were primarily concentrated along the Xianshuihe fault zone and Dadu River. These findings provide valuable insights into seismic landslide hazard assessments and offer scientific guidance for disaster prevention and mitigation strategies.

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1. Introduction

At 12:52 on September 5, 2022, an M_S 6.8 earthquake struck Luding County (Zhao B et al., 2022), located in the Ganzi Tibetan Autonomous Prefecture of Sichuan Province, triggering massive co-seismic landslides. These landslides caused severe damage to infrastructure, road blockages, and significant disruption in the Wandong River basin near the epicenter, where debris formed a barrier lake. As of September 13, 2022, the earthquake had caused 93 fatalities (55 in Luding County, Ganzi Prefecture, and 38 in Shimian County, Ya'an City), with 25 individuals missing (9 in Luding County and 16 in Shimian County). Therefore, conducting seismic landslide hazard assessments is important for mitigating earthquake disaster losses.

Current seismic landslide hazard assessment methods include the Newmark model and statistical analysis approaches based on mathematical models (Du GL et al., 2022). The Newmark method, first proposed by Newmark (1965), is grounded in the principle of limit equilibrium and adequately considers the occurrence mechanisms of seismic landslides. It has been widely applied to assess seismic landslide hazards following events such as the 1994 Northridge M_W 6.7 earthquake (Jibson RW et al., 2000), the 2015 Nepal M_W 7.9 earthquake (Gallen SF et al., 2017), and the 2014 Ludian M_W 6.1 earthquake (Chen XL et al., 2019). Based on simplified Newmark models, many optimization and improvement methods have been developed and extensively applied (Zang MD et al., 2020; Gupta K and Satyam N, 2022). In addition, statistical methods, such as the information value method (Demir G et al., 2013; Singh K and Kumar V, 2018), logistic regression (Dai FC et al., 2001; Lin L et al., 2017; Chen W and Yang ZF, 2023), fuzzy logic (Ercanoglu M and Temiz FA, 2011; Kritikos T et al., 2015), decision tree (Chen W et al., 2017; Gui JY et al., 2023), random forests (Sajadi P et al., 2022; Sun DL et al., 2022),

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and support vector machines (Yao X et al., 2008; Wang ZH et al., 2021) have proven effective for post-earthquake hazard assessments based on landslide data.

Following the Luding earthquake, numerous studies explored the spatial distribution and hazard assessment of co-seismic landslides. Zhao B et al. (2022) analyzed the influence of tectonic and geomorphic features on landslide distribution by integrating data on seismogenic structures, topography, and geology. Dai LX et al. (2023) predicted the spatial distribution of co-seismic landslides using a Deep Forest Algorithm and explored their spatial characteristics. Yang ZJ et al. (2023) examined the influences of lithology, elevation, slope, and proximity to faults on landslide distribution, whereas Li CH et al. (2023) used the Newmark cumulative displacement model based on Peak Ground Acceleration (PGA) and Arias intensity to rapidly assess landslide hazards. These studies have advanced our understanding of the spatial distribution and hazard assessment of co-seismic landslides induced by the Luding earthquake. However, the long-term activity of the Xianshuihe fault has resulted in distinct geomorphic and geological features in the active and passive blocks on each side of the fault. These differences significantly influenced landslide distribution patterns, underscoring the importance of a detailed comparative analysis to understand the mechanisms underlying these spatial disparities.

To address this issue, the study area was divided into western and eastern sections based on the Xianshuihe fault, allowing for a detailed examination of the differences in landslide distribution. Ten key factors were selected to analyze these variations: Elevation, slope, aspect, topographic wetness index (TWI), stream power index (SPI), distance to river, distance to seismogenic fault, seismic intensity, lithology, and land surface temperature (LST). These factors were systematically analyzed to investigate the spatial distribution of landslides on either side of the fault. Building upon this spatial analysis, this study further employed the Random Forest-Adaptive Boosting (RF-AdaBoost) algorithm to assess seismic landslide hazards within the study area, offering theoretical and technical support for disaster prevention and mitigation endeavors in the region.

2. Geological setting

The research area is located in the Hengduan Mountains, which form the southeastern edge of the Qinghai–Xizang Plateau. This region is characterized by a classic high-mountain canyon landform with dramatic elevational changes and complex terrain. The area includes Sichuan's highest peak, Mount Gongga, which rises 7556 m above sea level, creating an elevation difference of up to 6570 m (Liao HJ et al., 2021). The landscape is further characterized by deeply incised valleys and extensive water systems, including the Dadu River and its tributaries. Prolonged erosion and weathering have resulted in numerous exposed rock surfaces along riverbanks, providing favorable conditions for

earthquake-triggered landslides (Tie YB et al., 2022).

The Luding earthquake occurred in this region, with its epicenter located at 102.08°E and 29.59°N in the Hailuoguo Glacier Forest Park, near Mount Gongga (Fig.1). The earthquake, with a focal depth of 16 km, was located 39 km from Luding County, 47 km from Kangding City, and 226 km from Chengdu City. This seismic event was associated with the Moxi fault, a branch of the Xianshuihe fault zone that trends NNW–SSE and exhibits pronounced left-lateral strike-slip motion combined with thrusting. The western section of the fault represents a hanging wall.

The Xianshuihe fault zone is one of China's most prominent active fault systems (Allen CR et al., 1991) and forms a key component of the southern boundary of the Bayan Har active block on the Qinghai–Xizang Plateau. Extending from Donggu and Ganzi to the north, the fault generally trends NW–SE, passing through Luhuo, Daofu, and Kangding before reaching its southern terminus near Moxi, south of Luding. This fault zone has historically experienced frequent seismic activity, with nearly 20 earthquakes of magnitude 6 or greater recorded since 1725, including eight events exceeding the magnitude 7. Among these, the 1973 Luhuo earthquake (M_S 7.9) was the largest along the fault (Wen XZ et al., 2008). The Moxi fault, a Holocene-active segment of the Xianshuihe fault zone, lies at the eastern margin of the Gongga Mountain uplift. Its complex tectonic activity makes it a high-risk zone for major earthquakes, as evidenced by a significant magnitude 7.8 seismic event of 1786 that triggered extensive co-seismic landslides.

From a geological perspective, the study area encompasses strata from the Sinian system to the Quaternary. The predominant rock types include Mesozoic, Paleozoic, and Proterozoic metamorphic formations such as granite, quartzite, mica schist, and phyllite, along with unconsolidated Quaternary deposits. The intense tectonic activity in the region has led to pervasive rock fracturing and strength degradation, both of which critically affect slope stability.

3. Methods and data sources

3.1. Random Forest

Random Forest (RF) is an ensemble learning algorithm that consists of multiple independent decision trees. When constructing a Random Forest model, random sampling with replacement is first performed on the original dataset to generate multiple training subsets. Subsequently, for each training subset, a random selection of features was used to fit the model and construct several decision trees. During the construction of decision trees, the growth process of each tree is independent of the others without considering the results of other trees. Finally, by integrating the outputs of all the decision trees, the final prediction result can be obtained through voting or averaging. Owing to the adoption of ensemble learning, Random Forest model can effectively reduce overfitting, improve the generalization ability of the model, and handle large datasets, making it suitable for

