Analysis of Disaster Causing Factors of Avalanche Hazards in the Maerdang Dam Area

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Abstract. Numerous reservoirs and dams are distributed along the main stream of the Yellow River in China. The upper reaches of the Yellow River feature complex and steep terrain, where collapse geological disasters are frequent, often causing significant damage to reservoirs and dams, resulting in considerable economic losses and even human casualties. By quantitatively analyzing the contribution of collapse-inducing factors and assessing the risk of collapse disasters in the study area, theoretical support can be provided to mitigate these risks. In this study, geographic data and historical collapse hazard data were collected from the upper reaches of the Yellow River in the Maerdang dam area. Geographic features were analyzed and combined with existing research to identify seven major contributing factors to collapse hazards: slope height, slope gradient, rock quality, vegetation, rainfall, freeze-thaw cycle, and human activities. Each of these factors was analyzed using ArcMap distribution maps. After comprehensively comparing the pros and cons of various analysis and evaluation methods, the entropy weighting method was used to analyze the weights of collapse-inducing factors in the study area. The probability of collapse occurrence was superimposed using a multifactor comprehensive evaluation model, dividing the study area into three risk zones: low, medium, and high. By evaluating the contributing factors and risk of collapses in the study area, an effective basis for local collapse prevention is established.

Keywords: ArcMap; avalanche disaster; integrated analysis and evaluation method; disaster-causing factor analysis

1 Introduction

Along the main stream of the Yellow River, there are nearly 30 reservoirs, dams, and hydropower stations that play crucial roles in hydropower generation and ecological regulation in China. The development of hydropower in peripheral areas is often challenged by serious river erosion, high mountains, deep valleys, and steep slopes on both sides of the river. The unloading and rebound of slope bodies over time lead to the

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development of joints and fissures in the rock formations along reservoir banks. Coupled with extreme weather and seismic activities, these conditions often trigger serious collapse disasters, significantly restricting the construction and operation of hydropower projects, reducing safety and security during both phases. How to analyze the causes and assess the probability of collapse disasters so that people can take preventive measures in advance has become an urgent problem for people to solve.

Although scholars both domestically and internationally have conducted studies on the causal factors of collapse disasters, some existing studies lack sufficient samples, do not analyze the causal factors of all historical collapse disasters in a specific region, and mainly focus on qualitative research. Some existing studies did not classify the weights of the selected causal factors. For instance, they did not differentiate between natural causal factors (e.g., slope height, rainfall) and statistical causal factors (e.g., historical number of disasters, historical disaster density) in their causal factor analysis, leading to inaccurate assessment results. For instance, some studies did not differentiate between natural disaster-causing factors (e.g., slope height, slope gradient rainfall) and statistical disaster-causing factors (e.g., historical number of disasters, historical disaster density) in their analysis, resulting in cross repetition and inaccurate assessment results. Additionally, the evaluation indexes for disaster-causing factors selected in existing studies were inconsistent. For example, for the impact factor of human activities, different scholars used inconsistent evaluation indexes, leading to significant differences in assessment results.

Therefore, on the basis of fully reviewing the information, collecting the geographic data and historical collapse disaster data of the study area, this paper analyses the geographic features and identifies the collapse disaster causative factors by combining with the existing research experience, and produces the distribution maps of different collapse disaster causative factors by using ArcMap software. By comprehensively comparing the advantages and disadvantages of various analysis and evaluation methods and reasonably selecting and quantifying the indicators of the causative factors, this study employed the entropy weighting method to analyze the weights of the causative factors of collapse hazards in the study area. A multifactor comprehensive evaluation model was then used to classify the study area into three risk zones: low, medium, and high. This classification aims to provide a basis for the assessment and prevention of collapse geological hazards in the upper reaches of the Yellow River in China.

2 Geological and Environmental Conditions in the Study Area

The research object selected for this paper is the Maerdang dam area on the main stream of the Yellow River, located at the junction of Maqin County in Guoluo Tibetan Autonomous Prefecture and Tongde County in Hainan Tibetan Autonomous Prefecture, Qinghai Province. The study area encompasses both Tongde County and Maqin County.

2.1 Topography and Geomorphology

The Maerdang hydropower station dam site and its storage area are located in the north-central region of the Tibetan Plateau, with altitudes ranging from 2000 to 6000 meters. The study area features diverse geomorphology including mountains and rivers. The southern part comprises a hilly plateau with relative height differences generally in the hundreds of meters, characterized by relatively minor undulations and gentle terrain. In contrast, the northern part includes large-scale sedimentary basins often presented in high mountain valleys, with significant terrain height differences, such as from the Republic of China to the Guinan Basin. The regional terrain is high in the south and low in the north, high in the west and low in the east, descending in a ladder-like fashion. There are two groups of geomorphic terraces: NW to NNW (Yumen to Animaqing Peak, Chaka Beishan to Xinghai to Jiuzhi, Riyue Mountain to Guiade to the Yellow River Dakuangwan and Dahuangshan Mountain to Mengyuan to Xining to Ruorgui) and NE to NEE (Wuwei to Xining to Guiade and Zhuanglang River to Linxia to Maqu)[1]. The general topography of the region is dominated by a plateau, interspersed with basins and crisscrossing waterways.

2.2 Stratigraphical Lithology

The stratigraphic lithology near the Maerdang dam primarily consists of layered sandstone, slate, conglomerate, breccia, silty conglomerate, and mudstone. These rocks vary in hardness and have poor resistance to weathering. The strike of the rock strata and the bank slope form small angles, and the valley is steep. The thin-layered combination of soft and hard lithology, along with the oblique main longitudinal valley slope structure, provides the conditions for the development of undesirable geological bodies. Metamorphic sandstone and slate are mostly thin-layered and vary in hardness. The small angle between the strike and the slope, along with the rock layer inclination angle of 30°-60°, makes them susceptible to tilting or deformation along the layers. Factors such as tilting, pulling, unloading of rock layers, accelerated weathering, and groundwater infiltration after rainfall further accelerate rock body deformation. As a consequence of the processes of weathering and unloading, the surface rock mass is subject to sliding, deformation and the development of instability in the deeper strata. This can ultimately result in the occurrence of geological disasters, including landslides, collapses and toppling deformations.

