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Landslide Susceptibility Assessment based on GIS Technology

-- Take Beichuan Qiang Autonomous County as an Example

Zhengwei Shen

Xi'an University of Petroleum, Xi'an, Shaanxi 710065, China

Abstract

Landslides, as a typical geological hazard, pose a serious threat to the safety of people's lives and property in China. Conducting geological hazard susceptibility assessments plays a crucial role in formulating scientific disaster prevention and mitigation plans. With the development of GIS technology, its application in geological hazard evaluation has become increasingly widespread. This study focuses on Beichuan Qiang Autonomous County in Mianyang City, Sichuan Province, a region in China with frequent landslide occurrences. Slope angle, aspect, elevation, hydrological systems, distance from faults, and maximum NDVI values were selected as evaluation indicators for landslide susceptibility. Using ArcGIS's powerful spatial analysis capabilities and information modeling methods, we conducted a landslide susceptibility zoning analysis and completed the evaluation. The results show that high-susceptibility areas cover 884.1447 km² (29% of the total area), medium-susceptibility areas cover 811.737km² (26%), and low-susceptibility areas cover 851.4711 km² (28%). Non-susceptible areas total 522.3807 km² (17%). The evaluation results align well with actual conditions, providing a theoretical foundation for landslide early warning, forecasting, and prevention efforts in the region.

Keywords

Landslide Hazard; Susceptibility Assessment; ArcGIS; Information Quantity Model.

1. Introduction

Geological hazard susceptibility refers to the likelihood of [1] geological disasters occurring in a specific region. The evaluation of geological hazard susceptibility serves [2] as the foundation for regional geological disaster risk assessment [3]and plays [4]a crucial role [5] in formulating scientific [6] disaster prevention and mitigation plans. Various models [7] are applicable for geological hazard susceptibility evaluation, including the Analytic Hierarchy Process (AHP), Information Content [8] Model (ICM), Regression Model (RM), and Support Vector Machine (SVM) model. Among these, the Information Content Model has gained widespread application due to its clear physical interpretation. As a Geographic Information System (GIS), ArcGIS provides robust technical support for geological hazard susceptibility evaluation through its powerful capabilities in spatial analysis, data processing, and graphical output.

Landslides, a prevalent geological hazard in mountainous and hilly regions, pose a serious threat to human lives and property. With urbanization advancing, factors like complex geological environments and extreme weather have led [9] to a rising frequency of landslide disasters, creating significant threats to urban development and local livelihoods. Therefore, conducting landslide susceptibility assessments is of critical importance.

Beichuan Qiang Autonomous County, located in Mianyang City, Sichuan Province, was severely impacted by the Wenchuan Earthquake. With complex geological conditions and predominantly mountainous terrain featuring significant [10] elevation changes, the area has experienced multiple geological disasters including landslides, rockfalls, and debris flows, posing serious threats to local residents 'lives, property, and daily livelihoods. Among these hazards [11], landslides account for the largest proportion. Therefore, it is essential to conduct a landslide susceptibility assessment in Beichuan County. This study utilizes ArcGIS's spatial analysis tools and the information quantity model method, comprehensively evaluating six factors: slope gradient, aspect, elevation, hydrological systems, fault lines, and maximum normalized difference vegetation index (NDVI) values. These factors are integrated to delineate landslide-prone zones, aiming to provide a reference framework for landslide disaster prevention and mitigation in Beichuan County.

2. Overview of the Study Area and Data Sources

2.1. Overview of the Study Area

Beichuan Qiang Autonomous County (hereinafter referred to as Beichuan County) is located in the northwest of the Sichuan Basin, with geographical coordinates roughly within the range of north latitude 31°14′ to 32°14′ and east longitude 103°44′ to 104°42′. Administratively, Beichuan County is under the jurisdiction of Mianyang City, Sichuan Province, bordering Jiangyou City to the east, An County to the south, Mao County to the west, and Songpan County and Pingwu County to the north. The total area of the county is approximately 3,084 square kilometers (Figure 1).

