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Susceptibility assessment of Landslide Disasters in Yunnan-Guizhou-Sichuan Region Based on GIS and RS

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Abstract: This paper takes landslides in the Yunnan-Guizhou-Sichuan region as the research object. Based on grid and slope units respectively, the analytic Hierarchy Process (AHP) and information model are used to evaluate the susceptibility of landslides. The results show that all four evaluation results pass the rationality and accuracy tests, and the accuracy of the raster cell information volume model is the best. The study area as a whole is mainly composed of low-susceptibility zones, with a relatively small proportion of high-susceptibility zones. Spatially, it is generally lower in the west and higher in the east, concentrated in the middle. The spatial differentiation of susceptibility among Yunnan, Guizhou and Sichuan provinces is significant. In Yunnan, the susceptibility increases from south to north. In Guizhou, it is higher in the south and lower in the north. In Sichuan, it is higher in the west and lower in the east. In addition, by adopting the integrated comprehensive eval uation of multiple classifiers and standardizing the superimposed classification of the results of a single model, the evaluation accuracy has been significantly improved.

Keywords: Evaluation of susceptibility to landslide disasters Analytic Hierarchy Process Information volume model GIS, RS.

1. Introduction

Population growth and rapid social and economic development have exacerbated resource consumption and ecological environment damage, triggering various geological disasters such as landslides, collapses and ground subsidence, which seriously threaten regional ecological security and social stability. China has complex geological and geomorphic conditions, and geological disasters occur frequently. In 2016, geological disasters across the country caused significant casualties and economic losses. Among them, the geological environment in the Yunnan-Guizhou-Sichuan region is complex, and landslide disasters occur particularly frequently, with significant disaster losses. Conducting regional landslide susceptibility assessment is of great value for disaster prevention and control. At present, a large number of studies have been conducted on the evaluation of landslide susceptibility, focusing on the application of GIS technology, the selection of evaluation units, and the construction of evaluation models. The evaluation units mainly include types such as raster and slope. The evaluation methods can be classified into deterministic models, statistical models, and machine learning models. The applicability of various models and units varies significantly in different study areas, and the evaluation accuracy of a single model is limited. For this purpose, this paper takes landslides in the Yunnan-Guizhou-Sichuan region as the research object. Combined with GIS technology, two evaluation units, grid and slope, are selected. The Analytic hierarchy process (AHP) and information volume model are adopted to conduct the susceptibility evaluation of landslides. The multi-classifier ensemble method is introduced for comprehensive optimization. The spatial distribution law of regional landslides is analyzed, and the evaluation effects of different schemes are compared. With the aim of providing theoretical basis and practical reference for the risk prevention and control of regional landslide disasters.

2. Overview of the Study Area

The study area of this paper is the Yunnan-Guizhou-Sichuan region in China, covering Yunnan, Guizhou and Sichuan provinces. It is located in the southwest hinterland of China. The three provinces are adjacent to each other and share borders with many other provinces and cities, with a unique geographical location. The region as a whole has a subtropical monsoon climate, with abundant cloud cover, high humidity, relatively little sunshine, and abundant precipitation. The average annual precipitation varies greatly [1]. The temperature and heat are significantly affected by latitude and altitude, and the overall heat gradually decreases from south to north. The region is crisscrossed with a dense network of rivers and has a well-developed water system, belonging to multiple water systems such as the Yangtze River and the Pearl River. There are numerous rivers and abundant water resources [2]. The terrain of the study area is mainly composed of plateaus and mountains, with intense undulations and complex and diverse landform types. Karst landforms are widely developed in Guizhou Province, while in Sichuan Province, the terrain is high in the west and low in the east, with a very high proportion of mountains and plateaus. The regional geological structure is complex, the neotectonic movement is active, the folds and faults are well developed, the rock mass is fragmented, and the internal and external dynamic geological forces are intense, providing the inherent geological conditions for the breeding of geological disasters such as landslides. At the same time, various human engineering activities are frequent in the area. Engineering disturbances such as road construction, mining, agricultural cultivation and waste residue accumulation further undermine the stability of rock and soil masses and increase the risk of landslide disasters.

3. Data and Methods

3.1. Research Data

3.1.1. Basic Data

The data sources required for this research are extensive and diverse, mainly covering the following eight categories, all of which have undergone targeted preprocessing and are used for the relevant analysis of landslide susceptibility evaluation: The first is administrative division data, which comes from the National Geographic Information Resources Directory Service System and is used to crop other types of image data; The second is digital elevation data (500m), downloaded from the geospatial data cloud website (obtained by administrative divisions), and after preprocessing such as radiometric calibration, atmospheric correction, splicing, and cropping, it is used to calculate evaluation factors such as terrain undulation and slope. The third type is remote sensing images, which are taken from geospatial data clouds and undergo the same preprocessing to extract the normalized vegetation index. The fourth is the rainfall data, which is derived from the rainfall statistics of the Yunnan-Guizhou-Sichuan region from 2001 to 2020. The fifth is vector data of roads and water systems, downloaded from the Open Street Map website (obtained by administrative division), used to calculate the distance from the landslide point to the roads and water systems, and analyze the influence of distance factors on the occurrence of landslides; The sixth is land use data, which is obtained by cropping the global land use spatial distribution map and is used to analyze the impact of land use types on the occurrence of landslides. The seventh is the peak acceleration value data of ground motion, which is obtained through geographic registration and digital processing of tif format images. The eighth is the data on landslide sites, geomorphic types, soil types and stratum lithology, which are derived from the detailed geological disaster investigation data of the corresponding provinces in Yunnan, Guizhou and Sichuan