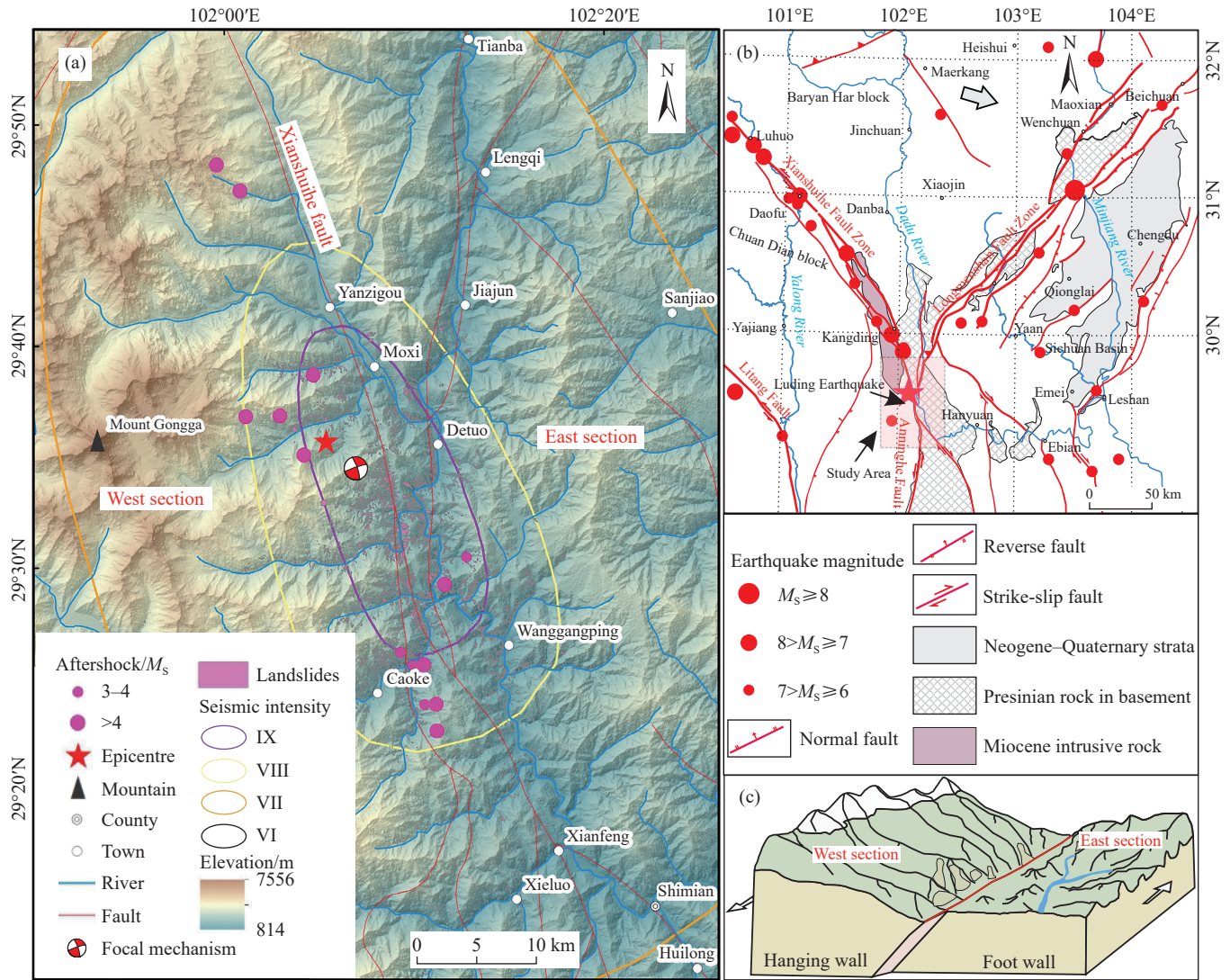


Fig. 1. Geological background map of the Luding earthquake. a–Regional geological structure and landslide distribution map; b–tectonic location of the Luding earthquake area; c–schematic representation of the Luding earthquake (after Yang ZJ et al., 2023).

various types of classification and regression problems.

3.2. Support Vector Machine

Support Vector Machine (SVM) is a linear classifier that seeks to achieve the maximum margin within a feature space. Its learning strategy focuses on identifying a hyperplane in a high-dimensional space that separates data points with the greatest possible margin. The main idea is to establish a hyperplane as the decision surface given the training samples. The essence of Support Vector Regression (SVR) is to find a linear hyperplane or a linear hyperplane in the form of feature mapping that is most likely to be close to all training sample vectors globally in the input vector space. This hyperplane was controlled only by the support vectors of the samples. The model function is as follows:

$$f(x) = \omega^T \phi(x) + b \quad (1)$$

$\omega = (\omega_1, \omega_2, \dots, \omega_d)$ is the weight vector that determines the direction of the hyperplane, $\phi(x)$ is a non-linear function, and

b is the intercept that determines the translation distance of the hyperplane, which in turn determines the distance between the hyperplane and the origin.

3.3. Back Propagation Neural Network

The Back Propagation Neural Network (BP) is a multilayer feedforward network with hidden layers trained using an error back propagation algorithm, consisting of input-hidden-output layers. The construction of the BP neural network model first requires determining the number of neurons in the input layer (n), hidden layer (ω_{ij}), and output layer (m). Next, determine the threshold of the hidden layer (a_j), threshold of the output layer (b_k), learning rate, number of training epochs, minimum target training error, and activation function. The connection weights between the input layer and the hidden layer are represented by ω_{ij} , and the connection weights between the hidden layer and the output layer are represented by ω_{jk} .

The formula for calculating the output of the hidden layer is as follows:

$$T_j = f \left(\sum_{i=1}^n \omega_{ij} x_i - a_j \right), j = 1, 2, \dots, u \quad (2)$$

where T_j is the output value of the hidden layer; u is the number of neurons in the hidden layer, and f is the activation function of the hidden layer.

The formula for calculating the output of the output layer is as follows:

$$D_k = \sum_{j=1}^i T_j \omega_{jk} - b_k, k = 1, 2, \dots, m \quad (3)$$

where D_k is the output value of the hidden layer neurons and k is the number of neurons in the output layer.

3.4. Adaptive Boosting algorithm

The Adaptive Boosting (AdaBoost) algorithm iteratively trains multiple weak regressors on the same dataset to achieve varying levels of prediction accuracy. Subsequently, these weak regressors were amalgamated to construct a more robust regressor with enhanced accuracy. Fundamentally, the algorithm achieves this by dynamically adjusting the data distribution: based on the conformity of each sample's predicted value to the target and the overall prediction accuracy from prior training iterations and modifying the weights of individual samples. Considering these weights, the updated dataset was utilized in the subsequent training of the weak regressors, culminating in the fusion of multiple weak regressors.

The algorithmic workflow of AdaBoost is as follows:

Given a training set $T = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, where N is the logarithm of the training set $x_i \in R^n, y_i \in R, i = 1, 2, \dots, N$.

(i) The weight distribution of the training samples was initialized. Initially, each training sample had an equal weight.

$$\omega_{1i} = \frac{1}{N} \quad (4)$$

$$D_1 = (\omega_{11}, \omega_{12}, \dots, \omega_{1N}) \quad (5)$$

(ii) Multiple iterations are performed. For $m=1, 2, \dots, m$, where m represents the number of iterations, that is, the number of weak regressors:

(a) Learn using the training dataset processed by weight D_m to obtain a weak regressor $G_m(x)$, where the training error of each sample x_i in the weak regressor is given by.

$$e_{i,m} = |G_m(x_i) - y_i| \quad (6)$$

(b) Calculate the prediction error rate of $G_m(x)$ for the training dataset.

$$E_m = P(e_{i,m} > \theta) = \sum_{i=1}^N \omega_{mi} I(e_{i,m} > \theta) \quad (7)$$

From the above equation, it is evident that the prediction

error rate of E_m on the training set $G_m(x)$ is the sum of the weights of the training samples for $(e_{i,m} > \theta)$, where θ is a predetermined threshold.

(c) Calculate the coefficient of $G_m(x)$, where α_m denotes the importance of $G_m(x)$ in the final predictor.

$$\alpha_m = \frac{1}{2e^{E_m}} \quad (8)$$

From the above equation, it is evident that α_m is inversely proportional to E_m , meaning that the larger the prediction error rate, the smaller the role of the weak regressor obtained in the strong regressor.

(d) Update the weight distribution of the training dataset.

$$\omega_{m+1,i} = \begin{cases} \frac{\omega_{mi} \times 1.1, e_i(t) > \theta}{\frac{\omega_{mi}}{Z_m}, e_i(t) \leq \theta} \end{cases} \quad (9)$$

$$D_{m+1} = (\omega_{m+1,1}, \omega_{m+1,2}, \dots, \omega_{m+1,i}, \omega_{m+1,N}) \quad (10)$$

Increase the weights of the training samples with larger errors in the weak regressor $G_m(x)$, while keeping the weights of the samples with smaller errors unchanged. Through this weight transformation, the AdaBoost method places more emphasis on samples with lower prediction accuracy, where Z_m is the normalization factor.

$$Z_m = \sum_{i=1}^N \omega_{mi} \quad (11)$$

(iii) A linear combination is constructed to obtain a strong regressor.

$$G_m(x) = \sum_{m=1}^m \alpha_m G_m(x) \quad (12)$$

3.5. Data source

To analyze the study area, a spatial database for landslide hazard assessment was constructed using GIS. Various parameters, such as elevation, slope, and aspect, were extracted based on a Digital Elevation Model (DEM) with a spatial resolution of 30 m. The LST was calculated using Landsat 8 OLI remote sensing images. Both DEM and Landsat 8 OLI data were sourced from the Geospatial Data Cloud (<https://www.gscloud.cn>). To further enhance the landslide database, the existing co-seismic landslide database compiled by Huang YD et al. (2023), which originally contained 5007 landslides, was supplemented with 2456 landslides. This expansion was achieved by interpreting Sentinel-2 multispectral imagery with 10 m resolution, in conjunction with Google Earth images. The identification methodology focused on distinguishing differences in tone, texture, forest cover, and other characteristics visible in the satellite imagery (Fig. 2). The sizes of the identified landslides ranged from 20 m² to 199979 m², with the majority being