Nestled in the Sichuan Basin, Beichuan County boasts a subtropical humid monsoon climate with abundant rainfall, mild winters, and refreshing summers. Its terrain is predominantly mountainous, featuring a network of gullies and dramatic elevation changes. The county's highest peak reaches 4,769 meters above sea level, while its lowest point at Xiangshui Ferry stands at 540 meters, creating a relative elevation difference of 4,229 meters. The landscape slopes from northwest to southeast, with rivers flowing along the mountain contours from northwestern to southeastern regions.

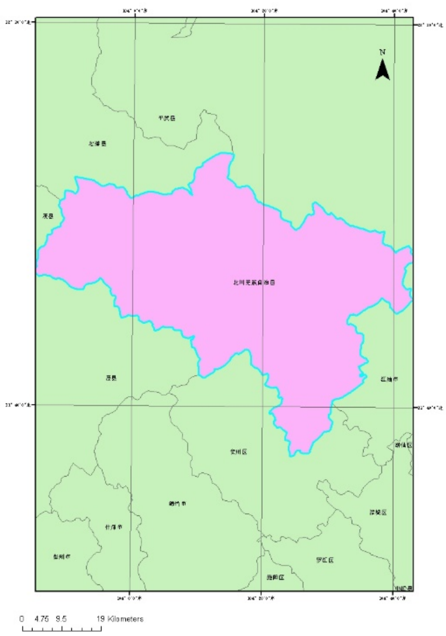

Figure 1. Location map of Beichuan County

2.2. Data Source

In the study area, 190 landslide events from recent years were selected as sample data. The DEM data was sourced from the Geospatial Data Cloud. This paper uses raster cells as the basic unit for landslide susceptibility assessment. Based on the specific conditions of the study area, the resolution of raster cells was set to 30m×30m, and the study area was divided into 3094 rows by 2462 columns.

3. Evaluation Methods and Factors

3.1. Information Volume Model

The information quantity model is grounded in probability statistics and comparative mapping principles. Its analytical approach involves calculating and analyzing the information [12] quantity values of various disaster-causing factors in historical landslide zones to estimate the likelihood of future landslides in the area. After obtaining the information quantity values for each factor, the calculated values are aggregated to determine the overall information quantity within each classified zone of the study area. A higher information quantity value within a zone indicates a greater probability of landslides occurring there, while a lower value suggests a smaller likelihood [13-14]

$$I(Xi, D) = \ln \frac{Si / Ai}{S / A}$$

I(xi, D) denotes the information content of evaluation index xi regarding geological hazard risks in the study area; Si indicates the number of geological hazard points distributed within index xi; Ai represents the area covered by this index; S denotes the total number of geological hazard points; A is the total area of the study region.

3.2. Natural Discontinuity Grading Method

The Natural Breaks method leverages inherent grouping patterns in data by identifying classification intervals to optimally cluster similar values, ensuring maximum similarity within groups while maximizing differences between groups. This approach divides [14] data into multiple categories and establishes category boundaries at locations with significant value variations [14]. While drawing inspiration from cluster analysis, the Natural Breaks method differs from traditional clustering by outputting category boundaries rather than cluster centers. Building on this foundation, the method categorizes susceptibility into four levels: low susceptibility, moderate susceptibility, high susceptibility, and very high susceptibility.

3.3. Evaluation Factor Analysis

Through analyzing the formation mechanisms of landslide hazards and their environmental factors in the study area, six key factors were selected for comprehensive evaluation: slope gradient, aspect, elevation, hydrological systems, fault lines, and the maximum value of Normalized Difference Vegetation Index (NDVI). Subsequently, these factors underwent classification processing on the ArcGIS platform.