3.1.2. Selection of Evaluation Factors and Layer Creation

The formation and development of landslides mainly rely on the natural geographical environment, geological conditions and human engineering activities of the region [3]. Based on the research of predecessors, three major categories of natural geography, geological structure and human activities in the study area are selected [1]. Sixteen subcategories of influencing factors, including elevation, slope, aspect, terrain curvature, terrain undulation, average annual rainfall, terrain moisture index, peak acceleration of ground movement, surface roughness, soil type, stratum lithology, normalized vegetation index, distance from water systems, distance from roads, population density, and land use type, are used as evaluation factors for landslide susceptibility.

①DEM elevation map: As the study area consists of three provinces, namely Yunnan, Guizhou and Sichuan, and the data obtained is by province, it is necessary to perform Mosaic and merge processing on the data in ArcGIS to obtain the DEM data of the study area [4]. ② Curvature, slope, aspect, terrain undulation, surface roughness and terrain moisture index data: The preprocessed DEM data of the Yunnan-Gui-Chuan region can be calculated for curvature, slope and aspect respectively in ArcGIS to obtain the corresponding layer data. Finally, the terrain undulation data can be obtained by subtracting the minimum elevation from the maximum elevation. After the slope of the DEM data is calculated, the roughness is then calculated using the roughness calculation formula to obtain the surface roughness layer of the study area. The dem data is successively calculated by filling the depressions - flow direction FD- flow rate FA- slope. Then, the slope unit is converted into radians, Tan radians are calculated, and the flow rate per unit area CA is calculated. Finally, the TWI data can be obtained by using the grid calculator with the TWI formula [5]. ③ Annual average rainfall and population density map: Add the rainfall attribute value to the vector map attribute table of the districts and counties in Yunnan, Guizhou and Sichuan provinces. On the symbol system page, select to display by rainfall, and then convert the area data into raster data to obtain the raster data of the annual average rainfall in the study area. Similarly, in the attribute table of administrative division data, add three fields: area, population, and population density [6]. Calculate the area of each district and county, add population data, and the population density can be obtained with the statistically analyzed population and area data. Similarly, convert the area data into raster data, and the raster data of population density in the study area can be obtained. ④ Stratigraphic lithology, geomorphic type, soil type, and ground motion peak acceleration map: Resampling the original stratigraphic lithology and soil type data with a grid size of 500m can obtain the stratigraphic lithology and soil type layer data. The obtained geomorphic type map needs to merge the geomorphic types into major categories, and then resampled the raster data to modify the raster size, thereby obtaining the geomorphic type raster map of the study area. The obtained ground motion peak acceleration map is a raster image. It needs to be vectorized, then the dynamic peak acceleration attribute should be added to the attribute table, and then the vector surface should be converted into a raster to obtain the dynamic peak acceleration raster data of the study area [7]. ⑤ Normalized vegetation index map: Load the obtained remote sensing images into the ENVI software, calculate the normalized vegetation index according to the formula, and then resampling it in ArcGIS to modify the pixel size, and the normalized vegetation index raster data of the study area can be obtained. ⑥ Road distance map and water system distance map: In arcgis, calculate the Euclidean distances of rural roads, county roads, railways, provincial roads, and national roads respectively. Then, based on the reference materials, assign different weights to roads of different grades, and the weighted road distance raster map of the road distance from the landslide point in the study area can be obtained. By using the same method to calculate the Euclidean distance of the water system, the base map of the Euclidean distance of the water system can be obtained.

3.1.3. Selection of Evaluation Factors

Principal component analysis Principal component analysis is to extract the main components from multiple original variables while retaining as much of the original information as possible, thereby reducing the correlation between factors. In this study, SPSS was used for principal component analysis [8]. Firstly, 3,000 random points were created in the study area using ArcGIS. The attribute values of 16 evaluation factors were extracted from the random points using the "Multi-Valued to Point Extraction Tool". By exporting the attribute data, the attribution acquisition information of the evaluation factors was obtained. In the SPSS software, the attribute information of each disaster evaluation factor is loaded and obtained [9]. Through principal component analysis, the purpose of "dimensionality reduction" of the 16 basic evaluation factors is achieved. A comprehensive analysis of the results of principal component analysis revealed that the initial values of the first five components were greater than 1, and the cumulative percentage of variance was 71.944%, as shown in Table 1. The extraction criteria for principal components are as follows: the initial eigenvalue is greater than 1 or the cumulative variance ratio is greater than 70%. Then, the five most important components can be identified as the key components for evaluating the variable factors [10].

