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A Landslide Susceptibility Evaluation of Highway Disasters Based on the Frequency Ratio Coupling Model

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Abstract: A landslide disaster, especially a highway landslide, may greatly impact the transport capacity of nearby roads. Keeping highways open, in particular, is crucial for supporting the functioning of the economy, society and people. Therefore, evaluating the highway landslide susceptibility is particularly important. In this paper, the city of Laibin, in the Guangxi Zhuang Autonomous Region of China, was taken as the study zone. According to data on 641 highway landslide disaster points measured in the field and a basic evaluation of the study area, nine evaluation factors—the elevation, slope, aspect, height difference, plan curve, profile curve, precipitation, Topographic Wetness Index (TWI) and vegetation coverage—were selected. We coupled a Frequency Ratio (FR) model, Analytic Hierarchy Process (AHP), Logistic Regression (LR), Back Propagation Neural Network (BPNN) and Support Vector Machine (SVM) to evaluate the susceptibility to highway landslides, with a Receiver Operating Characteristic (ROC) curve used to analyze the precision of these models. The ROC curve showed that the accuracy of the five models was greater than 0.700 and thus had a certain reliability. Among them, the FR-LR model had the highest accuracy, at 0.804. The study protocol presented here can therefore provide a reference for evaluation studies on landslide susceptibility in other areas.

Keywords: highway landslide disaster; frequency ratio; coupling model; ROC curve

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1. Introduction

Geological disasters occur frequently in China and cause huge losses to the country and its people each year. According to a report by the Ministry of Transportation and Communications Road Bureau, the total mileage affected by national highway disasters in 2020 was 6418.551 km, accounting for 0.87% of the total national highway, an increase of 23.3% compared to 2019. The cumulative cost of the direct loss of highway production was CNY 22.838 billion, an increase of 97.9% compared to 2019, among which the economic losses due to disaster damage and landslides accounted for more than 90%. Therefore, risk assessments of the susceptibility to a highway landslide are particularly important. A landslide is the main type of geological disaster in China. Highway landslides in particular greatly impact the transport capacity of roads. Keeping highways open is crucial for supporting the economy, society and the public, as they play an irreplaceable role in the transportation system. Assessing the distribution of previous highway landslide disasters and their distribution and doing a good job in statistically analyzing related data not only contributes to planning accurate highway infrastructure maintenance but

also highlights risks, meaning preventative measures may be taken. Further to this, such research also provides valuable data support for disaster reconstruction after the landslide disaster during the rush to ensure access to the route can be resumed with the highway reopened as soon as possible. Guiding reconstruction efforts to take the best course is of great significance for improving highway traffic safety and constructing a resilient Chinese transportation infrastructure.

In recent years, several experts have contributed significantly to the development of landslide susceptibility measures and risk assessment. Zhong Zhiwei used the information method to evaluate the risk of adverse geological phenomena along the stretch of the Sichuan–Tibet railway line marked by three parallel rivers, thereby establishing a geographic database of the study area that provides a foundation of geological information to support the upkeep of the railway line [1]. Xu Chong et al. used a Logistic Regression (LR) model to evaluate a landslide in the Wenchuan earthquake area and established a landslide risk index map of the target region [2]. Elsewhere, Li Zequn applied the Back Propagation Neural Network (BPNN) model to evaluate the landslide susceptibility of Dingcheng District, Changde City, China; the results provide a reliable basis for determining the local landslide susceptibility and thus help with local governments' geological disaster risk zoning work and prevention measures [3].

In other work, Saro Lee and Biswajeet Pradhan used Frequency Ratio (FR) and LR models to evaluate the landslide hazards in the Selangor area, Malaysia. Through a precise comparison, they concluded that the FR model was the most appropriate [4]. Closer to home, Man Hu et al. used an Analytic Hierarchy Process (AHP), Fuzzy Logic (FL) and Certainty Factors (CF) to evaluate the landslide risk in the Lenggu region of China. The results showed that among the three models, the accuracy of CF was the highest. Their landslide susceptibility maps of the research area provide a reference for further studies of the spatial distribution characteristics of landslide disasters in alpine valleys [5]. Sujit Mandal and Subrata Mondal used Support Vector Machine (SVM) and Artificial Neural Network (ANN) models to produce landslide susceptibility zonation maps of the Balason river basin of Darjeeling Himalaya [6]. Ge Yunfeng et al. used five different models—AHP, Information Value (IV), Fractal Theory (FT), BPNN and SVM—to create a landslide susceptibility map for the city of Longnan, Gansu Province, China, with the results showing that the SVM and BPNN models were the most accurate [7].

Although the evaluation accuracy of a single model is high, it still has defects; to make up for the defects of a single model, a coupled model may be employed, with the resulting research accuracy improved. Wen Fan et al. combined the CF and AHP methods to propose a new approach named CF-AHP, which they applied to evaluate the landslide susceptibility of Ziyang, located within the Qinba mountain area of China. The results showed that the coupled model was more appropriate for a landslide susceptibility evaluation in this zone than either of its origin models alone [8]. In other work, Senem Tekin evaluated previous landslide characteristics and carried out landslide sensitivity modeling in the Ceyhan Watershed, using FR and LR, and the results provide a reference for future watershed management in the area [9]. Sheng Mingqiang et al. applied the FR-SVM model for landslide susceptibility prediction, coupling the FR linkage method and SVM model, and compared the results with the single SVM model, showing that the FR-SVM model had a higher prediction accuracy [10].

With a focus on roadways, Du Guoliang et al. took the Sichuan–Tibet traffic corridor as the study area, and combined the advantages of traditional IV and LR, using a LR-IV model to assess the landslide susceptibility of the study region. The research results provide a reference for disaster prevention in high-incidence areas [11]. Shen Huaifei et al., meanwhile, selected Gansu Province as the study zone, an area where landslide disasters occur frequently in China, and used the IV and AHP to comprehensively assess landslides that had occurred in the study region, adding experience for the prevention and control of landslide disasters locally [12]. Elsewhere, Qin Yigen et al. used five evaluation models—CF, AHP, LR, CF-AHP and CF-LR—to produce a landslide susceptibility map for

Kaiyang County, China, with the results indicating that the CF-LR model was better than the others [13]. There are many kinds of landslide disasters, and while a lot of the research has focused on earthquake landslides, so far, there is very little research on highway landslide disasters.