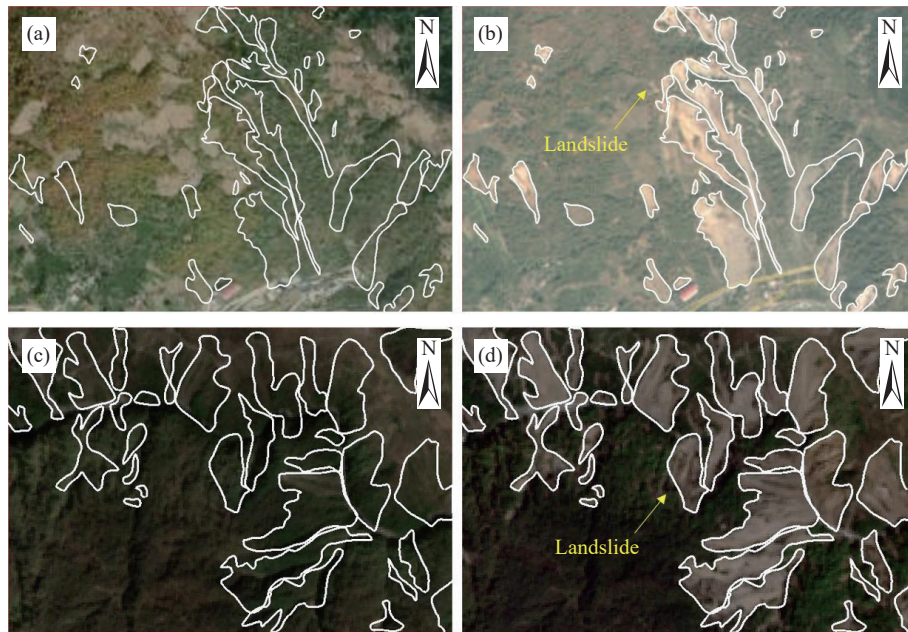


Fig. 2. Seismic landslides obtained from satellite images before (a, c) and after (b, d) the earthquake.

small to medium-sized. These landslides were predominantly distributed within Moxi Town, Detuo Town, Caoke, and Wanggangping, with concentrations along both sides of the Xianshuihe fault zone and Dadu River. Lithological and fault data were obtained from 1 : 200000 geological maps produced by the China Geological Survey. The seismic intensity data were obtained from the Ministry of Emergency Management of the People's Republic of China (https://www.mem.gov.cn/xw/yjglbgzdt/202209/t20220911_422190.shtml).

4. Factor analysis

Landslide occurrence is influenced by multiple factors, and landslide formation is a complex and dynamic process. In this study, elevation, slope, aspect, TWI, SPI, distance to the river, distance to the seismogenic fault, seismic intensity, lithology, and LST were selected as key indicators for seismic landslide hazard assessment in the study area, as illustrated in Fig. 3.

The landslide area is a commonly used statistical indicator that directly reflects landslide distribution. Given that the scale and extent of certain factors can vary significantly, incorporating Landslide Area Percentage (LAP) helps capture the relative dominance of landslide development (Xiao ZK et al., 2023). The 2022 Luding earthquake triggered 7463 landslides, covering a total area of approximately 33.87 km². To explore the relationships between landslide distribution and influencing factors, the study area was divided into western and eastern sections along the Xianshuihe fault (Table 1). This division facilitated a detailed comparative analysis of landslide distribution patterns across the two sections.

4.1. Elevation

Elevation refers to the vertical distance of a point along

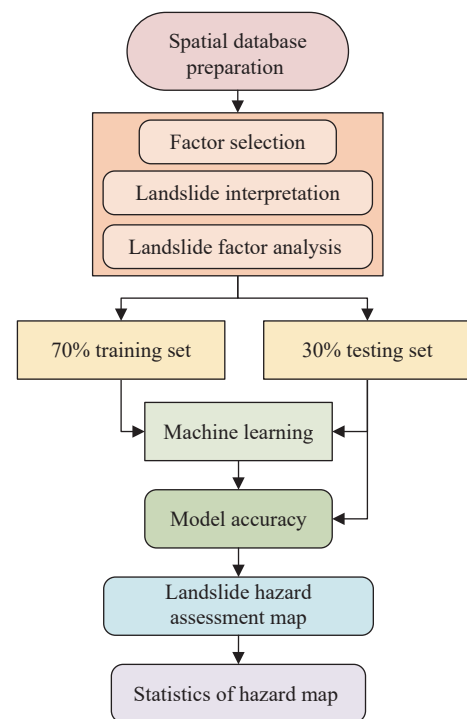


Fig. 3. Flow chart of co-seismic landslides hazard assessment.

the plumb line from an absolute reference plane and is a critical factor influencing landslides. Different elevation ranges are associated with distinct vegetation types and coverage, and elevation is strongly correlated with rainfall, which indirectly affects landslide development. In the study area, the elevation ranges from 814 m to 7756 m. The seven elevation categories used in this study were <1500 m, 1500–2000 m, 2000–2500 m, 2500–3000 m, 3000–3500 m, 3500–4000 m, and >4000 m (Fig. 4a). The area of co-seismic landslides in the study area was greatest (31.73%) in the range of 1500–2000 m. Co-seismic landslides in the western section

Table 1. Relationship between landslides and influencing factors.

Factors	Class	Class area/km ²	Landslide area/km ²	Landslide area on the western section/km ²	Landslide area on the eastern section/km ²	LAP of the western section/%	LAP of the eastern section/%
Elevation/m	<1500	330.833	10.300	1.915	8.385	3.204	3.093
	1500–2000	562.347	10.747	5.288	5.459	3.237	1.368
	2000–2500	801.529	7.922	6.768	1.155	2.900	0.203
	2500–3000	796.638	3.685	3.462	0.223	1.244	0.043
	3000–3500	558.627	0.910	0.884	0.026	0.266	0.012
	3500–4000	445.133	0.279	0.279	0.000	0.075	0.000
	>4000	1107.945	0.030	0.030	0.000	0.003	0.000
Slope/°	0–10	229.384	0.363	0.196	0.167	0.166	0.150
	10–20	576.334	1.491	0.830	0.660	0.287	0.230
	20–30	1051.178	4.682	2.399	2.283	0.451	0.440
	30–40	1488.123	11.067	5.341	5.727	0.668	0.831
	40–50	964.459	11.383	6.401	4.982	1.131	1.250
	50–60	260.291	4.214	2.896	1.318	1.608	1.643
	>60	33.282	0.675	0.563	0.111	2.033	2.001
Aspect	F	1.339	0.000	0.000	0.000	0.000	0.000
	N	553.236	2.909	2.056	0.853	0.627	0.379
	NE	619.289	4.228	2.617	1.611	0.693	0.667
	E	652.416	6.803	3.238	3.565	0.817	1.392
	SE	643.106	7.247	4.330	2.917	1.180	1.057
	S	557.862	5.454	3.702	1.752	1.258	0.665
	SW	548.453	3.040	0.996	2.044	0.396	0.688
	W	490.147	2.412	0.709	1.704	0.322	0.630
TWI	NW	537.205	1.780	0.978	0.802	0.354	0.308
	<4	1453.241	12.224	7.046	5.178	0.878	0.796
	4–6	1969.374	12.601	6.788	5.814	0.645	0.634
	6–8	777.670	6.415	3.332	3.083	0.779	0.881
	8–10	232.404	1.674	0.939	0.735	0.724	0.716
SPI	>10	170.363	0.959	0.521	0.437	0.522	0.620
	<1	79.579	0.125	0.056	0.069	0.167	0.149
	1–3	1369.959	5.876	3.017	2.859	0.435	0.422
	3–5	1918.589	15.287	8.631	6.656	0.808	0.783
	5–7	917.455	9.336	5.115	4.221	0.966	1.088
Distance to river/m	>7	317.469	3.250	1.807	1.443	0.964	1.110
	<200	332.052	5.284	2.691	2.593	1.841	1.395
	200–400	326.082	6.411	2.760	3.651	1.902	2.017
	400–600	318.673	4.718	2.282	2.435	1.594	1.388
	600–800	309.815	3.366	1.757	1.610	1.249	0.952
	800–1000	300.311	2.618	1.335	1.284	0.961	0.795
	1000–1200	288.730	2.081	1.120	0.961	0.816	0.635
	1200–1400	279.492	1.693	1.017	0.676	0.749	0.471
Distance to seismogenic fault/km	>1400	2447.895	7.703	5.663	2.040	0.371	0.221
	0–2	344.956	12.519	6.321	6.198	3.665	3.593
	2–4	344.766	8.280	4.041	4.240	2.344	2.460
	4–6	344.626	5.353	2.692	2.661	1.562	1.545
	6–8	344.439	2.478	1.366	1.112	0.793	0.646
	8–10	342.540	1.747	1.138	0.608	0.661	0.357
	10–12	329.893	1.311	1.161	0.150	0.674	0.095
	>12	2551.832	2.185	1.908	0.277	0.129	0.026
Seismic intensity	VI	706.484	0.000	0.000	0.000	0.000	0.000
	VII	3114.113	5.559	4.210	1.349	0.262	0.089
	VIII	505.640	8.395	4.672	3.723	1.652	1.671
	IX	276.815	19.920	9.744	10.176	6.855	7.556
Lithology	1	130.505	0.063	0.000	0.063	0.000	0.050
	2	332.416	4.290	4.290	0.000	1.291	0.000
	3	69.722	0.000	0.000	0.000	0.000	0.000

Table 1. (Continued)

Factors	Class	Class area/km ²	Landslide area/km ²	Landslide area on the western section/km ²	Landslide area on the eastern section/km ²	LAP of the western section/%	LAP of the eastern section/%
LST	4	219.865	0.007	0.000	0.007	0.000	0.003
	5	359.933	0.000	0.000	0.000	0.000	0.000
	6	109.605	0.015	0.000	0.015	0.000	0.014
	7	515.955	11.448	11.448	0.000	2.259	0.000
	8	548.128	0.369	0.018	0.351	0.005	0.173
	9	120.466	0.146	0.146	0.000	0.121	0.000
	10	121.428	0.552	0.552	0.000	0.455	0.000
	11	2073.933	16.983	2.164	14.820	0.289	1.118
	12	1.097	0.000	0.000	0.000	0.000	0.000
	<0.6	884.602	1.364	1.329	0.035	0.162	0.052
	0.6–0.7	1675.433	5.561	5.055	0.505	0.706	0.053
	0.7–0.8	1537.477	17.964	10.049	7.915	1.467	0.929
	>0.8	505.540	8.985	2.192	6.793	0.750	3.184

exhibited the highest LAP within the range of 1500–2000 m, whereas on the eastern section, the highest LAP occurred within the range of <1500 m range. This pattern was primarily influenced by the erosive activity of the Dadu River, which predominantly affected the regions below 1500 m, particularly in the eastern section (Fig. 5a).