Table 1. Component Matrix

component matrixa					
	component				
	1	2	3	4	5
surfaceroughness	.854	.059	-.445	-.167	.005
topographic wetness index	.854	.059	-.445	-.167	.005
exposure	.854	.059	-.445	-.167	.005
Peak acceleration of ground motion	.804	-.110	.371	-.167	-.144
density of population	.800	-.115	.392	-.184	-.126
Annual average rainfall	.739	-.109	.475	-.043	-.057
NDVI	.675	.039	-.259	.279	.038
geomorphic type	.564	-.109	.444	.312	.155
agrotype	.554	-.142	.348	-.029	.415
Terrain undulation	.014	.942	.224	-.094	.053
elevation	.212	.707	-.069	.119	-.153
land-use type	.276	-.057	.003	-.651	.001
Distance from the road	.475	.001	.031	.505	.151
slope	.382	.058	-.052	.439	.038
river system	.361	.049	-.086	.336	-.673
formation lithology	.168	.140	-.300	.124	.541
Extraction method: Principal component analysis method.					
Five components were extracted.					

As can be seen from the table, principal component 1 has a significant correlation with nine factors including roughness, slope direction, terrain moisture index, peak ground acceleration value, population density, rainfall, normalized vegetation index, geomorphic type, and soil type [11]. Principal component 2 has a strong correlation with terrain and height data, and principal component 4 has a significant correlation with the distance from the road [12]. Principal component 5 has a significant correlation with the lithology of the stratum.

(1) Analysis results

The figure clearly reflects the relationship among the weights of each evaluation factor index, among which the annual average rainfall accounts for the largest proportion, which is 0.0858. The proportion of land use types was only -0.00711, which was significantly smaller than that of other evaluation factors. Therefore, the evaluation factors of land use types were eliminated, and the remaining 15 evaluation factors were retained for further analysis.

(2) Correlation Analysis

Correlation analysis refers to the determination of the degree of correlation between two or more factors that are correlated with each other [13]. The prerequisite for conducting this analysis is that there is a significant correlation among the factors [14]. There are three methods for correlation analysis: Pearson correlation coefficient method, Kendall correlation coefficient method, and Spearman correlation coefficient method. Although all of them are used to analyze the correlation of factors, their applicable scopes are quite different [15]. Given that the Pearson correlation coefficient method is simple to operate and widely applicable, this study adopts this method to calculate the correlation coefficients between variables. The range of the Pearson correlation coefficient is [1, -1]. In this method, the correlation between two variables is often reflected by the absolute value of r. The range of r is shown in Table 2.

Table 2. Correlation Coefficient: r - Grade Classification Table

data range	0-0.3	0.3-0.5	0.5-0.8	0.8-1.0
dependency	Basically irrelevant	low correlation	Moderately correlated	High correlation

In the SPSS analysis software, open the attribute data of the random point evaluation factors in the study area, and use the "bivariate" tool for calculation and analysis. Finally, the correlation coefficient matrix of the evaluation factors is obtained [16]. It can be seen from the table that elevation has a significant correlation with terrain undulation, roughness has a significant correlation with normalized vegetation index, peak acceleration of ground motion, and population density, geomorphic type has a significant correlation with soil type, peak acceleration of motion, average annual rainfall, and population density, and normalized vegetation index has a significant correlation with surface roughness, slope data, and terrain moisture index. The slope data has a significant correlation with the peak acceleration of ground motion and population density [17]. The average annual rainfall has a significant correlation with the peak acceleration of ground motion and population density. Population density has a significant correlation with the peak acceleration of ground motion and the topographic humidity index. The remaining evaluation factors show a low correlation or almost no correlation among them. Taking into account curvature, undulation, terrain type, etc., it also includes features related to terrain such as slope, elevation, and ground roughness. Through a comprehensive analysis of these factors, elevation, slope direction and surface roughness were excluded, and the remaining 12 evaluation factors were retained as the final evaluation factors.

3.2. Research Methods

3.2.1. Analytic Hierarchy Process (AHP)

AHP is to arrange the various influencing factors in the entire event in a certain order according to the nature of the object being analyzed and the overall purpose of the decision. It can be roughly divided into the following three steps [18]:

(1) Establishing a system hierarchy.

When using the Analytic Hierarchy Process to solve problems, the first step is to structure the complex problem to be solved, decompose it into multiple elements according to the problem to be solved, and then construct a multi-level structure model based on the degree of association and subordination among different elements. Specifically: The topmost layer (goal layer): There is only one element, representing the original goal and the expected result. The intermediate layer (benchmark layer and indicator layer): It is the layer of the intermediate process. The lowest level (policy level, basic level): It includes various measures taken to solve problems, policies, etc. (2) Construction of the judgment matrix first, selection of the expert group

To avoid the deviation caused by subjective influence on the evaluation matrix, it is necessary to first select experts familiar with the problem to be solved to analyze the relative importance of each factor and its influencing factors, and then create the evaluation matrix. Second, judge the matrix structure. The relative weights of each factor were assigned according to the judgment matrix scale table, and finally the judgment matrices from A-B and B-C were obtained. The description of the judgment matrix scale is shown in Table 3.