Studies have shown that a coupled model has a high accuracy and applicability, but the FR model has rarely been applied in coupling analyses. To fill that research gap, this paper uses the FR model to couple AHP, LR, SVM and BPNN. Nine evaluation factors, including the elevation, slope and height difference, are selected to evaluate the highway landslide susceptibility of the city of Laibin, and the accuracy of each coupling model is compared. In this way, we determine the optimal model and provide experience that will benefit future landslide susceptibility evaluations in other regions.

2. Methodology

2.1. Study Region

The city of Laibin is located in the central Guangxi Zhuang Autonomous Region (as shown in Figure 1b), between 108°24′~110°28′ E and 23°16′~24°29′ N. It is characterized by high terrain in the middle and low terrain on both sides, with a total area of 13,411 square km. It belongs to the transitional monsoon climate area, where the four seasons are distinct and the rainfall is sufficient, gradually decreasing from the southwest to the northeast. The average annual temperature is 20.3 °C and the average annual rainfall is 1360 mm. According to statistics, there are 641 highway landslide points in Laibin, mainly distributed in the central area (as shown in Figure 1c).

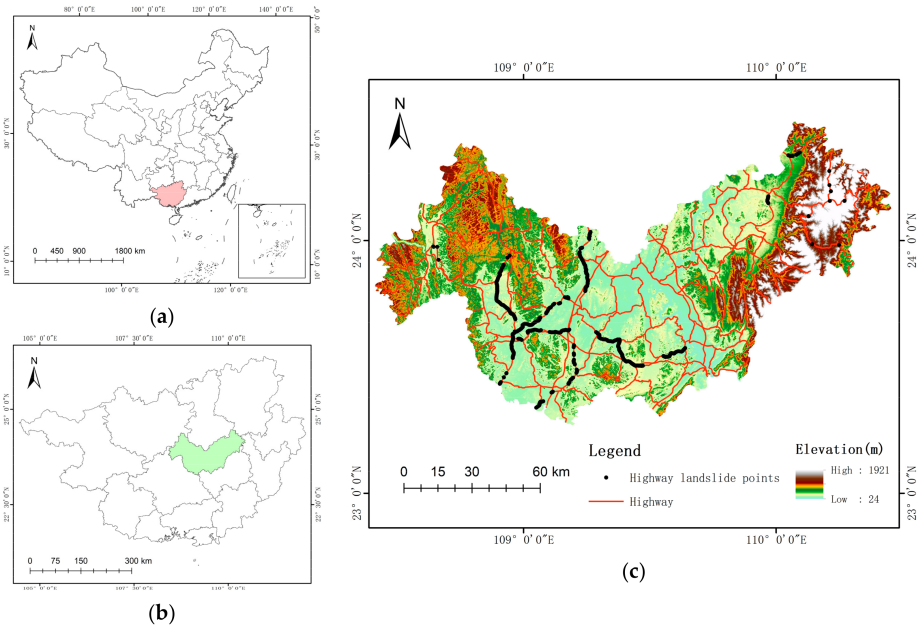


Figure 1. Research region. (**a**) Geographic location of Guangxi Zhuang Autonomous Region in China; (**b**) geographic location of Laibin in Guangxi Zhuang Autonomous Region; (**c**) distribution of highway landslide points and elevation in Laibin.

2.2. Data Sources

The elevation, slope and aspect data used in this paper are 90 m resolution STRM-DEM data, STRM-SLOPE data and STRM-ASPECT data, which all come from the Geospatial Data Cloud (http://www.gscloud.cn, accessed on 13 April 2022). Precipitation data, meanwhile, are from the National Meteorological Science Data Center (http://data.cma.cn, accessed on 13 April 2022). The vegetation coverage data, at a 1000-m resolution, come from the Institute of Geographical Sciences and Resources, Chinese Academy of Sciences (http://www.resdc.cn, accessed on 13 April 2022).

2.3. Research Technique

2.3.1. Variable Statistics Method

The FR model is based on assumptions. It holds that the probabilities of a landslide disaster are similar in areas with similar geological conditions. The model can thus correlate the spatial distribution characteristics of disaster points in the study region with the different levels of disaster-causing factors, to evaluate the susceptibility to landslides in the study region [14–16]. In doing so, the accuracy of the FR model mainly depends on the classification level of each disaster-causing factor. The formula for calculating the FR is as follows:

$$FR_{ij} = \frac{N_{ij}/N}{S_{ij}/S} \quad (1)$$

where FR_{ij} is the FR of the jth classification of the ith disaster-causing factor, N_{ij} is the number of disaster points of the jth classification of the ith disaster-causing factor, N is the number of disaster points in the whole study region, S_{ij} is the area of the jth classification of the ith disaster-causing factor and S is the area of the whole study region.

2.3.2. Data-Driven Models

1. AHP

First proposed by Saaty, this combines qualitative and quantitative methods, with its analysis determined by many factors. Its core approach is to first hierarchize the decision-making problem, whereby the problem is decomposed into decision-making objectives, middle layer elements, alternatives and so on. Second, it analyzes the proportion of each element in the middle layer elements versus the alternatives; in this way, the significance of each element is determined. Third, the judgment matrix is established according to the importance degree of each element, and the maximum feature root and corresponding feature vector are calculated. Finally, to determine that the results obtained by the AHP are applicable, the consistency of the established judgment matrix is verified. If the test is passed, the weight of influence for each factor can be obtained [17–19]. The calculation formula for this is as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (2)$$

$$CR = \frac{CI}{RI} \quad (3)$$

where CI is the consistency index of the matrix, λ_{max} is its maximum feature root, n is its order, CR is its consistency ratio and RI is its random consistency index (shown in Table 1).

Table 1. The value of *RI*.

n	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

When the value of RI is less than 0.1, the matrix is considered to have satisfactory consistency; otherwise, it is necessary to adjust the matrix until that is achieved.