2.3 Meteorology and Hydrology

The Maerdang dam area experiences a typical plateau continental climate, influenced by high-altitude westerly airflows and its distance from the sea. In winter, under the influence of the Mongolian high-pressure system, the weather is dry, cold, and clear, often with cold wave intrusions. January to February is the coldest period of the year. In spring, temperatures rise slowly and rainfall increases. During summer and autumn, the westward and northward expansion of the Pacific subtropical high pressure brings a large amount of water vapor, increasing air humidity and rainfall. Rainfall during this period accounts for more than 70% of the annual total[2].

The study area is located in the upper reaches of the Yellow River, and the surface runoff is mainly formed by precipitation in the watershed, with rainfall recharge as the main source and snowmelt recharge as a supplement, and the runoff changes are relatively stable due to the storage of natural lakes and swamps[3]. The annual change of runoff is affected by the circulation situation, precipitation, air temperature and subsurface, etc. The runoff volume from June to September during the flood season accounts for about 60% of the total annual runoff volume, and the runoff volume from December to March during the dry season accounts for about 10.4% of the total annual runoff volume[4].

3 Analysis of Avalanche Disaster Causing Factors

After reviewing extensive literature on collapse disaster analysis and collecting and analyzing the geological data of the study area, the author classified the causative factors of collapse disasters as follows (Table 1).

Based on current domestic and international collapse disaster analysis and the geological data analysis of the study area, this study selected seven causative factors for analysis: slope height, slope gradient, rock quality, vegetation effect, rainfall, freeze-thaw cycle, and human activities.

Table 1. Classification table of causative factors

classifications	disaster causing factors
geological environment category	slope gradient, slope height, slope type, vegetation cover, plant species, distribution of surface runoff, geotechnical type, strength of rock quality, water content of rock quality, roughness of structural surfaces, inclination of rock strata, degree of exposure of rock quality, steepness of rock quality, penetration rate of fissures, degree of development of joints in the rock quality, folding, the presence of faults or caves in the rock quality, the location of fracture zones, the formation of internal cavities in the mudstones and their location, etc.
natural activities category	seismic acceleration, period, duration of action, weathering, rainfall amount and intensity, river erosion, number of freeze-thaw cycles, temperature range, cycle length, temperature change, degree of groundwater development, etc.
anthropogenic impact category	underground mining, engineering excavation, reservoir water storage channel leakage, heap load, mechanical vibration, blasting, irrational mining, destruction of vegetation, engineering construction cut slopes and corners, etc.

3.1 Slope Height

Due to the complexity of the actual terrain, determining the location of the foot of the slope is more challenging. Therefore, the indicator of slope height is expressed as an elevation value. Elevation is one of the important causative factors of collapse hazards[5]. The terrain of the study area is steep, with significant topographic relief. The lowest elevation is 2601 meters, while the maximum elevation reaches 6295 meters, resulting in a substantial elevation difference. The elevation of the study area is generally higher in the west and south, and lower in the east and north, with more undulating terrain in the central area. Fig. 1 shows the DEM elevation map of the study area (Tongde and Maqin counties) produced using ArcMap software after collecting elevation data from the National Tibetan Plateau Scientific Data Centre.

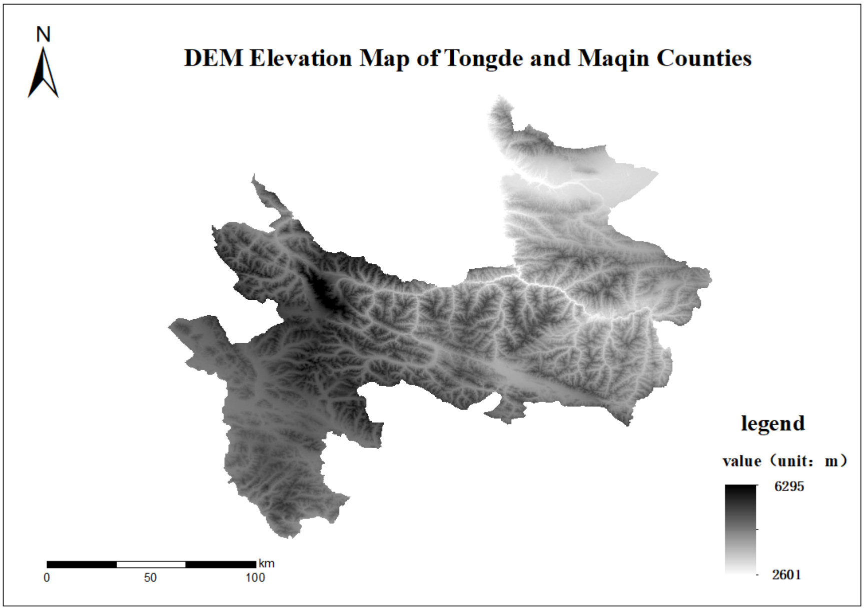


Fig. 1. DEM elevation map of Tongde and Maqin Counties

3.2 Slope Gradient

Fig. 2 shows the slope distribution map of the study area (Tongde and Maqin counties), calculated using ArcMap software based on the collected elevation and projection distance data. The map was divided into nine intervals using the natural breaks method. The slopes in the study area range from 0° to 75°, with relatively steep slopes in the central region, reflecting the characteristic of significant topographic relief in this area.