Table 3. Description of the scale of the judgment matrix

scale	implication
1	Indicate that the two factors are of equal importance compared to
3	It indicates that the former is slightly more important than the latter among the two factors
5	Indicate that the former is significantly more important than the latter
7	Indicate that the former is more important than the latter when comparing the two factors
9	Indicate two factors compared the former is more important than the latter
2, 4, 6, 8	Represents the median value of the above adjacent judgments
count backwards	If the ratio of the importance of factor ai to factor aj is aij, then the ratio of the importance of factor aj to factor ai is aji=1/aij

(2) Calculation of weight vectors and their consistency checks. The reliability of the judgment matrix needs to be determined by conducting consistency tests on the judgment matrix. The calculation formula for the consistency index is:

$$CI=(\lambda max-n)/(n-1) \quad (1)$$

In the formula: λmax is the maximum eigenroot of the judgment matrix; n is the order of the judgment matrix; CI is the consistency index of the judgment matrix. When CI=0, the judgment matrix is completely consistent. Conversely, the larger the CI, the worse the consistency of the judgment matrix. RI is the average random consistency index of the judgment matrix (Table 4).

Table 4. Average Stochastic Consistency Index

	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

CR=CI/RI.

When CR<0.1, it is considered that the judgment matrix has satisfactory consistency.

3.2.2. Information Volume Model

The information volume model is one of the statistical evaluation methods in information theory. It is simple in principle and highly accurate, and has been widely applied in the field of geological disasters [19]. This information volume model quantitatively shows the influence degree of each attribute interval of environmental factors on landslide disasters, and superimposes these attribute intervals to calculate the comprehensive information. The formula for calculating the amount of information is:

$$I(x, H)= \sum_{i=1}^{n} \ln\left(\frac{Ni/N}{Si/S}\right) \quad (2)$$

In the formula: x represents any uniform disaster factor, and n represents the total number of grades of factor x. I(x, H) represents the amount of information provided by factor x for the occurrence of landslides. Ni represents the number of landslide disaster points in the i-level area of factor x. N represents the total number of landslide disaster points in the study area. Si represents the area of the i-th region of factor x; S represents the total area of the study area.

When there are m disaster-causing factors, the expression of the total information quantity I is:

$$I= \sum_{i=1}^{m} I\,(xi, H) \quad (3)$$

In the formula: I is the total amount of information of factor x; m represents the number of disaster-causing factors, and the total information volume I is a quantitative expression of the susceptibility to landslides, which is the predicted information volume of the grid cell. When I is greater than 0, it indicates that the interaction of disaster-causing factors is conducive to the occurrence of geological disasters; conversely, it indicates that it is unfavorable. The larger the i value, the more likely landslide disasters are to occur.

4. Experimental Results

4.1. Evaluation Process and Results

4.1.1. Evaluation of Landslide Susceptibility Based on the Analytic Hierarchy Process

After creating the evaluation system and the judgment matrix, the weights can be calculated. Finally, the weight value of each evaluation factor can be calculated, as shown in table 5.

Table 5. The weight of factors based on AHP

factor	Distance from the road	population density	NDVI	Distance from the water system	agrotype	formation lithology
wight	0.025	0.0206	0.0825	0.0345	0.1073	0.1870
factor	Peak acceleration of ground motion	aspect	Annual average rainfall	geomorphic type	TWI	Terrain undulation
wight	0.0194	0.0748		0.0667	0.0667	0.0397

The classification results of the susceptibility to landslide disasters

For the division of areas prone to landslide disasters, the idea of the comprehensive index method is mainly adopted. By using various evaluation indicators, the respective weight values are multiplied by the corresponding weight values and added together to obtain the final assignment value. The existing plots are divided according to the GIS natural split point method and combined with sliding data to determine the grade standards.

This study is based on the weight values of each basic disaster evaluation factor calculated by AHP. In arcgis, each evaluation factor is multiplied by its corresponding weight and the weight of the index corresponding to its intermediate layer. All the indicators are added together to obtain the classification map of the occurrence degree of landslide disasters in the study area. Finally, the natural discontinuous point method is combined with the existing landslide data to divide it into five grades. By replacing the appropriate color bands in the symbol system, the final classification map of landslide susceptibility in the study area was obtained, as shown in Figures 1 and 2.