2. LR

This model is commonly used to study binary dependent variables; it can be seen as putting a linear regression model into a Sigmoid function. The outcome describes the relationship between multiple disaster-causing factors (X_1, $X_2 \ldots X_n$), or independent variables, and whether the dependent variable is a landslide [20,21]. The values of the target quantity predicted by regression are continuous, while the values predicted by the classification are discrete. Although the LR model is used to solve the classification problem,

its core lies in the reference of the function, and it can expand the range of variables. The formula is as follows:

$$P = \frac{1}{1 + e^{-Z}} \tag{4}$$

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{5}$$

where P is the possibility of landslide occurrence (range 0–1), Z is the expression of the relationship between the possibility of landslide occurrence and multiple disaster causing factors, $X_1, X_2 \ldots X_n$ are multiple disaster-causing factors, $\beta_0, \beta_1 \ldots \beta_n$ are the LR coefficients and β_0 is the constant term.

3. BPNN

There are four main types of neural networks: forward, feedback, stochastic and competitive. BPNN is a type of forward neural network that adds a backward propagation algorithm to the structure of the feed-forward network. The BPNN algorithm steps are as follows: first, initialize the network weights and those of each neuron, and randomly select the first input sample; second, perform forward propagation; third, calculate the error and perform backward propagation, where the error size is measured by minimizing the root mean square, and the error is minimized using the gradient descent algorithm [22]; next, adjust the network weights and those of each neuron; finally, determine whether the iteration is finished.

BPNNs are widely applied in remote-sensing image recognition and classification and ground object classification, and landslide risk assessment is essentially a problem of discrimination and classification. Therefore, a BPNN model can be reliably used for landslide risk assessment.

4. SVM

Alongside BPNN, this has gradually been applied to landslide susceptibility evaluation in recent years. SVM is designed by the statistical theory of the VC (Vapnik–Chervonenkis) dimension and the principle of structural risk minimization. It is a binary classification model used to solve non-linear problems, which has more advantages than other methods in solving small-sample and high-dimensional problems [23–25]. The basic principle of SVM is to find an optimal hyperplane to divide the samples. The principle of segmentation is to manipulate the optimal hyperplane to not only correctly distinguish the samples but also to maximize the geometric interval from the sample point to the optimal hyperplane [26] to obtain the best classification results.

2.4. Selection of Evaluation Factors

The occurrence of a highway landslide disaster is closely related to topography, geological structure, hydrometeorology and human activities, and selecting suitable evaluation factors is the most important part of a landslide susceptibility evaluation, but due to the complexity of the influencing factors, there is no unified selection standard yet [27,28]. A highway, as a typical line-fitting engineering structure, has to traverse different topographic and geomorphological units, especially in mountainous areas, often spreading over slopes, valleys and mountain ranges. Yet, the mountainous topography, complex geological formations and significant rainfall in the study region provide the necessary conditions for the occurrence of landslide disasters. Therefore, based on a previous study and the basic situation of the study region, nine evaluation factors—elevation, slope, aspect, height difference, plan curve, profile curve, precipitation, Topographic Wetness Index (TWI) and vegetation coverage—were selected.

The classification numbers and intervals of the evaluation factors are mostly determined by experience, which seriously affects the results of a landslide susceptibility evaluation. Che Wenchao used the inflection point method to determine the classification number, the natural break method to determine the classification interval and classified the continuous factors to obtain the optimal classification number [29]. Accordingly, in this

paper, the nine continuous evaluation factors were each divided into between three and nine categories by the inflection point method and natural break method.

1. Elevation

The soil hardness, precipitation distribution and vegetation coverage vary in different elevation ranges, along with the probability of a landslide disaster [30]. The elevation of the target region in this paper ranges between 24 and 1921 m (as shown in Figure 2a), which may be divided into six categories. According to Table 2, the landslide points are mainly distributed in the area between 24 and 171 m, where the proportion of landslide points is 91.89% and the FR is 1.97518.

Table 2. Classification and frequency ratio of landslide evaluation factors.

Landslide Evaluation Factors	Classification	Number of Landslide Points/pts	Classified Area/km^2	FR
Elevation (m)	[24, 171]	589	6239	1.97518
	(171, 307]	22	2694	0.17086
	(307, 474]	3	2162	0.02903
	(474, 687]	3	1178	0.05329
	(687, 966]	10	756	0.27678
	(966, 1921]	14	382	0.76607
Slope (°)	[0, 4]	522	4939	2.21118
	(4, 10]	77	2726	0.59089
	(10, 17]	21	2189	0.20075
	(17, 23]	14	1868	0.15679
	(23, 73]	7	1689	0.08673
Aspect	[−1, 0]	12	99	2.52719
	(337.5, 22.5]	48	1428	0.70312
	(22.5, 67.5]	69	1554	0.92900
	(67.5, 112.5]	98	1762	1.16389
	(112.5, 157.5]	109	1690	1.34979
	(157.5, 202.5]	69	1552	0.93024
	(202.5, 247.5]	67	1673	0.83789
	(247.5, 292.5]	80	1895	0.88322
	(292.5, 337.5]	89	1758	1.05899
Height difference (m)	[0, 22]	535	11464	0.97638
	(22, 51]	68	659	2.15842
	(51, 81]	21	575	0.76390
	(81, 114]	10	432	0.48470
	(114, 760]	7	281	0.52118
Plan curve	[−1.10, −0.05]	6	4577	0.02742
	(−0.05, 0.05]	629	2583	5.09579
	(0.05, 0.85]	6	6251	0.02008
Profile curve	[−1.04, −0.05]	1	1755	0.01192
	(−0.05, 0.05]	584	9175	1.33168
	(0.05, 1.24]	56	2481	0.47224
Precipitation (mm)	[1967.24, 2031.19]	257	1883	2.85587
	(2031.19, 2072.84]	231	3949	1.22385
	(2072.84, 2120.44]	90	2972	0.63346
	(2120.44, 2173.99]	9	2869	0.06563
	(2173.99, 2242.41]	21	1080	0.40692
	(2242.41, 2346.53]	33	658	1.04981
TWI	[−1.20, 3.25]	31	1941	0.33410
	(3.25, 6.25]	128	2866	0.93445
	(6.25, 8.67]	111	2886	0.80479
	(8.67, 10.70]	129	1938	1.39286
	(10.70, 13.02]	120	2641	0.95057
	(13.02, 23.46]	122	1139	2.24033
Vegetation coverage	[0.31, 0.60]	12	128	1.96509
	(0.60, 0.73]	104	885	2.45785
	(0.73, 0.81]	274	2314	2.47758
	(0.81, 0.86]	191	3839	1.04095
	(0.86, 0.90]	60	6245	0.20100