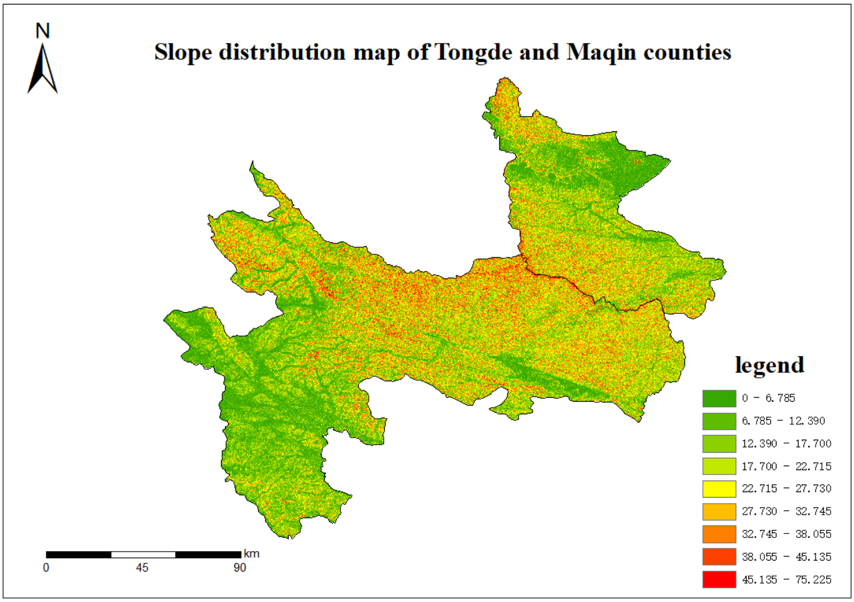


Fig. 2. Slope distribution map of Tongde and Maqin counties

3.3 Rock Quality

Fig. 3 shows the distribution of stratigraphic lithology in the study area (Tongde and Maqin counties), created using ArcMap software based on stratigraphic lithology data collected from the HWSD soil database. Most of the study area consists of mixed sedimentary rocks, followed by siliceous clastic sedimentary rocks, carbonate sedimentary rocks, and loose sediments. The mineral composition is complex and the structural characteristics vary widely, making it easy for fissures to form at weak locations and trigger collapses. In this paper, rock strength is used as the index value.

3.4 Vegetation Effect

To quantify the role of vegetation, the Normalized Difference Vegetation Index (NDVl) is usually used[6]. Fig. 4 shows the distribution of NDVl in the study area, produced using ArcMap software based on vegetation data collected from the Digital Earth Open Platform. The NDVl in the study area ranges from -0.2 to 0.8. Values from -0.2 to 0 indicate surface types with high reflectivity to visible light bands, such as clouds, water, and snow, whereas a value of 0 represents rocks or bare ground. Values between 0 and 0.8 indicate vegetation cover, with higher values representing denser vegetation. Overall, the vegetation cover is higher in the east and lower in the west of the study area.

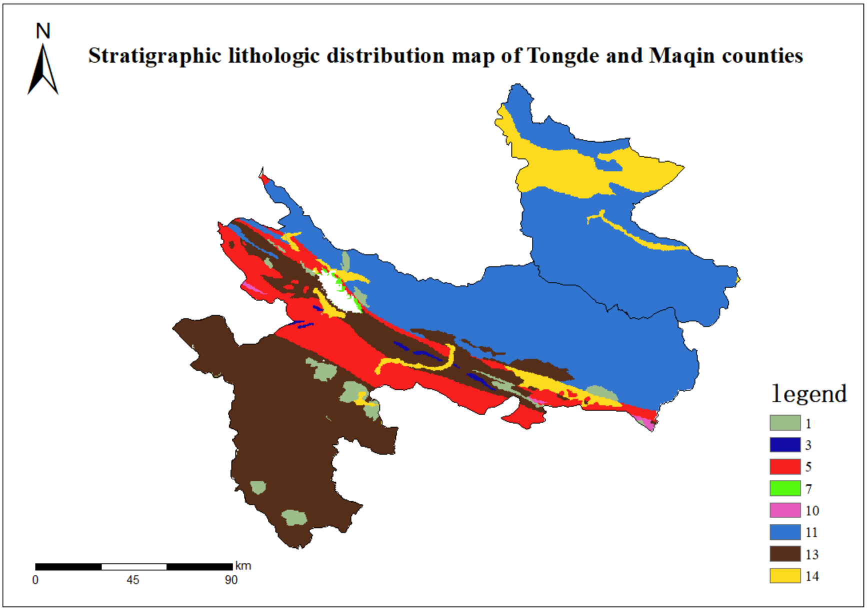


Fig. 3. Stratigraphic lithologic distribution map of Tongde and Maqin counties

Note:1. acid plutonic 2. acid volcanic 3. basic plutonic 4. basic volcanics 5. carbonate sedimentary rock 6. evaporite 7. ice and glaciers 8. intermediate plutonic 9. intermediate volcanics 10. metamorphic 11. mixed sedimentary rock 12. pyroclastics 13. siliciclastic sedimentary 14. unconsolidated sediment 15. Undefined

3.5 Rainfall

Rainfall is an important natural factor that triggers collapse disasters, providing an external driving force for their occurrence. The rainfall data for the study area were obtained from the National Tibetan Plateau Scien-tific Data Centre and processed using ArcMap software to create a monthly average rainfall distribution map for the study area from 2011 to 2020, as shown in Fig. 5. The rainfall distribution in the study area

is uneven, with the highest monthly average rainfall being up to twice that of the lowest. Overall, the rainfall shows an increasing trend from northwest to southeast.

3.6 Freeze-Thaw Cycle

The study area is located in the Tibetan Plateau, which has a plateau continental climate characterized by large daily temperature differences and small annual temperature differences. Changes in temperature can lead to changes in the mechanical properties of rock and soil, especially when fluctuating around 0°C. In such cases, the water within rock and soil undergoes freeze-thaw cycles, causing continual volume changes that deteriorate rock structures, potentially leading to collapses. Fig. 6 shows the distribution of the average diurnal temperature difference in the study area from 2011 to 2020, created using ArcMap software based on diurnal temperature difference data from the National Centre for Atmospheric Sciences, UK. Over the years, the average diurnal temperature difference in the study area ranges from a maximum of 15.06°C to a minimum of 13.21°C, increasing from southwest to northeast, but the overall fluctuation range is not large.