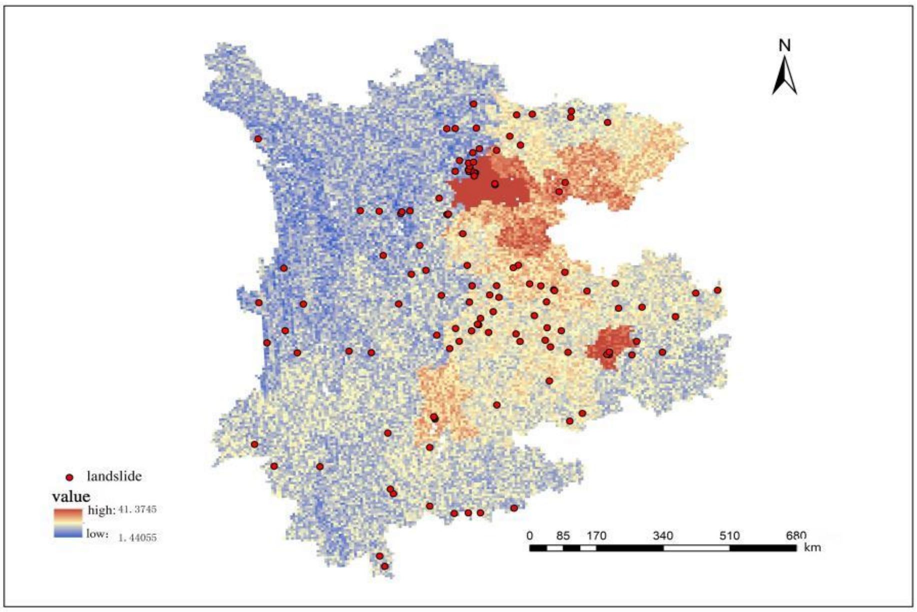

Figure 1. The evaluation results based on the Analytic Hierarchy Process

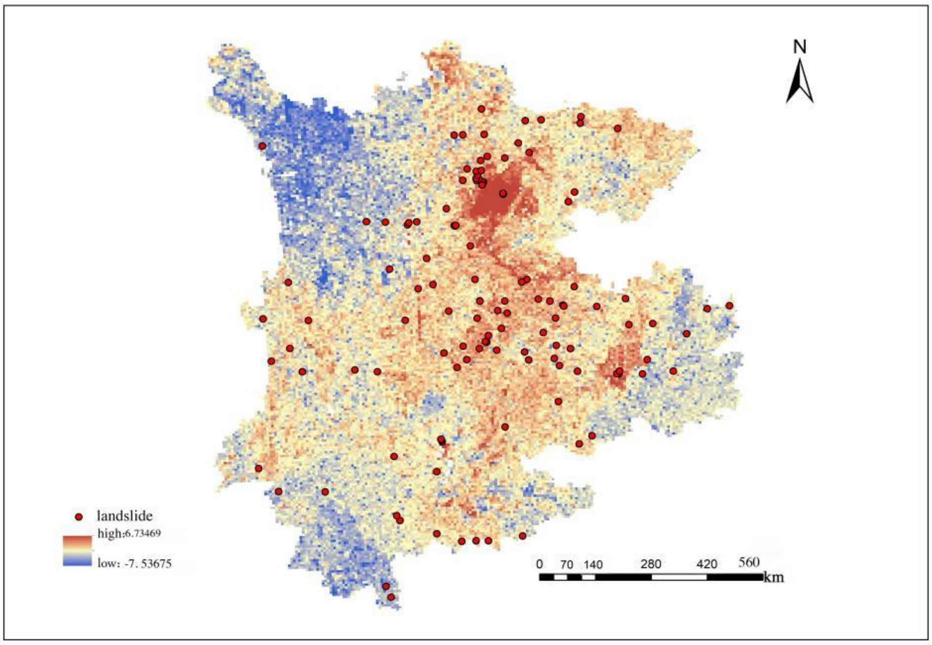

Figure 2. Evaluation results based on the information volume model

4.1.2. Evaluation of Landslide Susceptibility Based on Information Volume Model

(1) Load various disaster assessment factors in ArcGIS and complete the preprocessing work such as splicing, cropping and projection of each basic data. (2) Reclassify each evaluation factor and use the multi-value extraction to point function to assign attribute values of disaster evaluation factors to each landslide disaster point. The data was exported to Excel, and the information quantity values in different intervals of each disaster evaluation factor were calculated according to the information quantity calculation formula. The information in different intervals of each evaluation factor was reassigned, and the obtained single-factor information graph was layered and superimposed. The comprehensive information is shown in Figures 3 and 4.