4.2. Slope

The slope, defined as the degree of surface inclination relative to the horizontal plane, is expressed as the ratio of vertical height to horizontal distance. It plays a crucial role in determining the distribution of internal stress within slope materials, thickness of unconsolidated deposits, vegetation cover, and surface water runoff, all of which influence slope stability. Steeper slopes generally experience stronger gravitational forces acting parallel to the surface, increasing the likelihood of destabilization. In this study, slope was classified into the following categories: 0°–10°, 10°–20°, 20°–30°, 30°–40°, 40°–50°, 50°–60°, and >60° (Fig. 4b). Among these categories, landslides in the study area were primarily distributed within the 40°–50° range, accounting for approximately 33.60% of the total landslide area in the study area. The LAP of the co-seismic landslides in both the western and eastern sections tended to increase with increasing slope, reaching a maximum when the LAP exceeded 60°. This trend is attributed to terrain effects, where slopes steeper than 60° experience more pronounced seismic wave amplification, which further increases slope instability (Fig. 5b).

4.3. Aspect

This aspect represents the horizontal projection of the direction of the maximum inclination at a specific point on the ground. It significantly influences various factors, such as surface weathering, vegetation cover, and soil permeability. Differences in solar radiation across slope orientations lead to variations in vegetation growth and water evaporation, directly affecting landslide occurrence and development. In

this study, aspect was categorized as follows: Flat (–1°), North (0°–22.5°, 337.5°–360°), Northeast (22.5°–67.5°), East (67.5°–112.5°), Southeast (112.5°–157.5°), South (157.5°–202.5°), Southwest (202.5°–247.5°), West (247.5°–292.5°), and Northwest (292.5°–337.5°) (Fig. 4c). Statistical analysis indicated that landslides in the study area occurred predominantly along the southeastern slope direction, accounting for approximately 21.40% of the total area. Landslides mostly developed in the southeastern direction in the western section and in the eastern direction in the eastern section. The LAP values were the highest in the southern direction in the western section and in the eastern direction in the eastern section (Fig. 5c).

4.4. Topographic wetness index

The topographic wetness index (TWI) is a physical indicator that reflects the direction of regional topographic runoff and accumulation effects, quantifying the control of terrain on fundamental hydrological processes. A higher TWI value indicates higher soil moisture content, making the soil more prone to saturation and slippage. The formula is as follows:

$$TWI = \ln(\alpha / \tan \beta) \quad (13)$$

where α is the upstream specific catchment area that flows into the region and β is the gradient. In this study, the TWI was divided into the following categories: <4, 4–6, 6–8, 8–10, and >10 (Fig. 4d). Across the entire study area, the highest LAP occurred within the range of TWI <4, whereas the distribution of landslide areas was most significant in the TWI 4–6 range, accounting for approximately 37.20% of the total landslide area. Specifically, landslides were more likely to occur in the TWI <4 range in the western section, whereas in the eastern section, they were more common in the TWI 6–8 range (Fig. 5d).

4.5. Stream power index

The stream power index (SPI) is an indicator of the

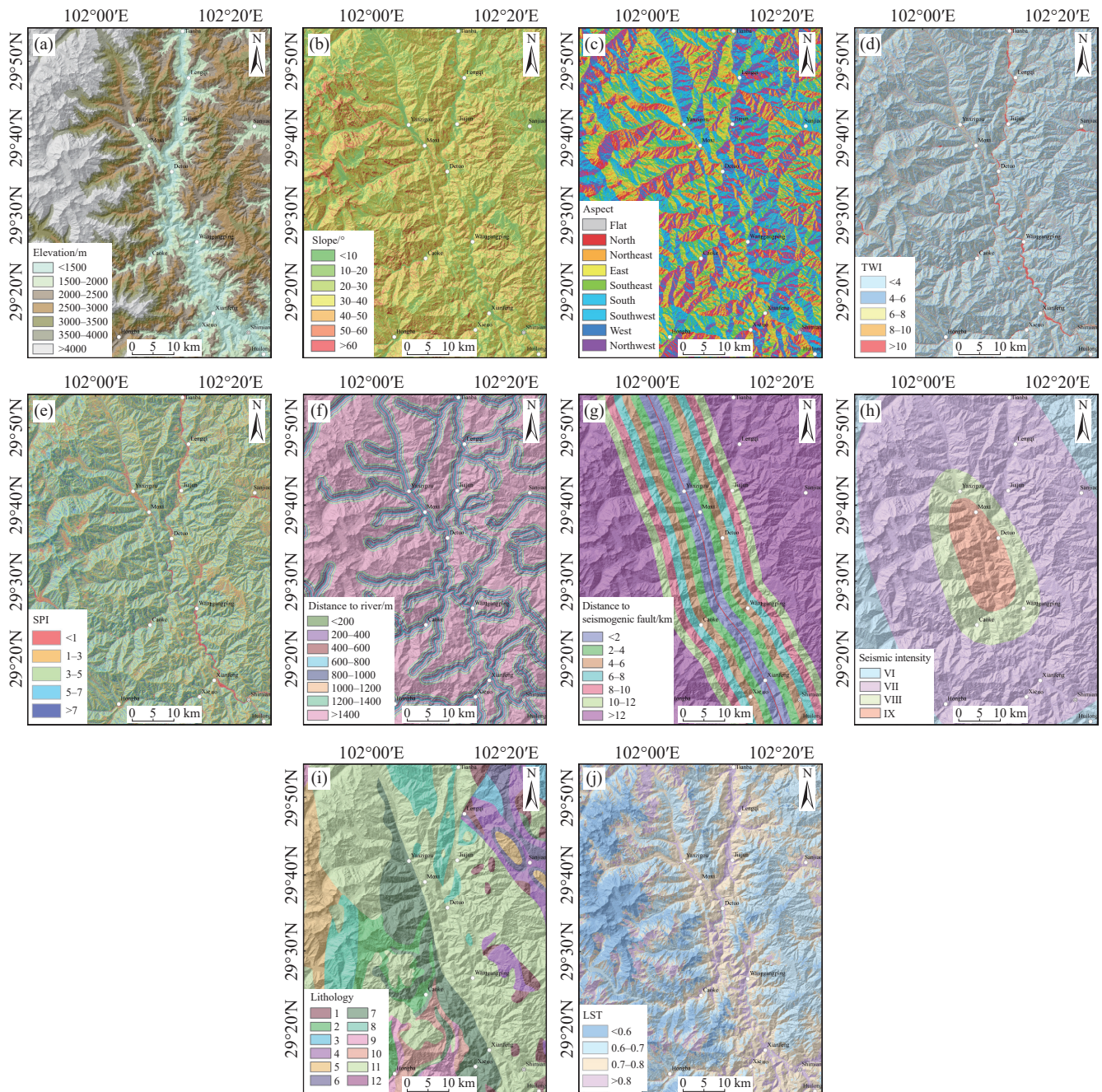


Fig. 4. Influencing factors of landslides. a–Elevation; b–slope; c–aspect; d–TWI; e–SPI; f–distance to river; g–distance to seismogenic fault; h–seismic intensity; i–lithology; j–LST. The Lithology code 1–12 in Fig. 4i can be found in Section 4.9.

erosive capacity of surface water flow. It can be used to identify the paths of concentrated water flow and potential locations for gully erosion. The erosive capacity of the surface water flow increased with increasing SPI values. The calculation formula is as follows:

$$SPI = \ln(\alpha \times \tan\beta) \quad (14)$$

where α represents the upstream specific catchment area that flows into the region, and β denotes the gradient. In this study, the SPI values were divided into the following categories: <1, 1–3, 3–5, 5–7, and >7 (Fig. 4e). Among these, landslides in the study area were the most widely distributed within the SPI 3–5 range, accounting for approximately 45.13% of the total

landslide area. The LAP values in both the western and eastern sections tended to increase with increasing SPI values, indicating that seismic landslides were more likely to occur in areas with higher stream power index values (Fig. 5e).

4.6. Distance to river

Rivers exert significant erosive effects that weaken rock and soil masses, thereby exposing slope surfaces to instability. Water infiltration into these materials reduces their shear strength, further compromising the slope stability. Additionally, river downcutting and lateral erosion remove accumulated rock and soil at the slope base, diminish the support for sliding masses and further destabilize the slopes.