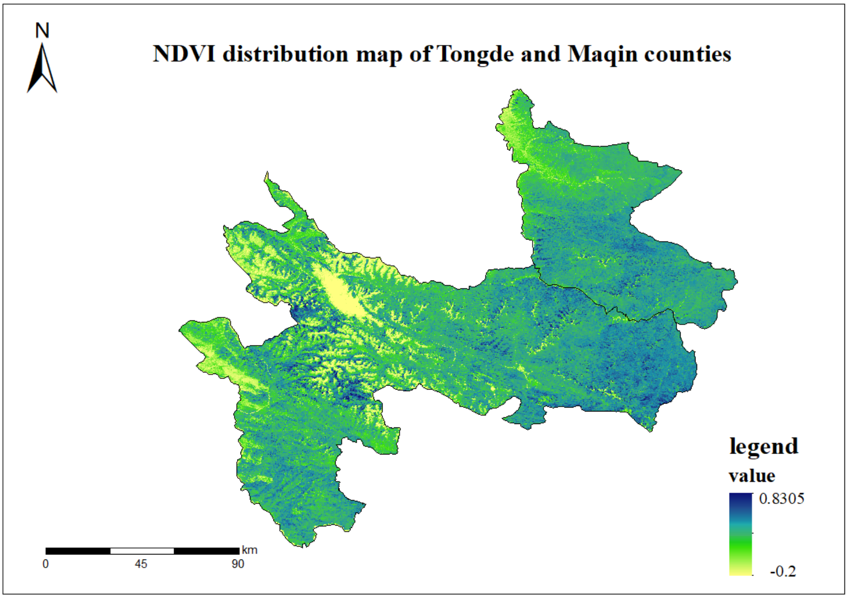


Fig. 4. Distribution of Normalized Difference Vegetation Index in Tongde and Maqin Counties

The mechanism of collapse disasters triggered by the freeze-thaw weathering of rock and soil bodies in the study area can be divided into two categories: the first is the weakening of cementation due to the differential uplift and contraction of the mineral components of rocks, leading to a decrease in rock quality and triggering collapse, the second involves the transformation of water in the microcracks of the rock body between liquid and solid states, causing volume changes that produce extrusion stress on the crack walls. As the cracks deepen and water refills them upon thawing, continuous freeze-thaw cycles result in further expansion and development of the cracks until the rock body is ultimately destroyed, leading to collapse. The weakening of cementation by water and differential expansion with the rock are the main causes of rock destruction[7]. The greater the number of freeze-thaw cycles and the larger the temperature difference between cycles, the stronger the effect of freeze-thaw cycles and the faster the rock body is destroyed. Since the natural temperature change cycle is one day, the quantitative index of the impact of freeze-thaw cycles can be expressed as the diurnal temperature difference.

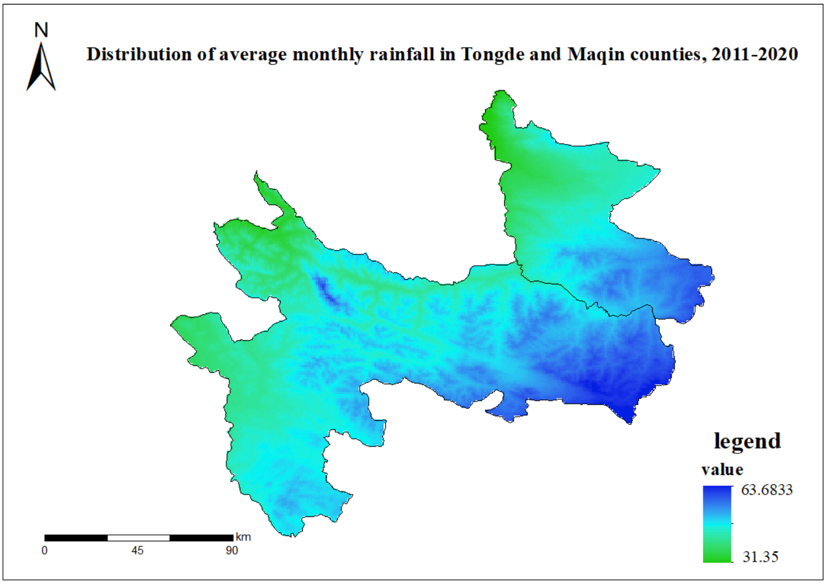


Fig. 5. Distribution of average monthly rainfall in Tongde and Maqin counties, 2011-2020