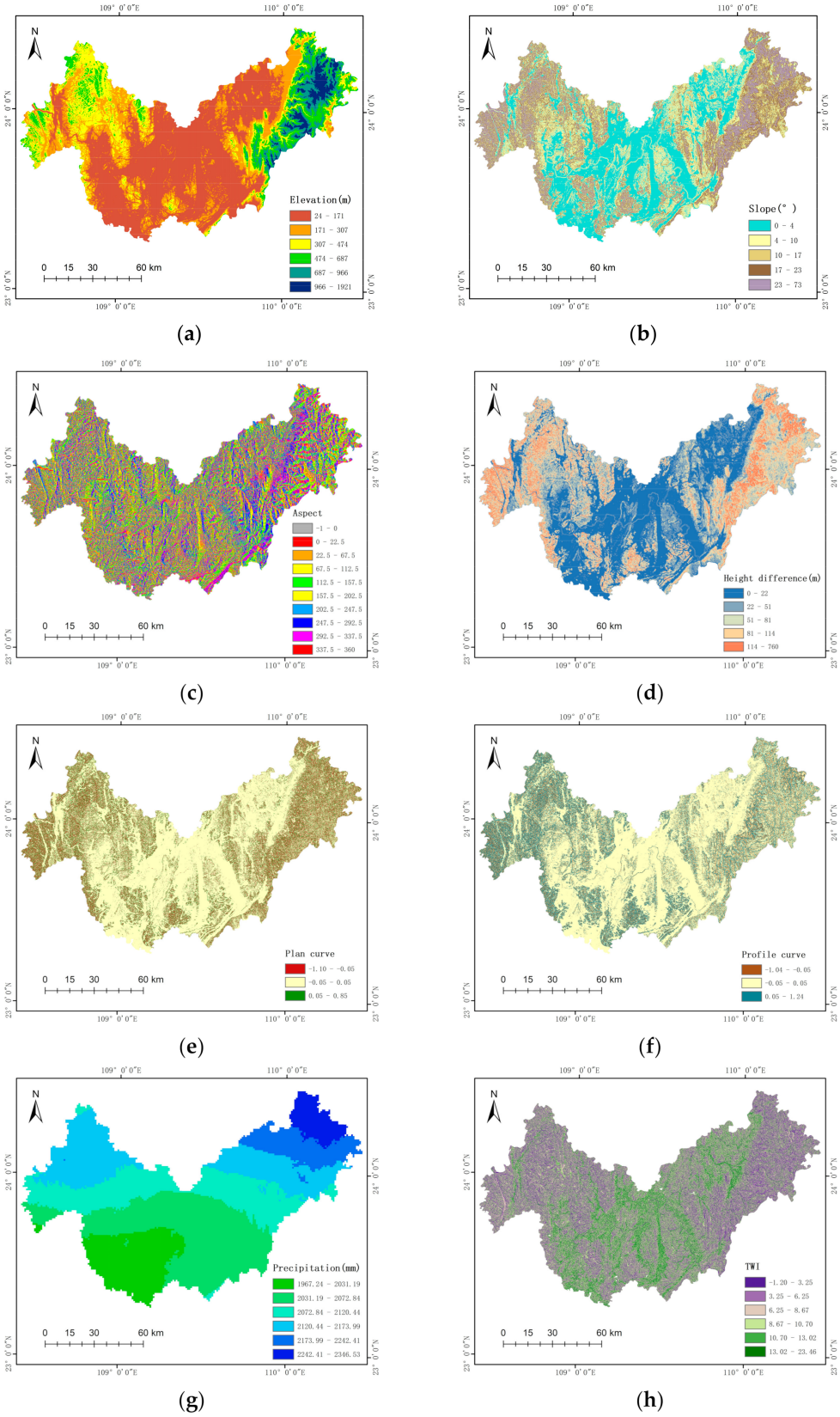
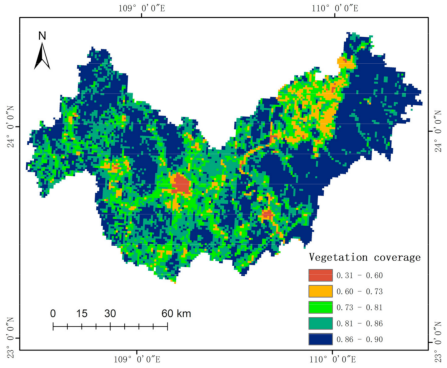


Figure 2. *Cont.*



(**i**)

Figure 2. Landslide evaluation factors: (**a**) elevation; (**b**) slope; (**c**) aspect; (**d**) height difference; (**e**) plan curve; (**f**) profile curve; (**g**) precipitation; (**h**) TWI; (**i**) vegetation coverage.

2. Slope

The slope is a crucial factor in determining whether there will be a landslide and can affect the degree of soil loss. Generally, increasing the slope will increase the shear force, resulting in an increased probability of a landslide, but it is not that the larger it is, the greater the chance a landslide disaster [31]. The slope of the target region in this paper is between 0 and 73° (as shown in Figure 2b), which may be divided into five categories. According to Table 2, the landslide points are mainly distributed in the area between 0 and 4°, where the proportion of landslide points is 81.44% and the FR is 2.21118.

3. Aspect

The aspect is closely related to the development of a landslide. Different aspects have different solar radiation intensities, water flow direction and wind intensity, which affect the stability of the surface soil [32,33]. The aspect of the target region in this paper is between −1 and 360 (as shown in Figure 2c), which may be divided into nine categories. According to Table 2, the landslide points are least distributed on the flat land with an aspect from −1 to 0°, accounting for only 1.87% of the total number of landslide points, while they are evenly distributed in other aspects.

4. Height difference

The height difference is the difference between the maximum and the minimum elevations within a certain range, indicating the topographic relief situation, which may provide the conditions for a landslide disaster to occur [34]. The height difference of the target region in this paper is between 0 and 760 m (as shown in Figure 2d), which may be divided into five categories. According to Table 2, the landslide points are mainly distributed in the areas between 0 and 22 m, where the proportion of landslide points is 83.46% and the FR is 0.97638.

