Scholar Publishing Group
International Journal of Engineering Technology and Construction
https://doi.org/10.38007/IJETC.2023.040103
ISSN 2789-7176 Vol. 4, Issue 1: 31-47

Geological Hazard Prediction of Regional Landslides Based on Geological Clouds and Meteorological Data

Li Wang*

Northwest Minzu University, Lanzhou, China

**corresponding author*

Keywords: Landslide Disaster, Landslide Disaster Assessment, Evaluation Factor, Disaster Prediction

Abstract: Landslide disasters are extremely harmful geological events. The occurrence of landslides will pose a great threat to human life and property safety, and will also cause huge damage to the environment and ecology, restricting human sustainable development. The survey data shows that the proportion of landslide disasters in China ranks first among all geological disasters, accounting for 74%. Therefore, it is of great economic value and social significance to take necessary and effective landslide disaster assessment studies to effectively predict landslide disasters. After decades of scientific exploration, China has made gratifying results in the study of landslide disasters, but there are still some problems in the quantification of the self-organized criticality of regional geological disasters, frequency and spatial dependence; The selection of evaluation factors in the analysis of landslide disaster susceptibility, the limit of risk assessment and susceptibility analysis also need to continue to explore. The purpose of this article is to predict regional landslide geohazards based on geological clouds and meteorological data. This paper fully absorbs the core idea of Logistical and solves the problem of sample quantification in the process of evaluation and prediction of large regions. Based on the comprehensive advantages of GIS technology and Logistical method, a risk assessment model is established. Taking Xinjiang landslide disaster as an example, the danger of landslide disaster is evaluated. This article concludes that the analysis of the landslide disaster in Xinjiang shows that when the cumulative landslide displacement is between 0. 2 and 0. 4m, the landslide is in a critical state, and an orange warning message is issued. When the cumulative landslide displacement value is greater than 0. 4m, the landslide is in danger. Status, release red warning information.

1. Introduction

With the continuous improvement of human society's transformation of nature in the course of development, nature's carrying capacity for human activities is also facing severe challenges. At the same time, humans are also facing challenges from nature. Among them, the occurrence of geological disasters such as landslides is An important factor affecting the eternal development of humankind. As the global crustal movement becomes more active, geological disasters have begun to develop in a more frequent and more frequent direction. Both China and the world have been widely affected by geological disasters in recent years. For example, a catastrophic debris flow in Zhouqu, Gansu, a landslide in Wamatsen, Yunnan, and a fugitive debris flow in Yunnan have caused great casualties and economic losses. It has seriously affected human production and life, and economic development has been severely hindered. A landslide is a"slope"rock-soil mass that shears and slides along a weak surface. About 70%of China's land is mountainous landforms and complex geological structures, which objectively determines that China is a country with very frequent and serious geological disasters. Geological disasters have many types, wide distribution and frequent occurrences. Since the 20th century, China's economy has entered a period of rapid development. With the expansion of human activity space and the expansion of the scope and scale of engineering activities, landslides and other geological disaster emergencies have been increasing year by year. China's vast territory, diverse climate, and complex topography have made most areas prone to geological hazards. After years of analysis of geological hazard statistics, we know that landslides and other geological hazards are most widely distributed in Sichuan, Yunnan, and Tibet. The main areas of distribution are also multi-type, large-scale, frequent, and widely distributed.