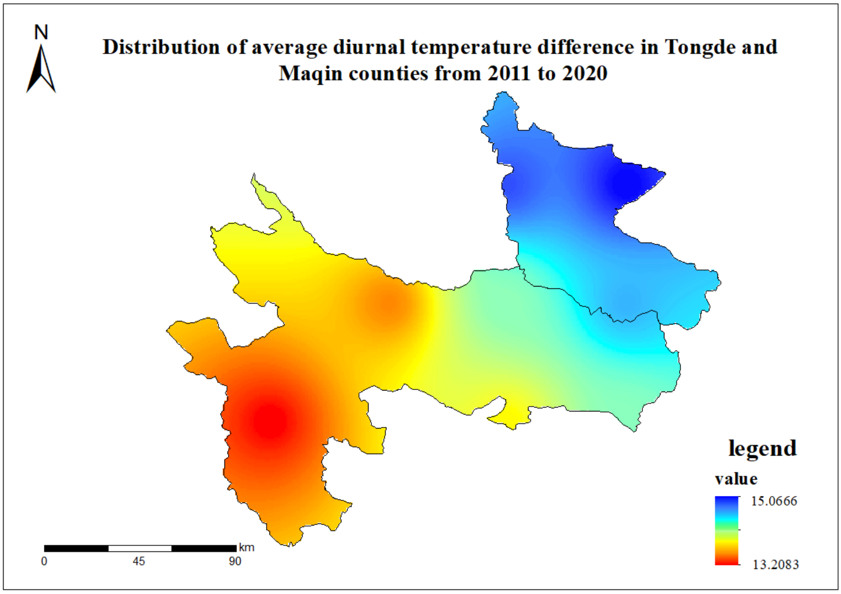
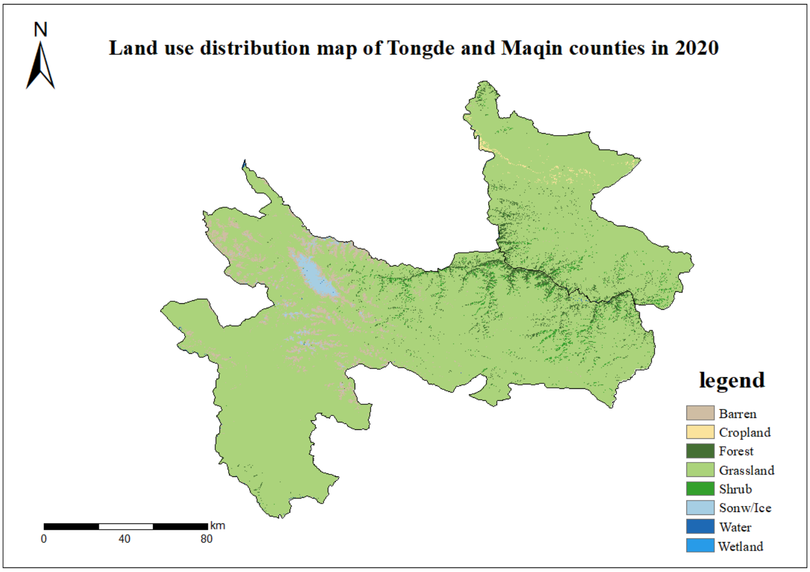
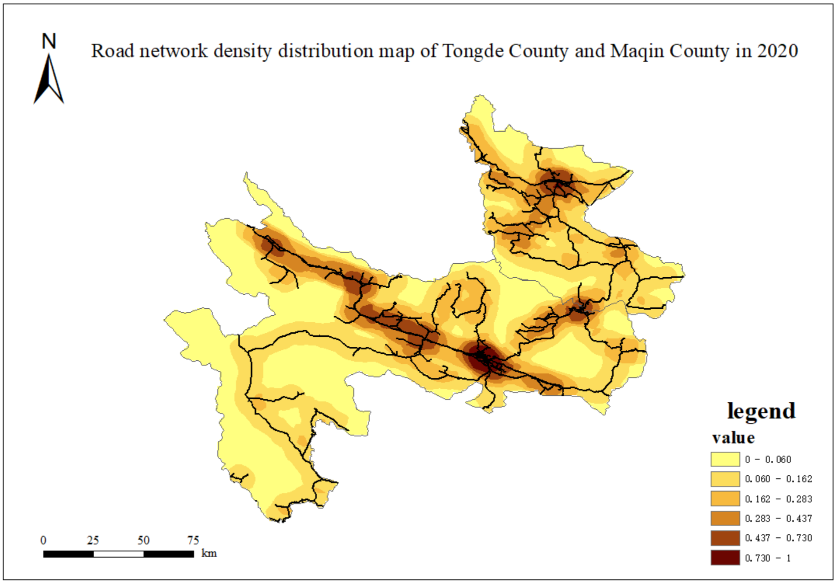


Fig. 6. Distribution of average diurnal temperature difference in Tongde and Maqin counties from 2011 to 2020

3.7 Impacts of Human Activities



(a) land use



(b) road network density

Fig. 7. 2020 Land Use and Road Network Density Distribution Map of Tongde and Maqin Counties

Human activities often have a significant impact on disaster-prone environments, and various scholars have conducted extensive research on the quantitative indicators of collapse disasters caused by human activities. However, it remains challenging to comprehensively evaluate the impact of human activities. In this paper, the impact of human activities on collapse disasters is assessed comprehensively through land use and road network density in the study area. For land use types in the study area, it is generally believed that higher industrialization levels lead to greater environmental damage and disaster potential, thus assigning higher values. Conversely, lower values are assigned to less industrialized areas. Based on existing research, shrubs are assigned a value of 1, grassland a value of 3, bare land a value of 5, and industrial land a value of 7. The product of the land use indicator value and the road network density indicator value is used to express the impact factor of human activities. Most of the study area consists of grassland, followed by shrubs, forests, and bare land. Fig. 7 shows the land use distribution map and road network density distribution map of the study area in 2020, calculated using ArcMap software based on collected land use data and road network distribution in the study area.

4 Integrated Analytical Evaluation Methodology

4.1 Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a systems analysis method proposed by American operations researcher T.L. Saaty in the mid-1970s. This method decomposes a complex system into levels such as objectives, guidelines, and programs, enabling multicriteria decision-making that combines qualitative and quantitative criteria[8]. AHP breaks down problems into a multilayer structure, describes the decision-making problem as a series of criteria and indicators, and compares the importance of each evaluation indicator factor according to expert scores to form a judgment matrix. The judgment matrix is then standardized to obtain the maximum eigenvalues, and the eigenvectors corresponding to these maximum eigenvalues are the weight vectors of the evaluation factors after normalization.

The judgment matrix in AHP is scored by experts, leading to the strong subjectivity of the results obtained by this method. Consequently, the accuracy of the evaluation results depends on the level of expertise of the experts. Therefore, few scholars nowadays use this method alone to conduct the weighting analysis of collapse hazards; it is usually combined with other evaluation methods for a more comprehensive analysis.

4.2 Entropy Weighting Method

The entropy weight method is an objective assignment method used to determine the weight of each evaluation index in decision analysis, primarily based on the concept of information entropy. This method deeply reflects the utility value of the information entropy of the indicators to determine their weights. As an objective assignment method, the entropy weight method provides indicator weight values with higher credibility and accuracy compared to subjective assignment methods[9]. The entropy weight method not only objectively reflects the actual situation of the data, avoiding the influence of subjective factors on the determination of weights, but also automatically assigns weights according to the degree of data variability, thereby improving the objectivity and accuracy of the evaluation results.

1.Data standardization

$$r_{ij} = \frac{x_j - x_{min}}{x_{max} - x_{min}} \text{ or } r_{ij} = \frac{x_{max} - x_j}{x_{max} - x_{min}} \tag{1}$$

x_j is the value of the j disaster-causing factor indicator, x_{max} is the maximum value of the j disaster-causing factor indicator, if there are m collapse geological disaster cases, n disaster-causing factor evaluation indicators, the formation of standardized raw data matrix $R = (r_{ij})_{m \times n}$

$$R = \begin{pmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{pmatrix}$$

r_{ij} is the evaluation value of the i collapse disaster case under the j causative factor indicator.