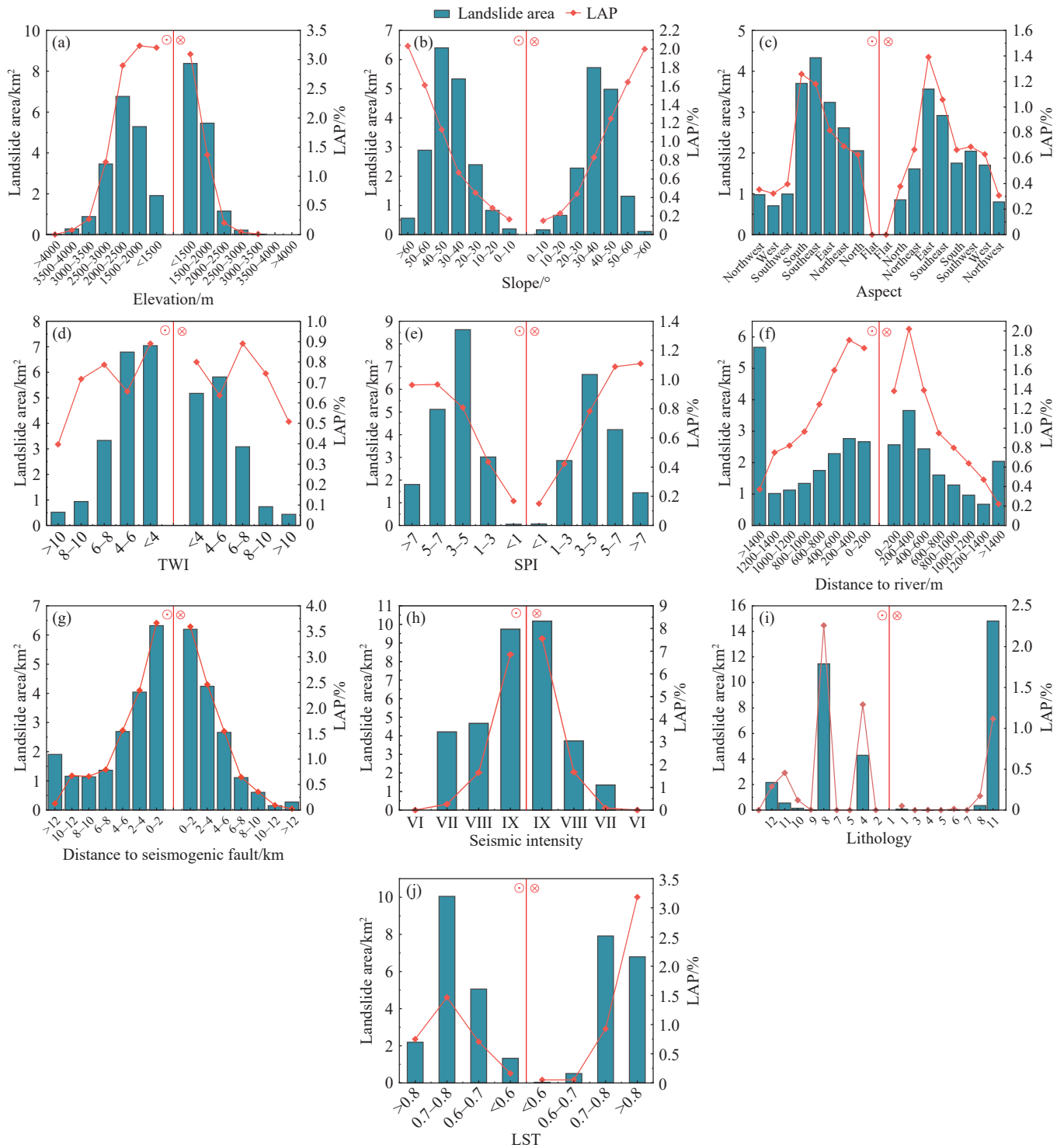


Fig. 5. Relationships between landslides distribution and influencing factors. a–Elevation; b–slope; c–aspect; d–TWI; e–SPI; f–distance to river; g–distance to seismogenic fault; h–seismic intensity; i–lithology; j–LST.

In this study, distance to the river system were categorized as follows: <200 m, 200–400 m, 400–600 m, 600–800 m, 800–1000 m, 1000–1200 m, 1200–1400 m, and >1400 m (Fig. 4f). As shown in Fig. 5f, LAP was the highest at 200–400 m from the river. When it exceeded 400 m, the LAP decreased with increasing distance from the river. Within the 200–400 m range, landslides in the eastern section were significantly influenced by the river compared to the western section, which was mainly affected by the Dadu River, where

severe river incision leads to landslide occurrences (Fig. 5f).

4.7. Distance to seismogenic fault

The geological activity around faults is highly intense and is characterized by numerous fractures and fragmented rock masses that significantly influence slope stability. Seismic landslides generally develop densely along seismogenic faults (Du GL et al., 2022). In this study, the distances to the

seismogenic fault were categorized as 0–2 km, 2–4 km, 4–6 km, 6–8 km, 8–10 km, 10–12 km, and >12 km (Fig. 4g). Fig. 5g shows that the closer the landslide area is to the active fault, the larger the landslide area is. Within 2 km of the seismogenic fault, landslides were the most abundant, accounting for approximately 36.96% of the total landslide area. As the distance from the strike-slip fault increased, the LAP on both sides of the fault gradually decreased (Fig. 5g).

4.8. Seismic intensity

Seismic intensity is a critical dynamic factor that influences the occurrence of landslides and is a key parameter for assessing earthquake-induced damage. The higher the seismic intensity, the more extensive the surface damage. In this study, the seismic intensity was classified into four zones: VI, VII, VIII, and IX (Fig. 4h). Within the study area, regions experiencing seismic intensity level IX exhibited the largest landslide areas, with the western and eastern sections registering landslide areas of 9.744 km² and 10.176 km², respectively. In the regions with seismic intensity level IX, the LAP was largest in the western and eastern sections, reaching 6.86% and 7.56%, respectively. The LAP and landslide area of the co-seismic landslides exhibited an escalating trend across the four intensity zones, corroborating the correlation between heightened intensity and increased landslide occurrence (Fig. 5h).

4.9. Lithology

The lithology forms the material foundation for landslides, with different rock types exhibiting distinct physical and mechanical properties that significantly influence landslide stability and resistance to surface erosion. To account for factors such as stratigraphic structure, age, and physical-mechanical properties, the study categorized lithology into twelve groups: (1) Hard thick layered sandstone; (2) hard medium-thick layered limestone and dolomite formation; (3) hard solid granite, andesite and diorite; (4) mid-hard medium-thick layered sandstone with conglomerate, mudstone and slate; (5) mid-hard thin-medium layered slate, phyllite, and metasandstone; (6) weak-mid thin-medium thick layered sand, mudstone, and interbed of gravel and mudstone; (7) soft-hard interbedding of medium-thick layered sandstone, mudstone mixed with limestone, and argillaceous limestone; (8) soft-hard interbedding of medium-thick layered limestone, dolomite mixed with sand, mudstone, phyllite, and slate rock formation; (9) hard solid basalt; (10) weak thin layered mud and shale; (11) weak-mid hard thin-medium thick layered phyllite, schist mixed with limestone, sandstone, and volcanic rock; (12) loose deposits (Fig. 4i). From the perspective of lithology, the eastern section exhibits the highest distribution of landslides and the maximum LAP values in lithological group 11, which is composed of weak-mid hard thin-medium thick layered phyllite, schist mixed with limestone, sandstone, and volcanic rock, whereas the western section shows the densest landslide distribution in lithological group 7, which

consists of soft-hard interbedding of medium-thick layered sandstone, mudstone mixed with limestone, and argillaceous limestone (Fig. 5i).

4.10. Land surface temperature

Variations in land surface temperature play a critical role in the physical properties, hydrological processes, and vegetation conditions of rock and soil masses, ultimately influencing slope stability and the potential occurrence of landslides. In mountainous regions, owing to lower elevations and poor vegetation coverage, land surface temperatures are typically higher. As elevation increased, there was a noticeable decrease in land surface temperature. LST was calculated using Landsat-8 imagery, according to the following formulas:

$$LST = K_2 / \ln[K_1 / B(T_s) + 1] - 273.15 \quad (15)$$

$$B(T_s) = [L_\lambda - L_\uparrow - \tau \times (1 - \varepsilon) \times L_\downarrow] / (\tau \times \varepsilon) \quad (16)$$

$$L_\lambda = gain \times DN + bias \quad (17)$$

$$\varepsilon = 0.004F_v + 0.986 \quad (18)$$

where $K_1 = 774.89 \text{ W}/(\text{m}^2 \cdot \text{sr} \cdot \mu\text{m})$ and $K_2 = 1321.08 \text{ K}$, based on querying the source files of the imagery; $B(T_s)$ is the blackbody thermal radiance; τ , $L_\uparrow$, and $L_\downarrow$ are the atmospheric thermal infrared transmittance, upward atmospheric radiance, and downward atmospheric radiance, respectively, based on querying the atmospheric data official website; L_λ is the top of atmospheric spectral radiance; ε is the land surface emissivity; *gain* and *bias* are the band gain and offset values, respectively; *DN* is the set of quantized and calibrated standard product pixel values; F_v is the vegetation coverage. In this study, the normalized LST values were divided into the following categories: <0.6, 0.6–0.7, 0.7–0.8, and >0.8 (Fig. 4j). In the study area, landslides are most widely distributed within the LST range of 0.7–0.8, accounting for approximately 53.03% of the total landslide area. The LAP was the highest when the LST was >0.8, indicating a higher susceptibility to landslides. Landslides are more likely to occur in the LST range of 0.7–0.8 in the western section, while in the eastern section, landslides are most likely to occur when LST is >0.8 (Fig. 5j).