Regarding the susceptibility and hazard evaluation of landslide disasters, both domestic and foreign have been extensively and deeply studied, but the pros and cons of various evaluation methods have not been uniformly and completely recognized, and a complete set of evaluation standards have not been formed. The landslide risk is based on the susceptibility factors such as earthquakes, rainfall, and human engineering activities. At present, the landslide risk assessment is still in the exploratory stage, especially the research on the theoretical system and framework of landslide risk assessment for geological disasters has not yet been unified. Since the 1990s, with the rapid development of GIS and RS as the basis, the research on the methods of geological hazards has become more abundant, such as logistic regression models in statistical classification models, discriminant analysis, and generalized additive models. Due to the complexity of topographical and geological factors and the occurrence of landslide disasters, more flexible non-linear methods have been applied to research, especially artificial neural networks, support vector machines, Gaussian process models, and random forests. However, the application effects of various models are different due to different regional geological environments and climatic factors, and the adaptability of different analysis area scales to each model method is different. Therefore, it is easy to analyze different landslide geological disasters through selected research areas. The applicability of the assessment model for occurrence of geological disasters, and the selection of the most effective assessment method of geological disaster-prone areas among various methods has important theoretical and practical significance. Explore the development characteristics of landslide disasters in the study area, and provide a certain theoretical basis for the landslide susceptibility and risk assessment, as well as the prevention and treatment of landslide disasters.

Dingde Xu put forward a realistic approach to the risk assessment of regional landslide geological hazards, that is, the evaluation can follow the process of"genetic mechanism analysis→subregional division→sensitivity factor analysis and qualitative analysis reasoning→mathematical model analysis→comprehensive evaluation"A process is well integrated into the"GIS system for the evaluation and prediction of regional landslide geological hazards"independently developed based on MAPGIS[1]. Ari J. Posner discussed the application and development trend of GIS, remote sensing(RS), grey correlation and Logistic regression analysis in the evaluation of landslide stability. Studies have shown that GIS and RS technologies have great application prospects in the evaluation of regional landslide stability with their powerful information acquisition and processing functions, and for the analysis of the relationship between factors affecting the stability of landslides, gray correlation and Logistic Regression analysis is easier to operate, economical, and has higher accuracy[2]. Peng Ling calculates the importance of each factor through rough sets and reduces the data. The neural network is used to simulate the reduced data to build a model for prediction. It takes full advantage of the ability of rough set theory to reduce data and the generalization of neural networks. And fault tolerance, so that the selection of the prediction index system is more basis, and the prediction results obtained are more interpretable, which can reduce the factors involved in the prediction and effectively improve the prediction efficiency[3]. W. Sai took the academic thought of"geological process mechanism analysis-quantitative evaluation"as the core, combined with detailed investigation of field geological hazards, established a set of landslide stability analysis and prediction methods, and formed a relatively complete study of landslide stability analysis. Technical route[4].

This paper fully absorbs the core idea of Logistic, and solves the problem of sample quantification in the process of evaluation and prediction of large regions. Based on the comprehensive advantages of GIS technology and Logistic method, a risk assessment model is established. Taking Xinjiang landslide disaster as an example, the danger of landslide disaster is evaluated. The results show that the integration of GIS technology and statistical methods is of feasibility and practical significance for the research on the assessment of geological disaster risk in large regions.

2. Proposed Method

2.1. Establishment of Spatial Database

In this study, by using the functions of graphic editing and data management in Arc GIS, graphics files in different formats were converted into formats that meet their own needs. The layer is subjected to spatial overlay analysis, and the number of landslides in each category is statistically analyzed to obtain the relationship between the landslide in the study area and its influencing factors. The data is transferred to a file and the data is entered into the spatial database from various files. [5-6].

The spatial database mainly has two parts: a graph database and an attribute database. Based on the GIS technology to establish a graphical database and attribute database of geological disasters, and to achieve seamless connection of graphical data and attribute data, and two-way query and retrieval of data [7]. Using the functions of grid calibration, vectorization of pictures, vectorization, rasterization, and coordinate projection of Arc GIS to process each evaluation factor layer, transform each indicator layer into a grid layer with the same projection coordinates, and apply the space of Arc GIS The analysis layer overlay function superimposes the selected landslide hazard factors together with the landslide disaster points, and statistically analyzes the number of landslides in the category [8-9]. Finally, the establishment of a landslide disaster spatial database, that is, a graphic database and an attribute database, and the connection between the two can be realized, and the data can be checked and browsed.

2.2. Analysis of Landslide Impact Factors

The formation of geological hazards is the result of a variety of factors, and each impact factor has a different degree of importance to the occurrence of geological hazards. Therefore, when evaluating the susceptibility of geological hazards, a reasonable choice of evaluation indicators (influencing factors) is an important prerequisite for evaluating hazards of geological hazards [10].