2.Calculate the weight of the indicator value of the i collapse disaster case under the j causal factor indicator p_{ij} :

$$p_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}} (0 \le r_{ij} \le 1) \tag{2}$$

From this, the weighting matrix of the data can be created $P = \{p_{ij}\}_{m \times n}$

Calculate the information entropy of the j collapse causality factor indicator e_j:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln P_{ij} \tag{3}$$

The value of information utility d for each indicator of the causal factor is:

$$d_j = 1 - e_j \tag{4}$$

The information utility value of the disaster-causing factor indicator depends on the difference between the information entropy of that disaster-causing factor indicator and 1. The greater the information utility value, the greater the impact on the collapse disaster, and the greater the weight of the disaster factor.

3.Calculate the entropy weight of the j causal factor indicator ω_j:

$$\omega_j = \frac{(1 - e_j)}{\sum_{j=1}^{n} (1 - e_j)} \tag{5}$$

4.3 Information Quantity Method

The information quantity method[10] is a statistical prediction method derived from information theory. It calculates the likelihood of a collapse disaster caused by a specific influencing factor using statistical information quantity. This method then converts the measured values of factors affecting collapse disasters into indexes for evaluating regional stability. In other words, the information quantity is used to evaluate the relationship between these factors and the likelihood of a collapse disaster occurring. The information quantity method relies on a large amount of accurate data and information. If the data is incomplete or contains errors, the accuracy of the assessment results may be compromised. Additionally, the grid is artificially delineated, resulting in a large workload and potential arbitrariness.

4.4 Other Methods

Fuzzy comprehensive evaluation method[11] makes a corresponding fuzzy evaluation of each indicator by determining the evaluation set of several grades of the evaluated object from good to bad and the weights of the evaluation indicators, determining the affiliation function, forming a fuzzy judgment matrix, and then performing fuzzy operations with the weight matrix to get the quantitative comprehensive evaluation results[12]. For the fuzzy and difficult to quantify problems, the fuzzy comprehensive evaluation method can be better solved, but the evaluation results of the fuzzy comprehensive evaluation method depend largely on the subjective judgment of experts or decision makers, which leads to a certain degree of subjectivity and uncertainty in the evaluation results, affecting the accuracy and scientificity of decision making, especially when determining the weights and subordinate functions, the subjectivity is especially obvious.

Logistic regression model can effectively deal with binary classification problems, but its assumptions and limitations need to be considered when using it. Logistic regression is sensitive to outliers in the data, and the presence of outliers may affect the results of the model, which generally needs to be combined with other techniques or models to improve the accuracy and reliability of the prediction.

4.5 Comparative Analysis of the Advantages and Disadvantages of Various Methods

The weights determined by the hierarchical analysis method are too dependent on the experience level of the evaluation experts and their knowledge of the region, and are too subjective. The weights obtained are not precise enough, and can only represent the approximate range of the quantitative values of the disaster-causing factors or a trend in the relative sizes of the disaster-causing factors, and can be used as an auxiliary method for other analytical methods.

For the analysis method of the information quantity method, it mainly relies on the statistical analysis of historical disaster data, using the historical disaster density of a certain region to express the probability of the occurrence of collapse disasters in that region, but the analysis using this method requires a premise, namely, "the probability of the occurrence of collapse disasters in a place where there were many such disasters in the past must be higher now". This is obviously not accurate enough, because the natural environmental conditions of the area are not constant, and will be affected by human activities and changes, for example, a certain area before the frequent occurrence of collapse disasters, but with the change of topography after the disaster occurred, as well as changes in the geographic environment and the implementation of preventive measures of reasonable human development and remediation, the probability of the area to continue to occur collapse disasters is greatly reduced, and then use the historical disaster density to calculate the weighting of collapse disasters is obviously not reasonable. In this case, it is obviously unreasonable to use historical disaster density to calculate the weight of collapse disaster. In addition, the information quantity model needs a large number of historical disasters as the basis, and the size of the study area, the number of historical disasters and the accuracy of the recorded historical disaster data will all affect the results.

In the application of the entropy weighting method to analyze the causative factors of collapse disasters, its essence is to quantify the factors that trigger such disasters. These causative factors interact with each other, so that a collapse disaster occurs when the comprehensive index value reaches a certain threshold. The change in the index value of each causative factor affects the index value of other factors, just enough to trigger a collapse disaster. For example, an increase in slope value requires less rainfall intensity to trigger a collapse disaster. Each historical collapse disaster case represents a combination of successfully triggered factors. The collapse cases in the study area with more detailed disaster data records can be selected for analysis as combinations of disaster factors. Additionally, the entropy weighting method does not assume that the probability of collapses is more suitable for analyzing the factors that cause collapses is necessarily higher in places with a high number of past collapses, making it more suitable for analyzing the factors that cause collapses.

5 Weighting Analysis of the Causative Factors of Collapse Hazards in the Study Area

5.1 Historical Data Collection on Collapse Hazards in the Study Area

A total of 19 cases of collapse hazards were collected in the study area. Table 2 provides detailed data for the 19 cases of collapse hazards, including the latitude and longitude coordinates, hazard class, elevation, slope, stratigraphic lithology, NDVl(Normalized Difference Vegetation Index), rainfall, diurnal temperature difference, land use, and road network density.