5. Seismic landslide hazard assessment

5.1. Multicollinearity test for factors

The initially selected landslide evaluation factors may exhibit statistical multicollinearity, which can lead to distorted model estimates or difficulties in accurately describing the true relationship between factors and landslides. Therefore, it is essential to assess multicollinearity before conducting landslide hazard assessments (Cao J et al., 2019).

Typically, two indicators, the tolerance (TOL) and the

variance inflation factor (VIF), are employed to assess multicollinearity among the evaluation factors. Multicollinearity was deemed present when either the tolerance was 0.2 or less, or the VIF was 5 or greater. Conversely, multicollinearity is considered absent when the tolerance exceeds 0.2 and the VIF is less than 5 (O'Brien RM, 2007; Dai C et al., 2023; Setargie TA et al., 2023). As Table 2 shows, the selected evaluation factors exhibited a minimum tolerance of 0.538 and a maximum VIF of 1.857. These results confirmed the absence of multicollinearity, indicating that these factors were suitable for subsequent landslide hazard assessments.

5.2. Seismic landslide hazard assessment

This study conducted a hazard assessment based on a landslide database established from the western and eastern sections of the Xianshuihe fault zone, using the percentage of landslide area for 10 factors as input variables and the hazard index as the output of the model. During model training, unequal sample distributions across classes can introduce bias, potentially leading to the omission or under-representation of data from less frequent classes. To mitigate this issue, non-landslide samples were treated as equally important to the landslide samples. Equal numbers of points

are randomly selected from the non-landslide areas to serve as non-landslide samples. The combined dataset of landslide and non-landslide samples was randomly split, with 70% allocated for model training and the remaining 30% reserved for testing and validation.

This study employed the RF-AdaBoost, SVM, and BP models to assess the hazard of seismic landslides within the study area. The natural breakpoint method was used to classify the landslide hazard assessment outcomes into five categories: very high, high, moderate, low, and very low (Fig. 6). According to the assessment results of the RF-AdaBoost, SVM, and BP models, 94.05%, 92.61%, and 91.7% of the landslide areas were classified as high or very high hazard regions, respectively. The LAP values for very low areas were 0.00%, 0.02%, and 0.01%, whereas those for very high areas were 7.90%, 6.41%, and 6.88%, respectively (Fig. 7). Across the landslide hazard prediction maps generated by the three models, the LAP values for landslides at the five hazard levels increased with increasing hazard level. Overall, the assessment results indicated that RF-AdaBoost performed the best. The assessment indicates that the very high and high areas in the study region primarily extend along the steep slopes flanking the deeply incised valleys of the Dadu River from Detuo to Xianfeng and on both sides of the Moxi section of the Xianshuihe fault. These areas include valleys with steep slopes, such as Mozi, Hailuo, Feishui, Dagou, and Shiyuehe, and exhibit a belt-like distribution pattern. The areas of low and very low intensity were predominantly located in regions where the intensity was less than VII.

5.3. Assessment results accuracy test

In this study, a receiver operating characteristic (ROC) curve and confusion matrix were used to evaluate the model accuracy. The abscissa of the ROC curve represents the specificity or the false positive rate, whereas the ordinate represents the sensitivity or true positive rate. The area under

Table 2. Results of multicollinearity test for factors.

Factors	TOL	VIF
Elevation	0.538	1.857
Slope	0.805	1.242
Aspect	0.922	1.084
TWI	0.936	1.069
SPI	0.870	1.149
Distance to river	0.836	1.196
Distance to seismogenic fault	0.560	1.787
Seismic intensity	0.698	1.432
Lithology	0.685	1.460
LST	0.702	1.425

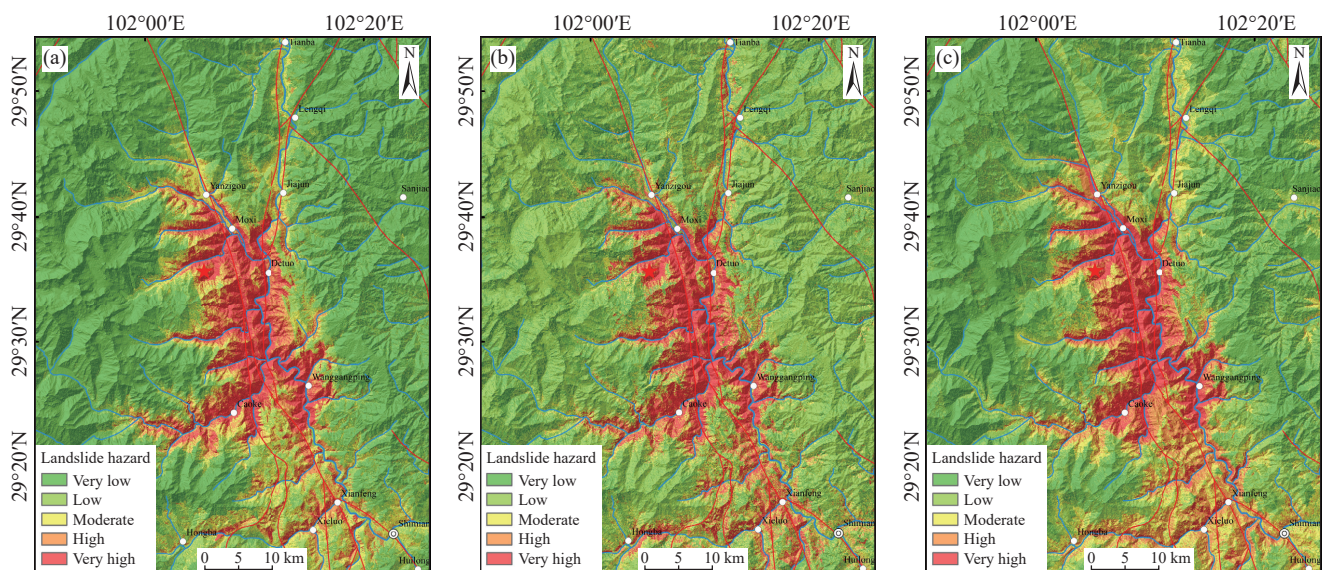


Fig. 6. Seismic landslide hazard assessment map. a-RF-AdaBoost model; b-SVM model; c-BP model.

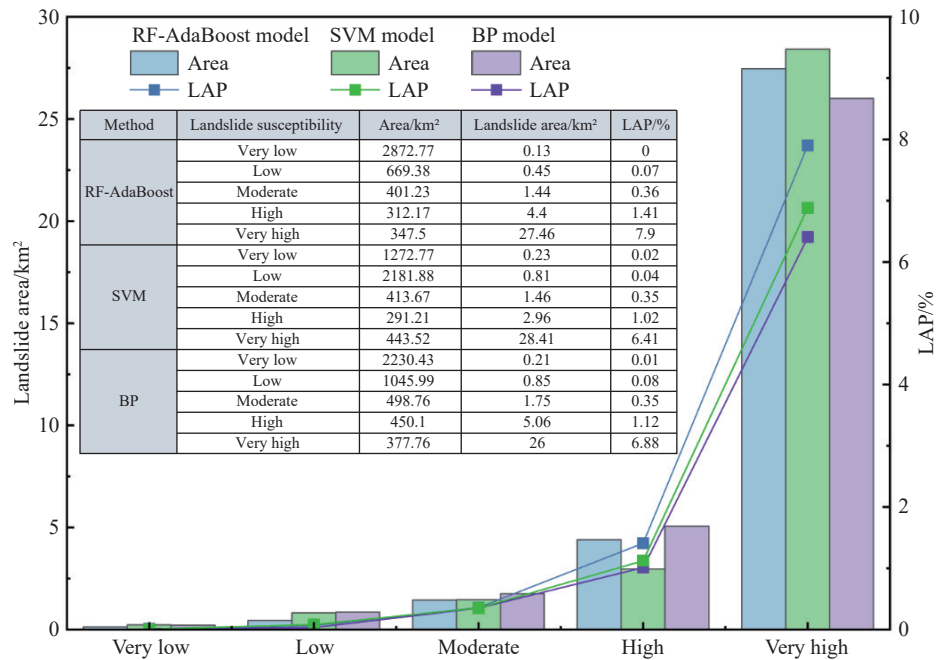


Fig. 7. Statistics of hazard map for three methods.

the curve (AUC) ranges from 0.5 to 1, with values closer to 1 indicating higher model accuracy. A curve approaching the upper-left corner indicates superior performance. The horizontal axis of the confusion matrix represents true values, and the vertical axis represents the predicted values. Using ROC curves and confusion matrices to assess the accuracy of the three models, the results indicated that the AUC values for RF-AdaBoost, SVM, and BP were 0.954, 0.929, and 0.934, respectively (Fig. 8). In the confusion matrix, the RF-AdaBoost model effectively improved the accuracy of true positives and true negatives and also partially reduced the errors of false negatives and false positives (Figs. 9a–c). These results confirm that the RF-AdaBoost model offers the highest predictive accuracy for seismic landslide risk within the study area.