5. Plan and profile curves

Curvature is a basic variable to describe the degree of distortion change a of slope surface [35]. The plan curve can reflect all ridge lines and valley lines on the surface in the horizontal direction, which can influence the convergence and dispersion of flows; the profile curve, meanwhile, can reflect the transformation degree of the slope in the vertical direction, which can influence the acceleration and deceleration of flows [36]. The plan and profile curves of the target region in this paper are between −1.10 and 0.85 and between −1.04 and 1.24, respectively (as shown in Figure 2e,f), and can be divided into three categories. According to Table 2, the landslide points are mainly distributed in the area with the plan curve from −0.05 to 0.05, where the proportion of landslide points is 98.12% and the FR is 5.09579 and are mainly distributed in the area with the profile curve from −0.05 to 0.05, where the proportion of landslide points is 91.11% and the FR is 1.33168.

6. Precipitation

Precipitation is a crucial factor affecting landslides. The erosion of rain will cause soil on the ground to become soft and lower the soil strength, thereby increasing the probability of a landslide [37]. The precipitation of the target region in this paper is between 1967.24 and 2346.53 mm (as shown in Figure 2g), which may be divided into six categories. According to Table 2, the landslide points are mainly distributed in the areas between 1967.24 and 2072.84 mm and these areas are classified into two, in both of which the proportion of landslide points is 76.13%.

7. TWI

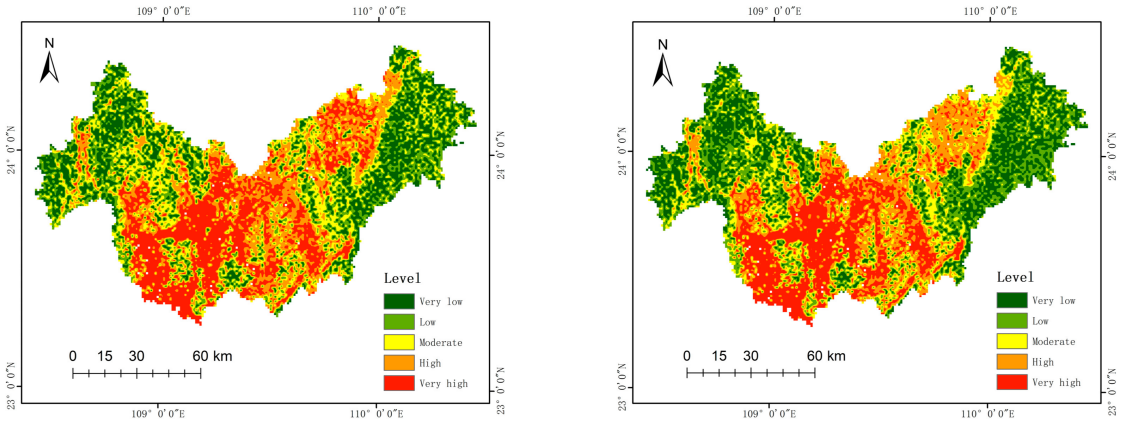
TWI is a crucial factor calculated by the elevation and slope, which comprehensively considers the impact of topography and the soil water content distribution on landslides [38]. The TWI of the target region in this paper is between −1.20 and 23.46 (as shown in Figure 2h), which may be divided into six categories. According to Table 2, the landslide points are least distributed in areas between −1.20 and 3.25, while they are evenly distributed in other classification areas.

8. Vegetation coverage

The vegetation coverage in an area not only has a fixed effect on the soil of the ground but also helps to slow water flow and underwater infiltration [39]. The vegetation coverage of the target region in this paper is between 0.31 and 0.90 (as shown in Figure 2i), which may be divided into five categories. According to Table 2, the landslide points are least distributed in areas with the vegetation coverage from 0.31 to 0.60, accounting for only 1.87% of the total number of landslide points, while they are most distributed in areas with vegetation coverage from 0.60 to 0.86 (includes three classifications zones), where the proportion of landslide points is 88.77%.

3. Results

In this paper, the susceptibility to highway landslides was analyzed and evaluated through a single model and four coupling models (FR-AHP, FR-LR, FR-BPNN and FR-SVM), and the natural break method were used to classify the result maps for each model into five categories: very high, high, moderate, low and very low (as shown in Figure 3 and Table 3).



(a) (b)