Table 2. Historical hazard data table for collapses

Longitude	Latitude	Peril rating	Elevation (m)	Inclination (°)	Rock quality (Mpa)	NDVI	Average monthly rainfall (mm)	Freeze-thaw cycle (°C)	Land use	Road network density (km/km2)
100.22	35.38	Small	2763	16.42	34.7	0.1482	33.15	14.80	3	0.244
100.25	35.37	Medium	3060	4.83	37.3	0.2752	34.45	14.81	3	0.242
100.89	34.94	Small	3953	18.78	75.2	0.12	51.725	14.63	3	0.259
100.69	34.68	Small	3320	8.51	82.5	0.1858	48.108	14.58	3	0.544
100.71	34.71	Small	3662	21.42	78.8	0.4588	49.542	14.61	3	0.450
100.80	34.74	Small	3424	14.04	64.5	0.4211	49.45	14.60	3	0.141
100.89	34.72	Small	3394	38.87	66.9	0.2047	50.467	14.57	1	0.135
100.91	34.74	Small	3429	7.30	74.3	0.2188	50.933	14.56	3	0.146
100.58	35.24	Small	3100	25.21	37.2	0.3882	40.167	14.88	3	0.734
100.10	34.50	Small	3983	18.94	56.1	0.4164	47.383	14.05	3	0.276
100.45	34.53	Small	3770	29.85	65.6	0.3741	50.925	14.24	3	0.233
100.46	34.54	Small	3811	29.76	69.5	0.3694	50.917	14.26	3	0.256
100.51	34.55	Small	3630	20.26	71.6	0.4117	51.525	14.30	3	0.251
100.53	34.54	Small	3551	50.04	76.5	0.3552	50.608	14.32	3	0.169
100.53	34.55	Small	3612	26.58	82.3	0.3694	50.225	14.32	3	0.207
100.55	34.55	Small	3607	28.58	61.5	0.3741	50.267	14.34	3	0.197
100.55	34.57	Small	3495	21.27	64.4	0.4541	49.33	14.36	3	0.229
100.58	34.65	Small	3393	17.66	78.4	0.4494	48.25	14.45	3	0.420
100.22	35.38	Small	2763	16.42	34.7	0.1482	33.15	14.80	3	0.244

5.2 Data Standardization

Normalize the data according to equation (1). The results were obtained, as shown in Table 3:

Table 3. Disaster data standardized post-processing data

elevation	inclination	rock quality	NDVI	rainfall	freeze-thaw cycle	anthropogenic
0.000	0.256	1.000	0.767	0.000	0.930	0.289
0.171	0.000	0.946	0.454	0.070	0.939	0.286
0.685	0.309	0.153	0.837	1.000	0.783	0.311
0.321	0.081	0.000	0.675	0.805	0.739	0.724
0.518	0.367	0.077	0.000	0.882	0.765	0.588
0.381	0.204	0.377	0.093	0.878	0.757	0.139
0.363	0.753	0.326	0.628	0.932	0.730	0.000
0.384	0.055	0.172	0.593	0.957	0.722	0.147
0.194	0.451	0.948	0.174	0.378	1.000	1.000
0.703	0.312	0.552	0.105	0.766	0.278	0.335
0.580	0.553	0.354	0.209	0.957	0.443	0.273
0.604	0.551	0.272	0.221	0.957	0.461	0.306

0.499	0.341	0.228	0.116	0.989	0.496	0.299
0.454	1.000	0.126	0.256	0.940	0.513	0.180
0.489	0.481	0.004	0.221	0.919	0.513	0.235
0.486	0.525	0.439	0.209	0.922	0.530	0.221
0.422	0.364	0.379	0.012	0.871	0.548	0.267
0.363	0.284	0.086	0.023	0.813	0.626	0.544
1.000	0.000	0.517	1.000	0.466	0.000	0.305

5.3 Calculation of Entropy Weights of Catastrophic Factors

Calculate the specific gravity matrix P through equation (2):

$$P = \begin{pmatrix} 0.000 & 0.037 & 0.144 & 0.116 & 0.000 & 0.079 & 0.045 \\ 0.020 & 0.000 & 0.136 & 0.069 & 0.005 & 0.080 & 0.044 \\ 0.080 & 0.045 & 0.022 & 0.127 & 0.069 & 0.066 & 0.048 \\ 0.037 & 0.012 & 0.000 & 0.102 & 0.056 & 0.063 & 0.112 \\ 0.060 & 0.053 & 0.011 & 0.000 & 0.061 & 0.065 & 0.091 \\ 0.044 & 0.030 & 0.054 & 0.014 & 0.061 & 0.064 & 0.022 \\ 0.042 & 0.109 & 0.047 & 0.095 & 0.064 & 0.062 & 0.000 \\ 0.045 & 0.008 & 0.025 & 0.090 & 0.066 & 0.061 & 0.023 \\ 0.023 & 0.065 & 0.136 & 0.026 & 0.026 & 0.085 & 0.155 \\ 0.082 & 0.045 & 0.079 & 0.016 & 0.053 & 0.024 & 0.052 \\ 0.067 & 0.080 & 0.051 & 0.032 & 0.066 & 0.038 & 0.042 \\ 0.070 & 0.080 & 0.039 & 0.034 & 0.066 & 0.039 & 0.047 \\ 0.058 & 0.050 & 0.033 & 0.018 & 0.068 & 0.042 & 0.046 \\ 0.053 & 0.145 & 0.018 & 0.039 & 0.065 & 0.044 & 0.028 \\ 0.057 & 0.070 & 0.001 & 0.034 & 0.063 & 0.044 & 0.036 \\ 0.056 & 0.076 & 0.063 & 0.032 & 0.064 & 0.045 & 0.034 \\ 0.049 & 0.053 & 0.054 & 0.002 & 0.060 & 0.047 & 0.041 \\ 0.042 & 0.041 & 0.012 & 0.004 & 0.056 & 0.053 & 0.084 \\ 0.116 & 0.000 & 0.074 & 0.152 & 0.032 & 0.000 & 0.047 \end{pmatrix}$$

Calculate the information entropy of each indicator through equation (3). The results were obtained, as shown in Table 4:

Table 4. Information entropy of catastrophic factors

norm	eleva-tion	inclina-tion	rock quality	NDVI	rain-fall	freeze-thaw cycle	anthropo-genic
information entropy	0.956	0.909	0.882	0.867	0.960	0.967	0.931

The value of information utility for each indicator is calculated through equation (4). The results were obtained, as shown in Table 5:

Table 5. Value of information utility of the causative factor

norm	elevation	inclination	rock quality	NDVI	rainfall	freeze-thaw cycle	anthropogenic
information utility value	0.044	0.091	0.118	0.133	0.040	0.033	0.069