During the data processing phase, detailed classification was implemented for all evaluation factors. Slope and aspect are key topographic factors influencing landslide susceptibility in the study area. This research utilized the reclassification function of ArcGIS software to generate slope and aspect layers based on DEM data. Specifically, slopes were categorized into eight grades: 0°-10°,10°-20°,20°-30°,30°-40°,40°-50°,50°-60°,60°-70°, and>70° (Table 1). Aspects were classified into eight types: north, northeast, east, southeast, south, southwest, west, and northwest (Table 2).

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Table 1. Slope factor information calculation

falling gradient	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
0-10	6	190	234553	211097700	3083573700	-0.773741167
10-20	44	190	568153	511337700	3083573700	0.333979824
20-30	90	190	1139517	1025565300	3083573700	0.353630842
30-40	41	190	1027800	925020000	3083573700	-0.329422869
40-50	9	190	380723	342650700	3083573700	-0.85266656
50-60	0.001	190	65655	59089500	3083573700	-8.199988099
60-70	0.001	190	8577	7719300	3083573700	-6.164658542
>70	0.001	190	1215	1093500	3083573700	-4.210318417

Table 2. Calculation of slope direction factor information

aspect	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
north	58	190	743049	668744100	3083573700	0.341861958
northeast	17	190	388619	349757100	3083573700	-0.237205146
east	23	190	413053	371747700	3083573700	0.004099241
southeast	26	190	416678	375010200	3083573700	0.117963736
south	16	190	367283	330554700	3083573700	-0.241363007
southwest	9	190	381126	343013400	3083573700	-0.853724513
west	18	190	359649	323684100	3083573700	-0.102575859
northwest	23	190	356736	321062400	3083573700	0.150679143

Table 3. Calculation of elevation factor information

altitude	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
0-800	30	190	282734	254460600	3083573700	0.648871794
800-1600	148	190	1597993	1438193700	3083573700	0.512889467
1600-2400	12	190	1002011	901809900	3083573700	-1.532676671
2400-3200	0.001	190	400688	360619200	3083573700	-10.00875741
3200-4000	0.001	190	136287	122658300	3083573700	-8.930337296
4000-4800	0.001	190	6480	5832000	3083573700	-5.88429485

Elevation factor analysis divides the study area into multiple elevation zones based on altitude, specifically categorized as 0-800m,800m-1600m,1600m-2400m,2400m-3200m,3200m-4000m, and 4000m-4800m (Table 3). Hydrological factor analysis classifies areas according to river proximity, divided into 0-400m,400m-800m,800m-1200m,1200m-1600m, and areas

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exceeding 1600m (Table 4). Fault factor analysis categorizes zones based on distance from faults, including 0-500m,500-1000m,1000m-1500m,1500m-2000m, and areas beyond 2000m (Table 5). The annual maximum NDVI value demonstrates the correlation between vegetation coverage and landslide risk, with lower vegetation coverage indicating higher landslide susceptibility (Table 6). The evaluation results of each factor are illustrated in Figure 2.

Table 4. Calculation of information content of hydrological factors

Distance from river	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
0-400m	31	190	2169	1952100	39177900	1.186170228
400m-800m	24	190	2224	2001600	39177900	0.90519571
800m-1200m	17	190	2153	1937700	39177900	0.592800381
1200m-1600m	10	190	2163	1946700	39177900	0.057538202
Greater than 1600m	108	190	34822	31339800	39177900	-0.341668888

Table 5. Fault information calculation

Distance from fault	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
0-500m	22	190	340549	306494100	4297472100	0.484602121
500m-1000m	13	190	261048	234943200	4297472100	0.224363748
1000m-1500m	13	190	194020	174618000	4297472100	0.5211068
1500m-2000m	8	190	145727	131154300	4297472100	0.321825222
>2000m	134	190	3833625	3450262500	4297472100	-0.129607621