Figure 3. *Cont.*

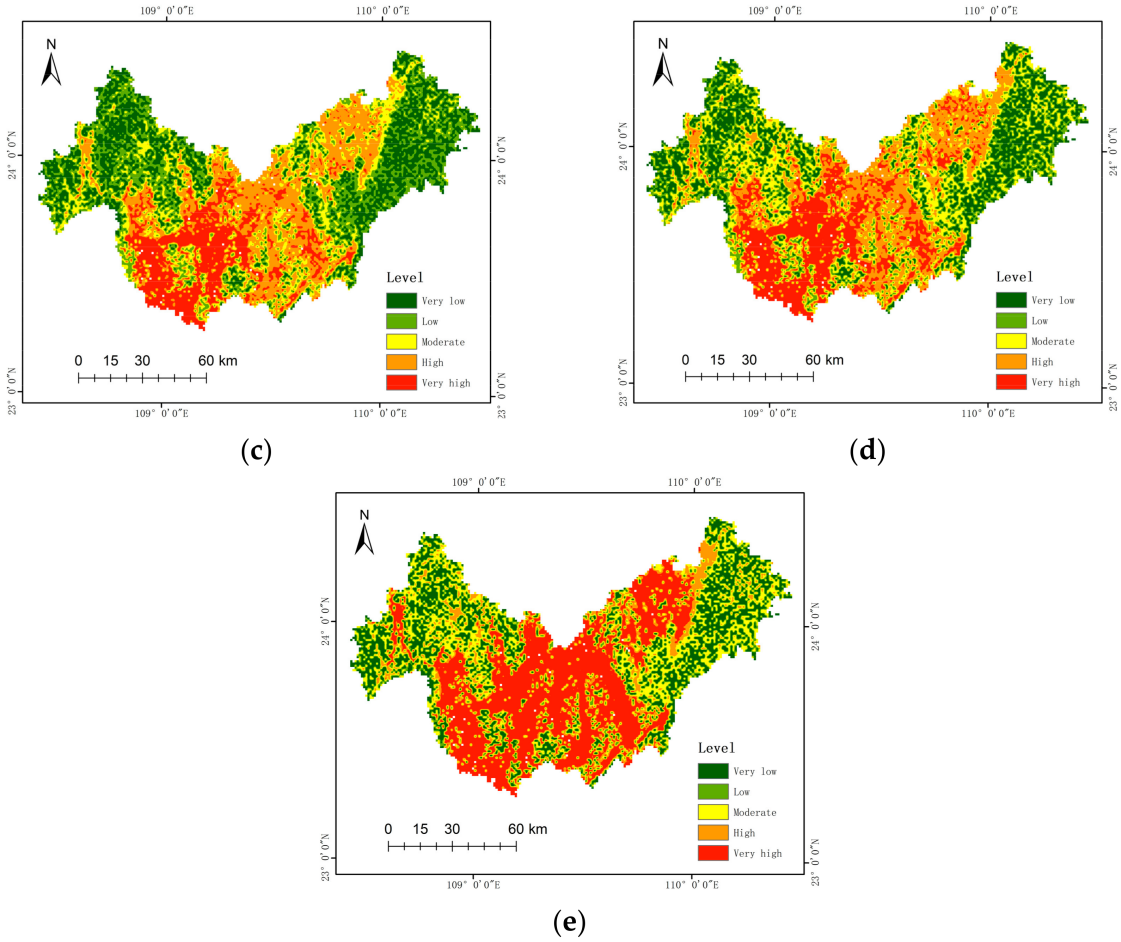


Figure 3. Evaluation results of five models: (**a**) FR model; (**b**) FR-AHP model; (**c**) FR-LR model; (**d**) FR-BPNN model; (**e**) FR-SVM model.

Table 3. Evaluation results of five models.

Models	Susceptibility Level	Classified Area/km^2	Proportion of Classified Area/%	Number of Landslide Points/pts	Proportion of the Number of Landslide Points/%	Density of Landslide Points/(pts/km^2)
FR	Very low	2335	17.41	5	0.78	0.00214
	Low	2870	21.40	39	6.08	0.01359
	Moderate	2508	18.70	44	6.87	0.01754
	High	2773	20.68	110	17.16	0.03967
	Very high	2925	21.81	443	69.11	0.15145
FR-AHP	Very low	2650	19.76	5	0.78	0.00189
	Low	3251	24.24	53	8.27	0.01630
	Moderate	2214	16.51	38	5.93	0.01716
	High	2665	19.87	125	19.50	0.04690
	Very high	2631	19.62	420	65.52	0.15964
FR-LR	Very low	2777	20.71	6	0.94	0.00216
	Low	3370	25.13	50	7.80	0.01484
	Moderate	2185	16.29	47	7.33	0.02151
	High	3141	23.42	139	21.68	0.04425
	Very high	1938	14.45	399	62.25	0.20588
FR-BPNN	Very low	2273	16.95	9	1.40	0.00396
	Low	2678	19.97	34	5.31	0.01270
	Moderate	2749	20.50	43	6.71	0.01564
	High	3215	23.97	122	19.03	0.03795
	Very high	2496	18.61	433	67.55	0.17348
FR-SVM	Very low	2245	16.74	6	0.94	0.00267
	Low	2104	15.69	32	4.99	0.01521
	Moderate	2720	20.28	34	5.30	0.01250
	High	1753	13.07	63	9.83	0.03594
	Very high	4589	34.22	506	78.94	0.11026

3.1. FR Model

The FR value was calculated previously based on the area of different categories of each evaluation factor and the number of landslide disaster points in the corresponding categories. The FR value of each evaluation factor in the study region was superimposed by GIS to obtain the FR model result for the city of Laibin.

3.2. FR-AHP Model

According to the previous research results, the judgment matrix was used to calculate the weight of each factor (as shown in Table 4).

Table 4. AHP of the judgment matrix and each factor weight.

Evaluation	Elevation	Slope	Aspect	Height Difference	Plan Curve	Profile Curve	Precipitation	TWI	Vegetation Coverage	Weight
Elevation	1	3	2	5	1	6	1	2	3	0.20970
Slope		1	2	2	2	6	1	2	4	0.16710
Aspect			1	4	1	4	1/2	2	2	0.11630
Height difference				1	1/2	1	1/3	1/4	1/3	0.04030
Plan curve					1	4	1/2	2	2	0.11880
Profile curve						1	1/2	1/4	1/2	0.03460
Precipitation							1	2	2	0.15730
TWI								1	1	0.08770
Vegetation coverage									1	0.06830

After obtaining the weights of each factor, the FR-AHP model results of the study region were determined by using the superposition function of GIS.

3.3. FR-LR Model

There are 641 highway landslide points in the study region, and an equal number of non-landslide points were randomly generated. A total of 1282 sample points were used as the statistical samples for the assessment of highway landslide susceptibility in the target region. We took a landslide as the dependent variable (0 indicates a non-landslide point, 1 indicates a landslide point) and the FR of each factor as the independent variable. We carried out binary logistic regression, relying on SPSS software to obtain the coefficients of each factor and bring them into the formula:

$$Z = -4.7 + 0.62X_1 + 0.371X_2 + 0.507X_3 - 0.01X_4 + 0.373X_5 - 0.097X_6 + 0.577X_7 + 0.104X_8 + 0.431X_9 \quad (6)$$

where X_1 is the elevation, X_2 is the slope, X_3 is the aspect, X_4 is the height difference, X_5 is the plan curve, X_6 is the profile curve, X_7 is the precipitation, X_8 is the TWI and X_9 is the vegetation coverage.

After obtaining the coefficients of each factor, the FR-LR model results of the study region were obtained by using the superposition function of GIS.

3.4. FR-BPNN Model

The 641 highway landslide points and randomly generated equivalent non-landslide points in the study region were analyzed as experimental data. BPNN model analyses were carried out using SPSS Modeler software to determine the importance of each factor. Then, the FR-BPNN model result for the study region was obtained by using the GIS superposition function.