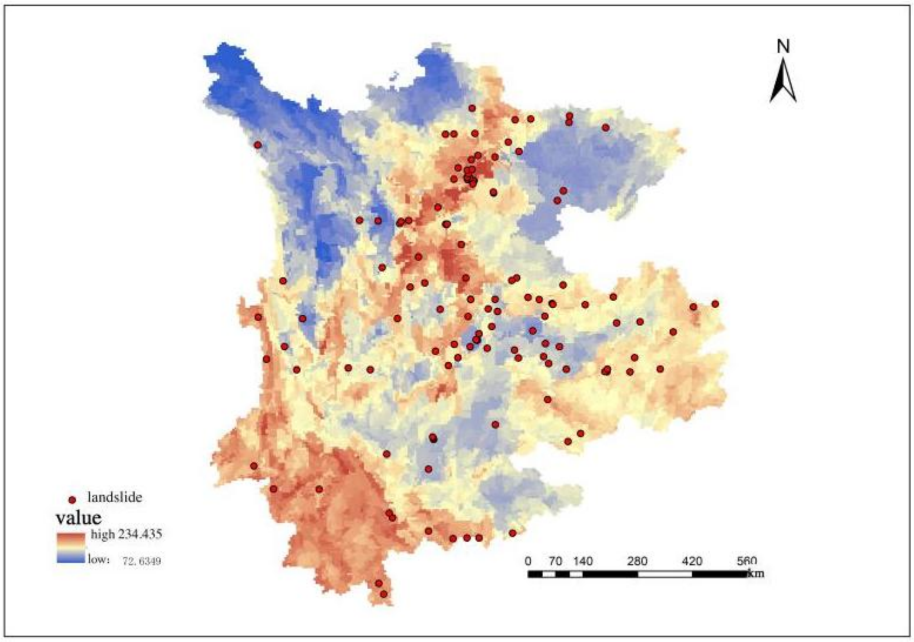

Figure 3. The evaluation results based on the Analytic Hierarchy Process

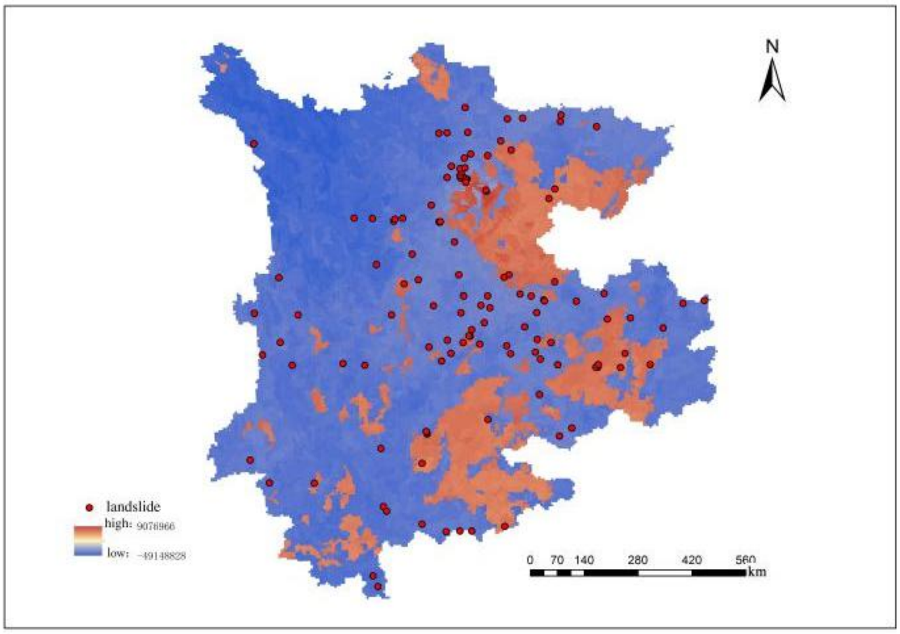

Figure 4. Evaluation results based on the information volume model

4.2. Inspection and Analysis of Evaluation Results

4.2.1. Precision Test

The receiver operating characteristic curve (ROC) is the most commonly used method for evaluating landslide susceptibility and the accuracy of classification results. In this article, we will analyze the accuracy of the landslide prediction model based on the ROC curve.

(1) ROC curve

The horizontal axis of the ROC curve represents specificity, that is, the ratio of non-landslide points in predicting landslide points in the model. The vertical axis coordinate represents the sensitivity of the landslide point ratio predicted by this model. The area below the curve represents the accuracy of the model, and the AUC indicates the range of [0.1]. The closer the value of AUC is to 1, the better the performance of the model. Import the data of each evaluation result into the SPSS software for analysis. The accuracy of the four evaluation results is shown in Figure 5 ~ 8.

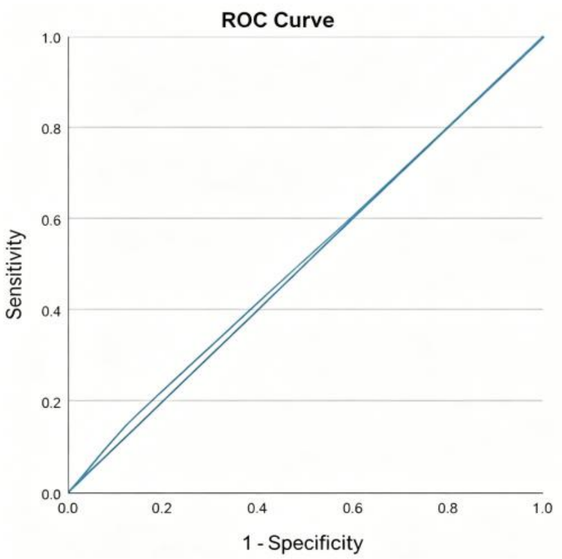

Figure 5. Evaluation Results of the Analytic Hierarchy Process Based on Raster Cells

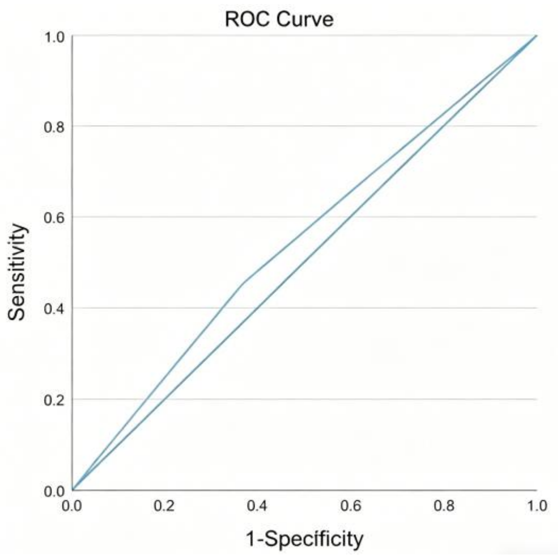

Figure 6. Evaluation Results of the Analytic Hierarchy Process Based on Slope Cells