The relationship between the occurrence probability of geological hazards and the evaluation indicators of geological hazards can be expressed in mathematical language, that is, the mapping relationship between the occurrence probability of geological hazards and the evaluation indicators:

$$P = f(x_1, x_2, \cdots, x_n) \tag{1}$$

Among them, P is the probability of occurrence of geological disasters, and $x_1, x_2, \cdots, x_n$ is the factor that affects the occurrence of geological disasters. Elevation, topographic relief, slope, river, fault structure, precipitation, etc. are all important factors affecting the probability of geological disasters [11].

2.3. Evaluation Factors of Geological Hazard Status

Geological hazard status evaluation factors include the number and scale of landslide geological hazards that have occurred [12]. Relative density refers to the occurrence of geological disasters per unit area, and it can quantitatively indicate the intensity of landslide activity in a unit area under an influence factor [13-14]. This method can overcome the change in the number or area of landslide impact factors in different values. The relative point density and relative area density is the number or area of landslide disaster points in each secondary classification factor, divided by the area of each secondary classification factor, and can be expressed by the following formula:

$$D = \frac{N_i / S_i}{N / S} = \frac{N_i / N}{S_i / S} \tag{2}$$

Among them, D is the relative density of landslide points or areas;S is the total area of the study area; S_i is the area containing an impact factor; N_i is the number or area of landslides distributed within an evaluation factor;N is the total number of landslides in the study area Or total area[15]. The value of relative density can reflect the frequency and activity intensity of landslide disasters.

2.4. Fractal Characteristics of Landslide Impact Factors and Spatial Distribution

Studying the fractal relationship between the distribution of landslides and its influencing factors can get the sensitivity of landslides to different influencing factors, and then provide basic data for the evaluation of susceptibility and zoning. However, in this type of related research, events that meet the constant-dimensional fractal strictly There is no such thing. At this time, the constant-dimension fractal cannot meet the needs of work [16]. In fractal, the fractal dimension D is not constant, but when there is some functional relationship with the feature scale r, we call it a variable-dimensional fractal. Its functional relationship is expressed as:

$$D = g(r) \tag{3}$$

For the functional relationship $N = f(r)$ between N and r, let $f(r) = C r^{-D}$, then

$$D = \frac{InC - Inf(r)}{Inr} \tag{4}$$

Studies have shown that the change law of any parameter A with the recurrence period can be transformed into a variable-dimensional fractal. If the constant-dimensional fractal is regarded as a first-order fractal, if the fractal dimension is $D = C' / r^{-D'}$, then the fractal of the first-order fractal can be performed again, and the fractal of N-order can be obtained by analogy [17-18]. Its expression is:

First-order fractal $N_1 = C_1 / r^{D_1}$, where D_1 is constant.

Second-order fractal $N_2 = C_1 / r^{D_1}$, where $D_1 = C_2 / r^{D_2}$; D_2; is a constant.

N-order fractal $N_2 = C_{n-1} / r^{D_{n-1}}$, where $D_{n-1} = C_n / r^{D_n}$; D_n;is a constant.

It can be seen that the variable-dimensional fractal of any order can be transformed into the form of constant-dimensional fractal. Multi-order fractal can be processed through order accumulation to derive cumulative and changing fractals[19]. The specific steps are:

(1)Project the original number of pairs of (N_i, r_i) into the double-logarithmic coordinate system according to the sequence from small to large, and calculate the $D_{i,i+1}$ in the double-logarithmic coordinate system between two adjacent points. Due to the large fractal dimension, there is no regularity[20]. The solution formula of $D_{i,i+1}$ is:

$$D_{i,i+1} = In(N_i / N_{i+1}) In(r_i / r_{i+1}) \tag{5}$$

(2)Accumulate and calculate $(N_1, N_2, ..., N_i, ..., N_n)$.