3.5. FR-SVM Model

The 641 highway landslide points and randomly generated equivalent non-landslide points in the study region were analyzed as experimental data. SVM model analyses were carried out using SPSS Modeler software to determine the importance of each factor. Then, the FR-SVM model result for the study region was obtained by using the GIS superposition function.

4. Discussion

In this paper, the susceptibility of a highway landslide in the study region was evaluated by using five models, and the results were discussed from four aspects: distribution of landslides, ROC curve, uncertainty analysis and comparison of several models.

4.1. Distribution of Landslides

The analysis of landslide distribution in different models is an important step in landslide disaster evaluation, which can preliminarily analyze the accuracy of models and the distribution of landslide susceptibility grades. A comparison of the landslide point density of five models and the percentages of different landslide susceptibility categories for five models are shown in Figures 4 and 5.

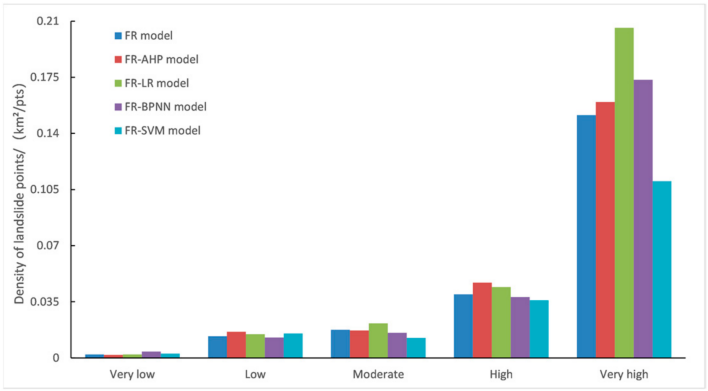
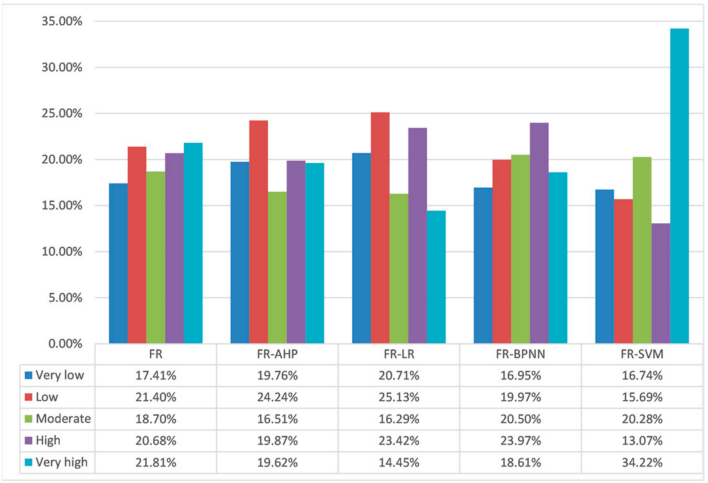


Figure 4. Comparison of the landslide point density of five models.



	FR	FR-AHP	FR-LR	FR-BPNN	FR-SVM
Very low	17.41%	19.76%	20.71%	16.95%	16.74%
Low	21.40%	24.24%	25.13%	19.97%	15.69%
Moderate	18.70%	16.51%	16.29%	20.50%	20.28%
High	20.68%	19.87%	23.42%	23.97%	13.07%
Very high	21.81%	19.62%	14.45%	18.61%	34.22%

Figure 5. Percentages of different landslide susceptibility categories for five models.

In the FR model, according to Figures 4 and 5, very low and low areas accounted for 38.81% of the whole area of the study region, but landslide points only accounted for 6.86% of the total; very high areas accounted for 21.81% of the whole area of the study region, and landslide points accounted for 69.11% of the total.

In the FR-AHP model, according to Figures 4 and 5, very low and low areas accounted for 44.00% of the whole area of the study region, but landslide points only accounted for 9.05% of the total; very high areas accounted for 19.62% of the whole area of the study region, and landslide points accounted for 65.52% of the total.

In the FR-LR model, according to Figures 4 and 5, very low and low areas accounted for 45.84% of the whole area of the study region, but landslide points only accounted for 8.74% of the total; very high areas accounted for 14.45% of the whole area of the study

region, and the landslide points accounted for 62.25% of the total. The density of landslide points in the very high areas was the highest among the five models.

In the FR-BPNN model, according to Figures 4 and 5, very low and low areas accounted for 36.92% of the total area of the study region, but landslide points only accounted for 6.71% of the total; very high areas accounted for 18.61% of the total area of the study region, and landslide points accounted for 67.55% of the total.

In the FR-SVM model, according to Figures 4 and 5, very low and low areas accounted for 32.43% of the whole area of the study region, but landslide points only accounted for 5.93% of the total; very high areas accounted for 34.22% of the whole area of the study region, and the landslide points accounted for 78.94% of the total. The density of landslide points in the very high areas was the lowest among the five models.

The FR-LR model was the highest with 45.84% and the FR-SVM model was the lowest with 32.43% in the very low- and low-risk areas, the FR-LR model was the highest with 0.20588 and the FR-SVM model was the lowest with 0.11026 for the very high-risk density of the landslide points. Meanwhile, the FR-LR model was the lowest with 14.45% and the FR-SVM model was the highest with 34.22% in the very high-risk areas.

4.2. ROC Curve

To test the precision of the evaluation results of the five models on the landslide susceptibility in the study region, a ROC curve was used to verify the results. The area under the ROC curve, AUC (Area Under the Curve), was used to reflect the reliability and accuracy of the resulting data [40]. The value of the AUC was between 0 and 1, and the larger the area was, the more reasonable the result and the higher the feasibility of the research method. In this paper, the abscissa was the accumulation percentage of the regional areas from high to low, and the ordinate was the accumulation percentage of the number of corresponding highway disaster points. The ROC curve test results for the five models in this paper are shown in Figure 6. The AUC values of the FR, FR-AHP, FR-LR, FR-BPNN and FR-SVM models were 0.783, 0.786, 0.804, 0.792 and 0.798, respectively. The results show that the accuracy of the five models was greater than 0.700, meaning they had certain reliability. Among them, the FR-LR model had the highest accuracy of 0.804, indicating that this model is most suitable for assessing highway landslide susceptibility in the study region.