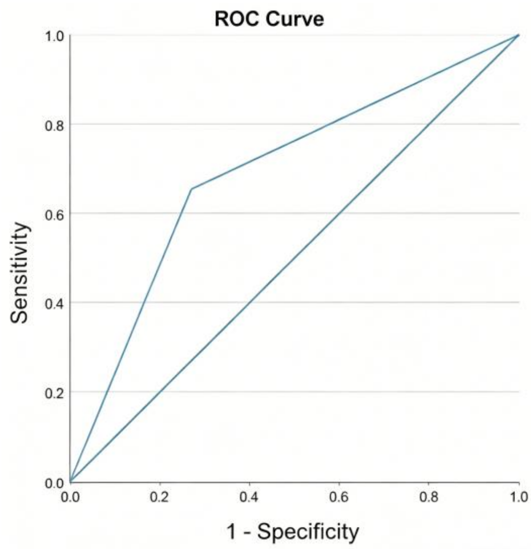

Figure 7. Evaluation Results of Information Quantity Model Based on Raster Cells

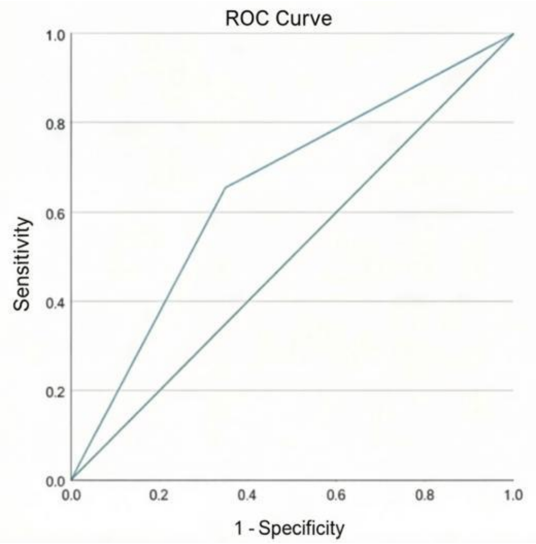

Figure 8. Evaluation Results of information quantity Model Based on Slope Cells

Through analysis, it can be known that the accuracy of the two evaluation results under the Analytic Hierarchy Process (AHP) model is relatively lower, while the accuracy of the two evaluation results under the information volume model is higher. The following explains the accuracy test results from three perspectives:

Evaluation units, evaluation models, and the integration of evaluation units and evaluation models. From the perspective of evaluation units, in the evaluation results based on raster units, the accuracy of the evaluation results of the information quantity model is higher than that of the analytic hierarchy Process. In the evaluation results based on slope units, the accuracy of the evaluation results of the information quantity model is higher than that of the Analytic Hierarchy Process. Through comprehensive analysis, it can be concluded that in the study of landslide susceptibility in the Yunnan-Guizhou-Sichuan region, the accuracy of the evaluation results of the information quantity model is significantly higher than that of the Analytic Hierarchy Process. From the perspective of the evaluation model, among the two results evaluated by the hierarchical classification method, the accuracy of the evaluation results based on the two evaluation units is not very high, while the accuracy of the evaluation results based on the slope unit is slightly better. Among the two results evaluated by the information quantity model, the accuracy of the evaluation results under both evaluation units is relatively high, and the accuracy of the evaluation result based on the raster unit is higher than that based on the slope unit. From the comprehensive analysis of evaluation units and evaluation models, it is found that the results evaluated by the information quantity model based on raster cells have the highest accuracy, and the evaluation results are closest to the real situation of landslide susceptibility in the study area.

4.2.2. Analysis of Evaluation Results

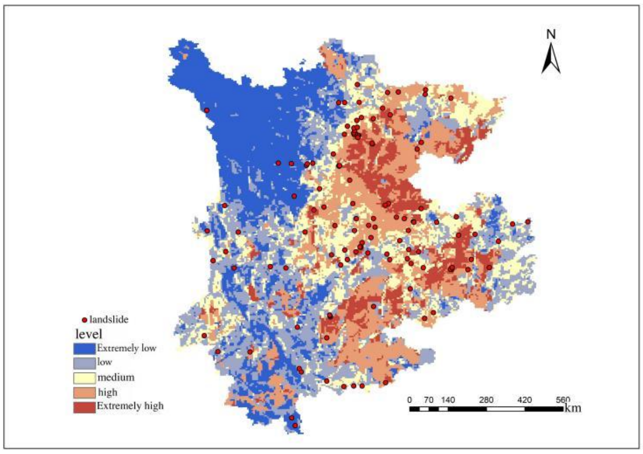

Figure 9. Evaluation Results of landslide Susceptibility in the Yunnan-Guizhou-Sichuan region

Based on the above analysis, it can be known that the evaluation result of the information quantity model based on grid cells has the highest accuracy and is closest to the real situation of landslide susceptibility in the study area. Therefore, we take this result as our final evaluation result (as shown in Figure 9). After analysis, it can be known that:

Most areas in the study zone are at a low risk level, while a small number of areas are at a high risk level. According to statistical analysis, the area at the extremely low risk level is the largest, accounting for 29.9% of the study area, approximately 315,500 square kilometers. Among them, Yunnan, Guizhou and Sichuan account for 35.4%, 14.9% and 49.3% of the area respectively. The low-susceptibility area ranks second, accounting for 23.1% of the study area, approximately 144,000 square kilometers. Among them, Yunnan, Guizhou and Sichuan account for 42.5%, 19.1% and 38% respectively. The moderately prone areas accounted for 22.3% of the total study area, approximately 235,000 square kilometers. Among them, Yunnan, Guizhou and Sichuan accounted for 37.9%, 17.7% and 44% of the area respectively. The high-susceptibility areas account for 15.2% of the total study area, approximately 161,000 square kilometers. Yunnan, Guizhou and Sichuan respectively account for 33.7%, 16% and 50% of the area. In Guizhou Province, they are mainly concentrated in Bijie City, Liupanshui City, Zunyi City and Qiannan Yi and Miao Autonomous Prefecture. The extremely high-risk areas account for 9.3% of the total area, approximately 98,000 square kilometers. Yunnan, Guizhou and Sichuan respectively make up 26.5%, 15% and 58% of them. In Yunnan Province, the extremely high-risk areas are mainly concentrated in Zhaotong City, Qujing City and Honghe Hani and Yi Autonomous Prefecture. In Guizhou Province, the extremely high-risk areas are mainly concentrated in Liupanshui City and Guiyang. The medium-high incidence areas in Sichuan Province mainly occur in the following regions: Mianyang City, Deyang City, Chengdu City, Meishan City, Leshan City, Yibin City, Luzhou City and Bazhong City. Overall, research

(2) From the perspective of spatial location, the overall susceptibility level of landslides in the study area shows a phenomenon of lower susceptibility in the west and higher susceptibility in the east. Among them, the high-susceptibility and extremely high-susceptibility areas are concentrated in the central part of the east. Landslides in Yunnan Province show a phenomenon of lower susceptibility in the south and

higher susceptibility in the north. The high susceptibility and the high susceptibility are mainly concentrated in the northeast direction. Landslides in Guizhou Province show a phenomenon of higher susceptibility in the south and lower susceptibility in the north, mainly concentrated in the central region and the southwest region. Landslides in Sichuan Province show a phenomenon where the incidence is lower in the west and higher in the east, and they are mainly concentrated in the central part and some areas in the middle and lower reaches.

5. Conclusion

(1) Taking into account the formation conditions of landslides in the study area comprehensively and combining the results of various statistical analyses, 12 influencing factors in three major categories, namely natural geography, basic geology, and human engineering activities, are retained as the evaluation factors for landslide disasters. And an evaluation factor index system for the susceptibility of landslide disasters in the study area was established.

(2) Based on the grid cells and slope cells as the basic data, the Analytic Hierarchy Process (AHP) and the information volume model were respectively selected to evaluate the susceptibility of landslide disasters in the study area. The results show that the evaluation results based on analytic hierarchy process and the two evaluation units are not very accurate, while the results of the two evaluation units based on the information quantity model are relatively accurate. To assess the susceptibility of landslides in the Yunnan-Guizhou-Sichuan region, it is best to use the information volume model for evaluation and prediction.

(3) In the case of evaluation based on the information volume model, the accuracy of the evaluation results based on grid cells is higher than that of slope cells. Based on this, it can be concluded that in the evaluation of landslide susceptibility in the Yunnan-Guizhou-Sichuan region, the information volume model based on 500m grid cells is the combination of evaluation units and evaluation models with the highest prediction accuracy in this study.

(4) By using the natural discontinuity point method in combination with the existing landslide data, the evaluation results are classified into five grades - extremely low, low, medium, high and extremely high - according to the degree of susceptibility, and the rationality of the classification results is tested. The results show that in terms of the specific density of landslides, the results of the two evaluation models of the two evaluation units both exhibit good rationality, that is, as the degree of vulnerability increases, the specific density of landslides increases. In terms of area ratio, the four evaluation results also demonstrated good rationality. That is, the higher the susceptibility level, the smaller the area ratio. The rationality test accuracy of the two results evaluated by the information volume model method was the highest.

(5) In the Yunnan-Guizhou-Sichuan region, the majority of areas are at a low susceptibility to landslides, with only a few regions having a relatively high susceptibility to landslides. The susceptibility to landslides in the three regions of Yunnan-Guizhou-Sichuan is also at a relatively low level, with only a few areas having a relatively high susceptibility. Among them, there are many areas in Sichuan Province with a high susceptibility to landslides, mainly concentrated in several regions such as Mianyang City, Deyang City, Chengdu City, Meishan City, Leshan City, Yibin City, Luzhou City and Bazhong City. Finally, there is Guizhou City. The relatively high-risk areas are mainly concentrated in Bijie City, Liupanshui City, Zunyi City and the southern Qianxi Yi and Miao Autonomous Prefecture within Guizhou Province.

(6) In terms of spatial location, the susceptibility to landslides in the Yunnan-Guizhou-Sichuan region shows a phenomenon of being lower in the west and higher in the east, and in the east, it is mainly concentrated in the central region. Among them, landslides in Yunnan Province show a phenomenon of lower susceptibility in the south and higher susceptibility in the north. The high susceptibility and the high susceptibility are mainly concentrated in the northeast direction. Landslides in Guizhou Province show a phenomenon of higher susceptibility in the south and lower susceptibility in the north, mainly concentrated in the central region and the southwest region. Landslides in Sichuan Province show a lower incidence in the west and east.

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