$$\{S1_i\} = \{N_1, N_1 + N_2, N_1 + N_2 + N_3, ...\};\ i = 1,2,3,...,n \tag{6}$$

$$\{S2_i\} = \{S1_1, S1_1 + S1_2, S1_1 + S1_2 + S1_3, ...\};\ i = 1,2,3,...,n \tag{7}$$

$$\{S3_i\} = \{S2_1, S2_1 + S2_2, S2_1 + S2_2 + S2_3, ...\}\ i = 1,2,3,...,n \tag{8}$$

$$\{Sn_i\} = \{S(n-1)_1, S(n-1)_1 + S(n-1)_2, S(n-1)_1 + S(n-1)_2 + S(n-1)_3, ...\};\ i = 1,2,3,...,n \tag{9}$$

Among them, S1, S2, S3, . . . Sn are the cumulative sum sequence of the corresponding fractal orders.

(3)According to the above formula, from the logarithmic coordinate system, n-1 line segments with unequal slopes can be obtained. The opposite numbers of these slopes are the first-order cumulative and variable-dimensional fractal dimensions;the same can be obtained Above the first-order cumulative and variable-dimensional fractal dimension[21-22]. With the increase of the fractal order, the data points accumulated and formed by each order in the double logarithmic coordinate system will eventually show a good linear relationship. At this time, a linear regression model can be used to calculate the parameters of the linear relationship to obtain its constant fractal dimension D[23].

1)The fractal characteristics of landslide and slope In the relationship between landslide and slope, the slope step is 10°, and the landslide area and step are counted. With the increase of the slope, it will appear, and the graph trend of first increase and then decrease, the peak appears between 20°and 30°. After performing double logarithmic processing on the data, it does not show the characteristics of constant-dimensional fractals[24]. The data are accumulated and transformed at a higher order, and the spatial distribution of the landslide area and the slope show a good linear relationship on the third-order accumulation sum curve. The linear regression fitting is performed on the third-order cumulative sum transformation data, and the fitting correlation coefficient is close to 1, which indicates that the landslide spatial distribution and the slope have a third-order cumulative and variable-dimensional fractal relationship, and its fractal dimension value is $D_3 = 2.5316$.

2)Fractal characteristics of landslides and elevations

The increase in elevation will affect the probability and scale of landslide geological disasters. The step size of the elevation is 500m for statistical classification, and a level greater than 3500m is a level[25]. It can be analyzed that there is no obvious linear relationship between landslide area and elevation. The high-order accumulation and variable-dimensional fractal are performed between the landslide area and the elevation, which has a good linear relationship in the second-order accumulation and the double logarithmic model with the characteristic scale r, indicating that there is a second-order accumulation between the landslide area and elevation And the variable dimension fractal relationship, its fractal dimension $D_2 = 3.1693$, the correlation coefficient R=0. 9946[26-27].

3)Fractal characteristics between landslide area and fault buffer zone

In Arc GIS, the step length of the fault is 1km, and a buffer zone with a buffer radius of 10km is made, and the area of landslide geological disasters in each buffer zone is counted. By calculating the double logarithmic relationship, there is no constant-dimensional fractal feature between the landslide area and the fault buffer zone[28]. A high-order accumulation and transformation is performed on the data pairs of the landslide area and the fault buffer to establish different-order fractal models. It is found that the linear relationship between the landslide area and the fault buffer in the first-order cumulative and double logarithmic model is better than that of the second-order cumulative sum model. The linear regression curve fitting degree R=0. 9987 is closer to 1. We believe that there is a first-order cumulative and variable-dimensional fractal relationship between the landslide area and the fault buffer, and its fractal dimension is $D_1 = 1.3215$.

4)Fractal characteristics between landslide area and lithology

According to the softness and hardness attributes of lithology, a double logarithmic relationship between landslide area and lithology is established using numerical codes. In the high-order cumulative and variable-dimensional fractal, there is an optimal linear relationship between the landslide area and the lithology in the first-order cumulative and double-logarithmic coordinate system, and the fitting correlation coefficient R=0. 9927. Therefore, there is a first-order cumulative and variable-dimensional fractal between the landslide area and lithology, and its fractal dimension is $D_1 = 2.1925$.