Table 6. NDVI Factor Information Content Calculation

NDVI crest value	Number of disaster points	Total disaster points	Number of gridded cells	Graded raster area	Total raster area	Information value
0-0.2	0.001	190	3465	3118500	3647018700	-5.09046615
0.2-0.4	3	190	56513	50861700	3647018700	0.12414335
0.4-0.6	12	190	165205	148684500	3647018700	0.437721285
0.6-0.8	97	190	1549816	1394834400	3647018700	0.288821247
0.8-1	78	190	2277244	2049519600	3647018700	-0.31401063

4. Landslide Hazard Prone Zoning

In the ArcGIS platform, the raster calculator was employed to overlay single-factor information quantities, enabling multi-factor analysis and ultimately determining the comprehensive information values of each raster cell in the study area (Table 7). The study area's comprehensive information values ranged from-19.2449 to 3.48936, where higher values indicate greater susceptibility to landslide hazards. Using the natural break method, these values were categorized into four susceptibility levels: high, medium, low, and low susceptibility.

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This process completed the landslide hazard susceptibility zoning evaluation for Beichuan County (Figure 1).

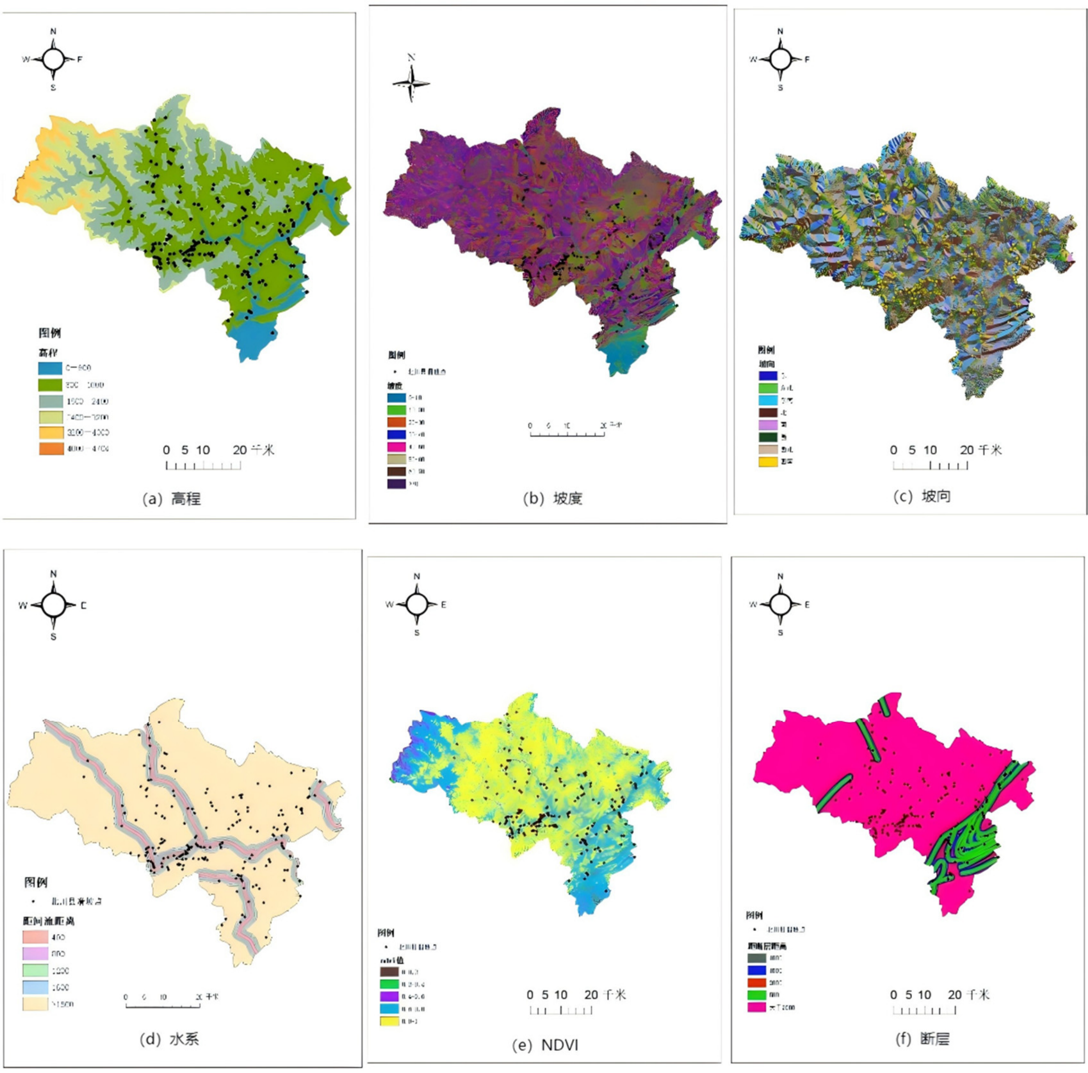

Figure 2. Evaluation Factor Classification

Table 7. Information volume model susceptibility landslide susceptibility statistical table