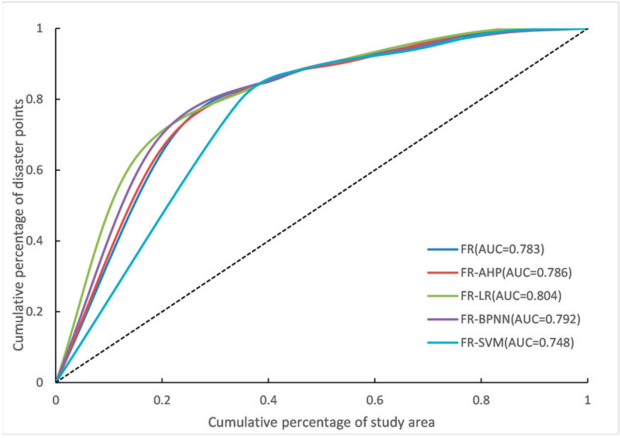


Figure 6. The ROC curves of the five models.

4.3. Uncertainty Analysis

In landslide disaster evaluation, selecting suitable factors and models are the two most critical steps. In terms of factor selection, the occurrence of landslide disasters is closely related to topography, geological structure, stratum lithology, hydrometeorology, human activities and other factors. Due to the complexity of its formation mechanism, there is no one set of factors applicable to the evaluation of landslide susceptibility in all regions. Instead, the selection of factors is generally determined by the specific conditions of the

study area [41,42]. In terms of model selection, the basis for landslide disaster assessment has developed from statistical to machine learning modeling, and again there is no uniform standard for model selection. In this paper, we used the FR model, a statistical model that depends too much on the richness of basic data and the classification of evaluation factors [43]. AHP is a subjective method, and the discrimination of importance of evaluation factors is subjective to some extent; meanwhile, the use of a single weight for the same evaluation factor does not easily reflect the different contributions of different levels to landslide disasters within the factor [44]. LR is suitable for areas with sufficient data and detailed landslide historical data [45]. BPNN and SVM are machine learning models, and they have the problem of modeling a black-box operation [46]. The precision of a single model is limited, so it is necessary to couple these models.

Previous studies have focused on earthquake landslides, and little research had been carried out on highway landslides. According to the characteristics of highways, this paper selected appropriate factors and evaluation models to evaluate highway landslides in the study region and verified their accuracy. The results showed that this approach has certain reliability, and the results can provide a reference for risk management along highways. Unfortunately, the factors and models in this paper are only applicable to this research area at present, and the accuracy for other areas has not been verified due to limited data, which are problems that remain to be solved.

4.4. Comparison of Several Models

In this paper, five models were used to evaluate the risk of highway landslide disasters in the study region, and a comparative analysis was carried out. Among them, the FR value was calculated from the number of disaster points and disaster areas, so the FR model can represent the probability of landslide occurrence related to disaster-causing factors in different classification intervals, but it assigned equal weights to different factors, without considering the influence and interaction among different factors. In the FR-AHP model, AHP can give different weights to different factors according to the experience of different experts, which made up for the shortcomings of the FR model, but its subjectivity was strong, which may reduce the credibility of the results. Based on the historical landslide data of LR, the calculation results had a high stability and objectivity, which avoided the shortcomings of the FR-AHP model. However, there was a common problem of multicollinearity in the linear regression analysis, which made the FR-LR model sensitive to multicollinearity data, so it was necessary to screen the data before use. The weights of different factors can be obtained by BPNN. The FR-BPNN model overcame the shortcomings of the FR model, but it was over-dependent on the samples. If the quality of sample data is not high, it is difficult to obtain high-precision results. In the FR-SVM model, SVM can still achieve high statistical law effect when facing a relatively small sample size, and it can handle non-linear data with less constraint on factors, which made up for the defects of the FR-LR model. However, it was difficult to implement large-scale training samples, which limited its practical applicability to a certain extent. In this paper, these methods were compared, and they were applied to highway landslides that had not been used before. By comparing the results, some progress was made.

5. Conclusions

1. Summary and key findings

In this paper, nine evaluation factors including the elevation, slope and aspect were selected using the FR model, and AHP, LR, BPNN and SVM were coupled with this to evaluate the susceptibility to highway landslides. In this way, a highway landslide susceptibility classification map for the city of Laibin was obtained, which provides experience for future landslide susceptibility evaluations in other areas.

Very high- and high-risk areas in the study region are mainly distributed in the central zone with a low elevation, low vegetation coverage and frequent human activities. Very

low-risk areas, meanwhile, are mainly distributed in the west and east, with high altitudes and fewer human activities.

As the landslide susceptibility grade increases from very low to very high, the number of highway landslide points also gradually increases. However, among the five models, the FR-LR model had the highest density of highway landslide points in the very high area, while the FR-SVM model had the lowest, which reflected the accuracy of the models to a certain extent. The precision of the five models for evaluating the highway landslide susceptibility was verified by an ROC curve, which showed the FR-LR coupling model was the best.

2. Managerial and policy implications

In this paper, five models were used to evaluate the landslide susceptibility in the study region. Susceptibility was graded, and the very high-risk regions for landslides could be determined according to the obtained susceptibility grading map. Landslides on highways have a large, wide-ranging impact, but we can use various information methods to grasp the disaster situation, such as obtaining 48-h images before and after the disaster to evaluate it, geological disaster detection based on InSAR technology, etc. Yet, these are only post-disaster evaluations, while a landslide susceptibility evaluation offers pre-disaster predictions of the disaster situation according to past data to prevent such a scenario from occurring or to reduce the losses in advance. For local government departments, landslide susceptibility zoning maps can help them conduct a comprehensive survey of high-incidence areas, delineate key prevention and control areas and take prevention and control measures.

3. Insights for future research and limitations

The evaluation factors and evaluation models of landslide disaster assessment are developing all the time. While the evaluation model has developed in the direction of complexity, it does not fully consider the differences of regional geological environment and weakly integrates it with geological analysis, and its prediction accuracy and universality need to be further improved. Meanwhile, since the factors in a landslide disaster are very complex, there is no uniform selection standard at present. To remedy that, determining a set of universal selection criteria should form the direction of continuous development in the future.

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