2.5. Logistic Regression Model

Logistic regression model is a statistical analysis method commonly used for regression analysis when the dependent variable will only occur in two cases. It mainly analyzes the independent variable for the dependent variable. Regression analysis reveals the correlation between the various evaluation variables and predicts the dependent variable the trend of. Its advantage lies in the lower requirements on the data freedom of independent variables. The data can be discrete, normal distribution, or binary classification, which makes it widely used in landslide disaster risk assessment.

Logistic regression model, the expression is:

$$P = (y_i = 1 | x_i) = \frac{1}{1 + e^{\varepsilon i}} \tag{10}$$

$$\varepsilon_i = \alpha + \beta_i \tag{11}$$

In the formula, χ_i is an independent variable, α and β_i are coefficients, and ε_i is a linear function composed of evaluation indexes. The independent variable and the probability of occurrence of the event P are non-linear monotonic functions. The conditional probability P increases with the increase of χ_i, and the value range changes between 0-1. The function curve is S-shaped. This characteristic of the logistic regression model fits well the relationship between the occurrence of landslide disasters and the evaluation indicators.

Therefore, the conditional probability of an event P_i:

$$P_i = \frac{1}{1+e^{-(\alpha+\beta i)}} = \frac{e^{\alpha+\beta i}}{1+e^{\alpha+\beta i}} \tag{12}$$

The conditional probability that an event does not occur is:

$$1\text{-}P_i = 1-\frac{e^{\alpha+\beta i}}{1+e^{\alpha+\beta i}} = \frac{1}{1+e^{\alpha+\beta i}} \tag{13}$$

Taking the natural logarithm of the ratio of P to(1-P), we obtain a continuous function, which is recorded as Logit P, and its value range is(-∞, ∞). This establishes a parameter with $\chi_1, \chi_2, ..., \chi_n$ as the independent variable and P as the dependent variable. Regression equation:

$$LogitP = In[P/(1-P)] = \alpha_0 + \beta_1 \chi_1 + \beta_2 \chi_2 + ... + \beta_n \chi_n \tag{14}$$

$$P = \frac{e^{\alpha_0+\beta_1\chi_1+\beta_2\chi_2+...+\beta_n\chi_n}}{1+e^{\alpha_0+\beta_1\chi_1+\beta_2\chi_2+...+\beta_n\chi_n}} \tag{15}$$

In the formula, α_0 is a constant term, which represents the logarithm of the ratio of the conditional probability of occurrence to the conditional probability of non-occurrence without being affected by any influence factor; $\beta_1, \beta_2, ..., \beta_n$ is the logistic regression coefficient. Logistic regression model error terms obey the binomial distribution.

In the risk assessment of landslide geological hazards, the occurrence of landslides is a dependent variable. There are only two cases. They are a typical binary classification variable. Various evaluation indicators(slope, rainfall, earthquake, stratum lithology, Body structure and human engineering activities, etc.)can be used as independent variables. As long as the regression coefficient is calculated through regression analysis, the probability of landslide occurrence P can be obtained, which indicates the possibility of landslide occurrence, and then the landslide disaster danger level is divided according to the P value.

The logistic regression model uses the maximum likelihood method to estimate the regression coefficients. It is not used in the conventional least square method of the linear function. The logistic regression model is a nonlinear evaluation model, which is slightly different from the conventional linear model. Firstly, the dependent variable of the logistic regression model is a binary classification variable, only 0 or 1. Secondly, the dependent variable of the logistic regression model and the multivariate independent variable have a non-linear relationship, and the distribution conditions of the independent variable are relatively low.

After the logistic regression model is built, it is necessary to conduct a feasibility test. The test of the model mainly evaluates the model from the aspects of the significance of the regression coefficients, the fit of the model, and the multicollinearity of the independent variables. Only through a series of tests can we get the most reasonable evaluation model and the final accurate results.