6. Discussion

6.1. Distribution patterns of landslides

The Luding earthquake was associated with the Xianshuihe fault, which is a left-lateral strike-slip fault characterized by south-southeast movement of the southwestern block. The tectonic activity in this region is driven by the continuous southeastward extrusion of crustal material from the southeastern margin of the Qinghai–Xizang Plateau. This process caused the Chuan–Dian block, located west of the fault, to extrude southeastward relative to the Bayan Har block to the east. The western section of the Xianshuihe fault, which represents the hanging wall, is regarded as an active tectonic block that demonstrates significant seismic activity.

A prominent feature of the landslide distribution is the “hanging wall effect (Zhao B et al., 2022; Qin YG et al., 2023)”, where the western section (hanging wall) experienced

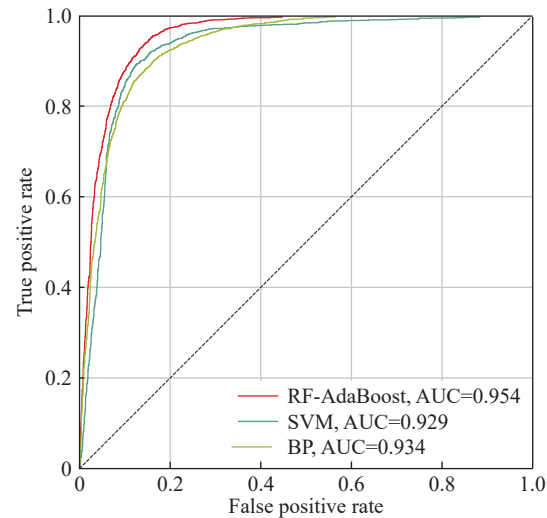


Fig. 8. Receiver operating characteristic (ROC) curve.

18.63 km² of landslides compared to 15.24 km² on the eastern section. A linear relationship exists between the seismic magnitude and the total area affected by landslides (Fan XM et al., 2019). However, the total landslide area caused by the Luding earthquake exceeded that predicted by the linear model. It is significantly larger than the areas impacted by nearby earthquakes of similar magnitudes, such as the M_s 7.0 Jiuzhaigou earthquake (8.11 km²) (Fan XM et al., 2018a) and the M_s 7.0 Lushan earthquake (18.88 km²) (Xu C et al., 2015) (Fig. 10).

A quantitative analysis of the landslide size distribution revealed that the cumulative number ratio of landslides decreased as the landslide area increased. Smaller landslides are more prevalent in the eastern section of the fault, whereas medium and large landslides are more dominant in the western section (Fig. 11a). The frequency density of

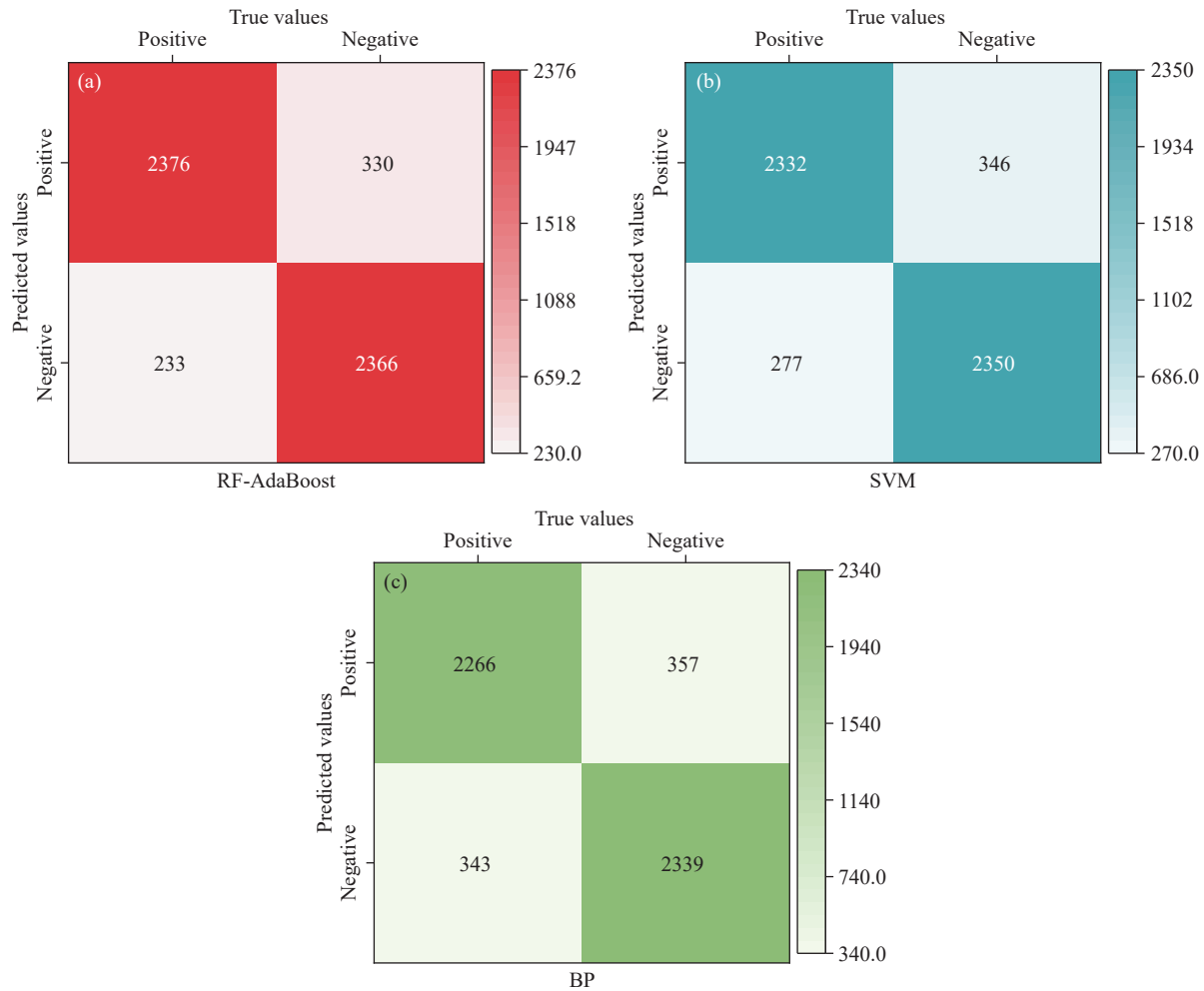


Fig. 9. Confusion matrix. a–RF-AdaBoost; b–SVM; c–BP.

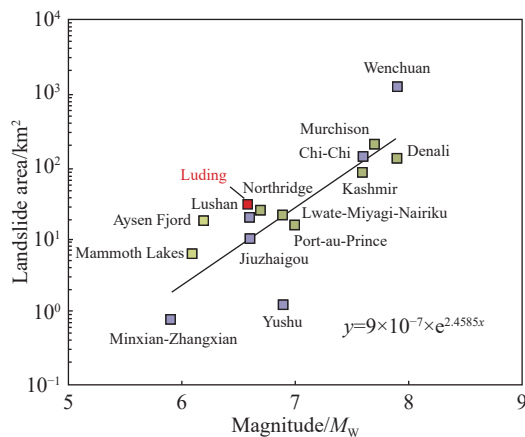


Fig. 10. Relationship between seismic magnitude and landslide area in Luding (Du GL et al., 2022; Dai LX et al., 2023; Yang ZJ et al., 2023).

landslides initially increased with increasing landslide area but then declined (Fig. 11b). This pattern indicates that co-seismic landslides were primarily small to medium in size, with fewer large-scale events. Fig. 11b exhibits a characteristic inverse-gamma distribution, displaying a “roll-over” shape for small landslides and a power-law shape for medium and large landslides. The spatial distribution of co-

seismic landslides revealed distinct patterns along the Xianshuihe fault. Landslides are predominantly concentrated within a 10 km radius of the fault, where the attenuation of seismic energy is less pronounced, and their density decreases significantly beyond this range. This spatial pattern was consistent with the results of previous studies (Wu CH et al., 2018). In terms of the relationship between landslides and elevation, the landslides in the western section occurred at significantly higher elevations than those in the eastern section. However, in the eastern section, the Dadu River Basin, characterized by the lowest elevations, exhibits a dense distribution of landslides.

The landslide distribution was also strongly correlated with the seismic intensity zones. Previous research (Tie YB et al., 2022) found that landslides predominantly occur in seismic intensity zones IX and VIII, a pattern confirmed by our analysis. A particularly strong association between landslides and seismic intensity was observed in zone IX. Fan XM et al. (2022) suggested that areas with slopes of 50° – 55° are more prone to landslides. However, our findings indicate that maximum LAP occurs on slopes steeper than 60° .