The weight of each causative factor is calculated by equation (5). The results were obtained, as shown in Table 6:

Table 6. Weighting of factors contributing to rock failure

norm	elevation	inclination	rock quality	NDVI	rainfall	freeze-thaw cycle	anthropogenic
weights	0.084	0.173	0.223	0.251	0.075	0.063	0.131

The results show that the weights of the disaster-causing factors for collapses in the study area are, in descending order: the role of vegetation, the quality of rock mass, slope, human activities, slope height, rainfall, and freeze-thaw cycle. The highest-weighted disaster-causing factor is the role of vegetation, with a weight value of 0.251. The study area has complex and hazardous terrain, making the vegetation's ability to protect slopes and regulate the ecology relatively important. The lowest weighted disaster-causing factor is the freeze-thaw cycle, with a weight value of 0.063. The weight values of slope height, rainfall, and freeze-thaw cycle are relatively close to that of the slope, with the slope's weight being about twice that of the slope height. The weight of the rainfall factor in the study area is 0.075, which is relatively low, corresponding to the highland continental climate characterized by low rainfall.

6 Hazard Assessment of Collapses in the Study Area

6.1 Evaluation Models

Considering the comprehensive influence of each disaster-causing factor of collapse disasters, the following multifactor comprehensive evaluation model was used to calculate the collapse disaster hazard in the study area. This was achieved by using the evaluation index value of each disaster-causing factor and the calculated weights of these factors:

$$P = \sum_{i=1}^{n} \omega_i x_i \tag{6}$$

Where P is the collapse disaster hazard index, the larger the value of P indicates the larger the collapse disaster hazard in the study area, ω_i is the index weight of the i collapse disaster-causing factor; x_i is the index value of the i collapse disaster-causing factor; n is the number of collapse disaster-causing factors.

6.2 Classification of Collapse Hazard in the Study Area

Using the raster calculator in ArcMap software, the weights of each disaster-causing factor for the collapse disaster were calculated using the entropy weighting method, and the index values of each factor were computed according to formula (8). This resulted in the probability distribution map of geologic hazard risk in the study area.

To divide the hazard class intervals based on the calculated hazard index of existing collapse geohazards, and to exclude outliers or special cases, the collapse cases were arranged in descending order by their calculated hazard index. The hazard index at the 90th percentile was taken as the demarcation value for the middle-high hazardous area, and 80% of this value was used as the demarcation for the low-medium hazardous area. Thus, the study area was divided into three hazard class intervals: low, medium, and high. The results are shown in Fig. 8.

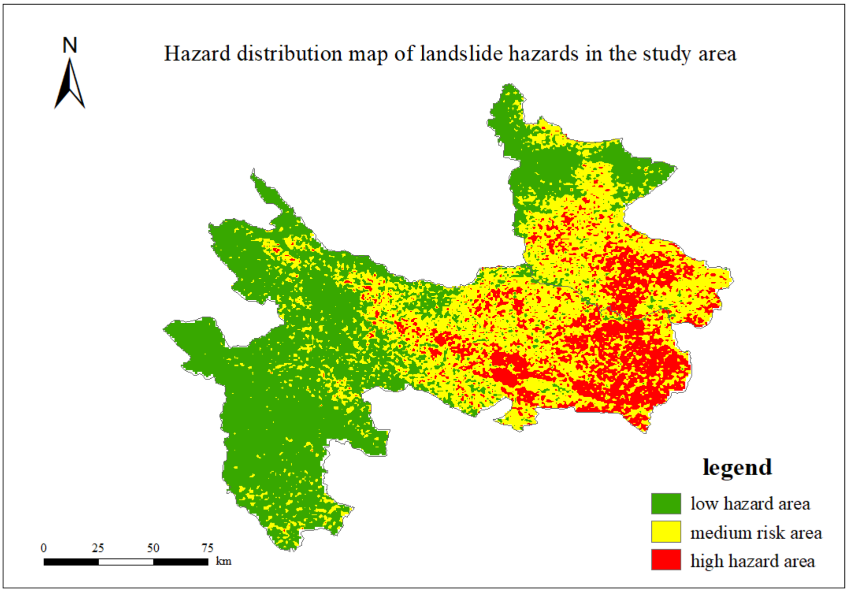


Fig. 8. Hazard distribution map of collapse hazards in the study area

The results show that the hazard indicators of collapses in the study area generally increase from northwest to southeast. The elevation of the study area rises from north to south, and the southeastern part is actually located in the middle of the area, with relatively moderate elevation. The topographic relief is greater in the central part and less in the northern and southern parts, thus the southeastern part has a greater slope and steeper topography. Most of the study area consists of mixed sedimentary rocks, with considerable variation in rock quality due to their complex composition, and vegetation is more evenly distributed, with relatively low vegetation cover in the northwestern part. Rainfall in the study area increases from northwest to southeast, while the freeze-thaw cycle increases from southwest to northeast, generally from west to east. The southeastern part of the study area, which is Maqin County's seat, has a well-developed road network and strong human activities, leading to a higher risk of collapse hazards in the southwestern part.

7 Conclusions

Through the collection and analysis of geographic data and collapse hazard data in the study area, as well as evaluation and analysis using ArcMap software and the entropy weight method, the following main conclusions were drawn:

1) The weights of the contributing factors in the study area, in descending order, are vegetation, rock mass, slope, human activities, slope height, rainfall, and freeze-thaw cycle. Slope height, rainfall, and freeze-thaw cycle have close and relatively low weights, while rock mass and vegetation have relatively high weights. Slope has about twice the weight of slope height.

2) According to the assessment model, hazard zoning of collapse hazards in the study area was carried out. The high-hazard zones were concentrated in the southeastern part of the study area, while the low-hazard zones were distributed in the western and northern parts. The hazard indexes generally showed an increasing trend from northwest to southeast.

Therefore, in environmental management, relevant workers can take targeted preventive and control measures in different disaster-prone areas according to the distribution of collapse risk and disaster-causing factors in the study area. This will help reduce the occurrence of collapse disasters and the losses they cause.

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