Frequency Level	Number of landslide points	Landslide ratio/%	Partition percentage/%	area /km^2	Information value
Less likely to be affected	0	0.00	17	522.3807	-19.244925 ~ -5.544512
Low-risk area	10	5.26	28	851.4711	-5.544512 ~ -0.584181
Zhongyifa District	47	24.74	26	811.737	-0.584181 ~ 0.974101
High-risk area	133	70.00	29	884.1447	0.974101 ~ 3.489363

5. Conclusion

This study investigates landslide hazards in Beichuan County by analyzing six key factors: slope gradient, aspect, elevation, vegetation coverage (NDVI), fault lines, and hydrological systems. Using ArcGIS's advanced spatial analysis tools, we developed information quantity models for each factor and calculated multi-factor composite indices through spatial overlay analysis, ultimately delineating susceptibility zones. The findings reveal that high-risk areas cover 884.1447 km^2 (29% of the study region), medium-risk areas span 811.737km^2 km^2 (26%), and low-risk areas occupy 851.4711 km^2 (28%). Non-risk areas total 522.3807 km^2 (17%). These results clearly define landslide-prone regions, showing strong alignment with historical landslide occurrence patterns. The study provides a reliable scientific foundation for future landslide prevention and disaster mitigation efforts in Beichuan County.

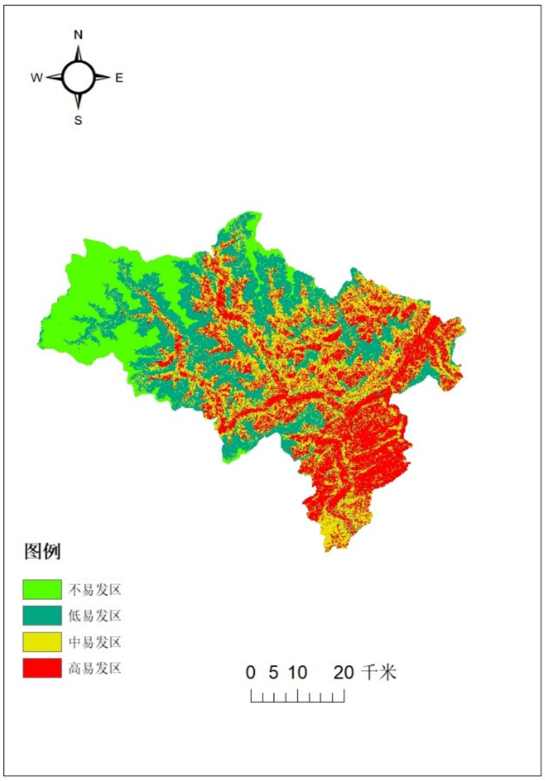

Figure 3. Information volume model landslide susceptibility zoning

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