The slope aspect significantly influenced the co-seismic landslide development. During seismic wave propagation, the landslides in this study predominantly occurred on slopes

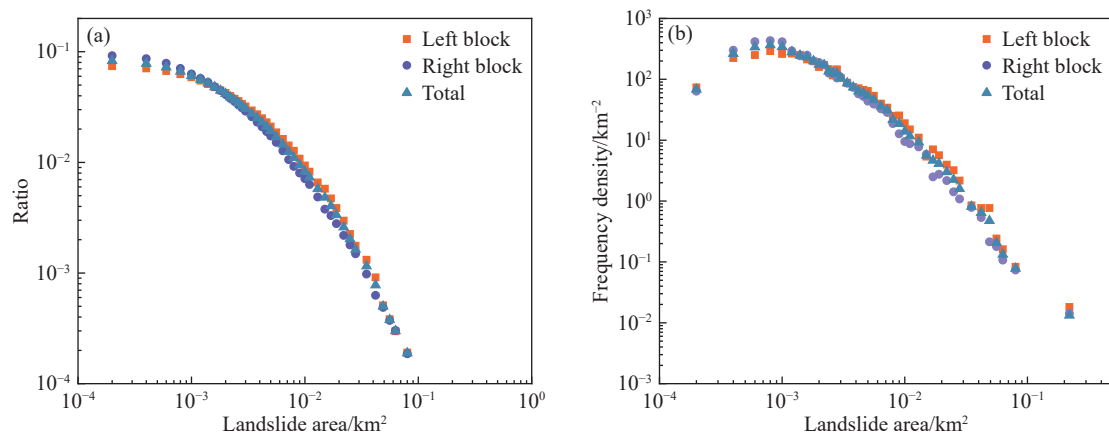


Fig. 11. The distribution of landslides in the eastern and western sections. a–Relationship between the cumulative number of landslides and the landslide area; b–Landslide area versus the frequency density relationship.

facing east and southeast, with the highest concentrations occurring on southeast-facing slopes. This southeastward concentration is strongly associated with the direction of seismic wave propagation (Yang ZJ et al., 2023). The distribution pattern is influenced by the uplift of the Qinghai–Xizang Plateau and the topographic barrier of the western Hengduan Mountains (Zhong YS et al., 2024). Additionally, prevailing southeastern winds exacerbate weathering on windward and sunlit slopes, contributing to a higher landslide density (Fan XM et al., 2018b). In the western section of the fault, landslides are more likely to occur on southern-facing slopes, whereas in the eastern section, they predominantly occur on eastern-facing slopes.

6.2. Model performance and applicability

The application of machine learning to landslide hazard assessment has gained widespread recognition (Shahabi H and Hashim M, 2015). This study employs the RF-AdaBoost algorithm, integrating the strengths of the Random Forest (RF) and AdaBoost techniques. The random forest technique reduces the risk of overfitting (Zhou XY et al., 2020), whereas AdaBoost enhances predictive accuracy through iterative weighting (Khafaga DS et al., 2023). RF-AdaBoost effectively handled data irregularities by adaptively learning key features and distributions, making it flexible and suitable for real-world applications. Moreover, feature importance analysis within RF-AdaBoost highlighted critical predictors of landslide occurrence, such as elevation, slope, aspect, and seismic intensity (Fig. 12). The parallel computing capability of the model enables the efficient processing of large datasets, providing valuable insights for hazard assessment.

The RF-AdaBoost model outperformed the SVM and BP models in this study, achieving the highest AUC value of 0.954, compared to 0.929 for SVM and 0.934 for BP. SVM excels in handling high-dimensional data and avoids local minima but is slower during training and testing (Joachims T, 1998; Brown MP et al., 2000; Pham BT et al., 2017). BP demonstrates strong learning and generalization abilities but suffers from slow convergence and susceptibility to local

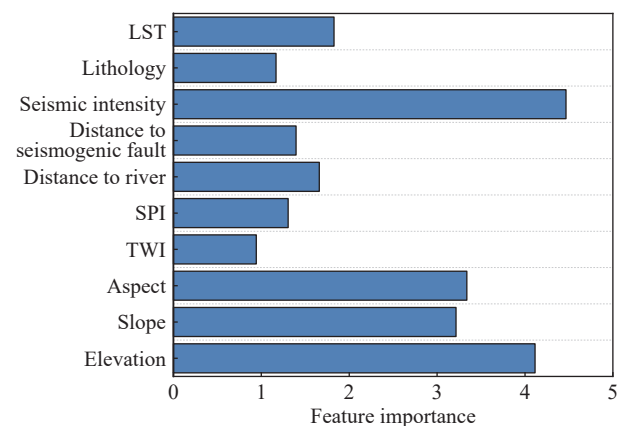


Fig. 12. Importance ranking of landslide influencing factors.

minima (Niu HT, 2020; Tao P et al., 2022). Despite RF-AdaBoost's higher computational demands and model complexity, parameter tuning and feature selection significantly enhanced its predictive power, making it a more accurate and reliable choice for landslide hazard predictions in the study area.

However, the inherent limitations of this study merit consideration. Variations in the methodologies and technical approaches employed by different researchers can significantly influence the interpretation of landslide morphology and scale. Factors such as complex geological conditions, the concealed nature of landslides, and variations in satellite imagery resolution and quality contribute to discrepancies in landslide inventories. For example, Zhao B et al. (2022) documented 4528 landslides, Dai LX et al. (2023) identified 5336, Zhang JQ et al. (2023) reported 8685, Yang ZJ et al. (2023) recorded 6233, Zhang R et al. (2024) noted 5004, while Shao XY et al. (2024) interpreted 16000 landslides in the same study area. This study identified 7463 landslides, building upon and refining the dataset provided by Huang YD et al. (2023). Although resolution constraints may have excluded smaller landslides, spatial distribution patterns remained consistent across studies.

Employing partial landslide data for broader regional assessment is a practical and widely adopted approach.

Saponaro A et al. (2015) successfully applied susceptibility mapping using data from a single province in Kyrgyzstan to achieve nationwide applicability. Similarly, Robinson TR et al. (2017) demonstrated the reliability of fuzzy logic in modeling landslide distributions with incomplete inventories. Lee JH et al. (2018) addressed small dataset challenges by developing an optimized support vector machine model. These studies collectively highlight the fact that robust assessments of earthquake-triggered landslides can be achieved even with limited data.

7. Conclusions

The 2022 M_s 6.8 Luding earthquake triggered numerous co-seismic landslides, resulting in widespread damage to buildings, road blockages, and significant casualties. This study analyzed the spatial distribution of landslides along the Xianshuihe fault zone and investigated the influence of factors such as elevation, slope, aspect, TWI, SPI, distance to rivers, seismogenic faults, seismic intensity, lithology, and LST on landslide distribution. Landslide hazard predictions for the region were assessed using RF-AdaBoost, SVM, and BP models based on landslide data. The main conclusions are as follows.

(i) In the western and eastern sections of the fault zone, co-seismic landslides were more likely to occur at elevations of 1500–2000 m and below 1500 m, respectively. The TWI values are less than 4 in the western section and range of 6–8 in the eastern section, with landslides occurring most frequently at distances of 200–400 m from the rivers. The occurrence of co-seismic landslides in both blocks showed a positive correlation with slope, SPI, and seismic intensity and a negative correlation with the distance to the seismogenic fault. The direction of the slope is closely related to landslide distribution, with south-facing slopes in the western section and east-facing slopes in the eastern section being more prone to landslides. An LST range of 0.7–0.8 in the western section is conducive to landslide occurrence, while the eastern section shows the highest probability of landslides at LST values exceeding 0.8. Overall, the likelihood of landslides increased with increasing surface temperature.

(ii) The RF-AdaBoost model demonstrated the best performance among the three methods, achieving the highest AUC value of 0.954, compared to 0.929 for SVM and 0.934 for BP. RF-AdaBoost effectively classified 94.05% of landslide-prone areas as high or very high hazard, compared with 92.61% for SVM and 91.7% for BP. The LAP values for the very high hazard zones were 7.90%, 6.41%, and 6.88%, whereas the very low hazard zones had LAP values of 0.00%, 0.02%, and 0.01%. Areas of high and very high hazard were concentrated along the Xianshuihe fault zone, particularly in regions such as Moxi, Detuo, and Wanggangping, with steep slopes near the Dadu River and its tributaries showing belt-like distribution patterns.

(iii) Assessment of seismic landslide hazards revealed that areas with very high and high risk were mainly concentrated

along both sides of the Xianshuihe fault zone and the steep slopes near the Dadu River and its tributaries in the study area. The earthquake destabilized numerous slopes, leaving large amounts of loose material in the region. Subsequent rainfall can further destabilize these areas, increasing the likelihood of landslides and debris flows. Therefore, it is crucial to implement long-term monitoring, early warning systems, and preventive measures in high-risk areas. Additionally, particular attention should be paid to inspecting mountainous areas fractured by earthquakes to mitigate the potential for long-term disasters, such as ice avalanches and rockfalls.

CRedit authorship contribution statement

Li-ying Gu, Guo-liang Du, Ling Zou and Xin Wang conceived of the presented idea. All authors discussed the results and contributed to the final manuscript.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability statement

The data presented in this study are available on request from the corresponding author.

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