2.6. Evaluation Index Normalization

The core of Logistic regression analysis is to obtain the logistic regression coefficient. According to formula(14), the regression coefficient is calculated by logistic regression on the basis of the influence factor index value. However, due to the different scales and dimensions of each evaluation index, in order to facilitate the calculation in the Logistic regression model, it is necessary to unify the dimensions of each evaluation index, as shown in the following table. This paper adopts the dimensionality normalization method of the evaluation index proposed by Ayalew of Japan:First, the evaluation index is classified, and then the historical landslide disaster area S_{ij}^{z} and the secondary index area S_{ij} in the secondary factor under a single evaluation index are used to find the ratio R_{ij} . (6), and then normalize the R_{ij} , as shown in equation(17).

$$R_{ij} = \frac{S_{ij}^{z}}{S_{ij}} \tag{16}$$

$$X_{ij} = \frac{R_{ij}}{\sum_{j=1}^{m} R_{ij}} \tag{17}$$

In the formula: i is the i-th evaluation index; j is the j-th subset of the i-th evaluation index; and m is the number of the subset in the i-th evaluation index.

Table 1. Evaluation index normalization index

Evaluation index	Index classification	Landslide area (km^2)	Area (km^2)	R_{ij}	X_{ij}
	0~20 °	1. 31	54. 36	0. 0136	0. 1218
slope	20 °~40 °	19. 63	163. 95	0. 2052	0. 9315
	40 °~60 °	2. 96	225. 53	0. 0213	0. 0752
	>60 °	0. 12	4. 63	0. 0015	0. 0081
	0~400	12. 15	63. 92	0. 2135	0. 4157
Tug of War	400~1000	16. 17	93. 66	0. 1426	0. 3917
Elevation	1000~1500	3. 19	153. 68	0. 0217	1. 1633
	1500~2000	0. 057	103. 62	0. 0036	0. 0082
	>2000	0. 001	42. 19	0. 0073	0. 0052
Slope	Reverse slope	8. 16	65. 31	0. 1285	0. 5693
structure	Horizontal slope	15. 62	253. 47	0. 0518	0. 1963
Evaluation index	Consequent Slope	5. 39	75. 73	0. 0763	0. 4219

2.7. SPSS Determine Regression Coefficient

The regression coefficient of the logistic regression model is generally determined by SPSS software. Before calculating the regression coefficient, you need to make some preparations:

(1)The landslide disaster distribution map in the study area is coded. The area where the landslide occurred is assigned a value of 1 and the rest are 0, and rasterized.

(2)Based on the discussion of the landslide control factors in the study area, 7 indicators such as slope, tug-of-war elevation, slope structure, river system, rainfall, and human engineering activities were selected as the independent variables x_i , and the indicators determined based on the normalization of the indicators The value X_{ij} is rasterized.

(3)Use the grid transformation function of ArcGIS to convert each thematic layer into ASCII code, import SPSS, remove invalid data, and perform logistic regression analysis.

Stepwise regression analysis was used in SPSS software to determine the regression coefficient. According to the regression coefficients, it can be seen that the factor that has the greatest impact on landslide disasters in the study area is the lithology of the formation. On the one hand, the main reason for this is that the landslides in the study area are mostly lithologically dominated by carbonaceous phyllite, with thin rock layers. The stratigraphy is good, the lithology is soft, and deformation and damage are easy to occur. On the other hand, strata dominated by carbonaceous phyllite are mostly developed along the mainstream of the Zagunao River. The river flow intersects with the stratum at a small angle, forming The longitudinal river valley is a slope structure that is favorable for slope deformation and damage.

3. Experiments

3.1. Overview of the Study Area

Xinjiang has a vast area, complex topographical and landform changes, large differences in topography, significant development of fault zones, active tectonic movements, and fragile geological environments. Therefore, it is extremely easy to induce various types of geological hazards under special conditions, and the frequency of outbreaks is high and the impact range is wide. There are also many historical disaster points in Xinjiang.

During the early years, after analysis and statistics, it was found that about 70%of landslide disasters occurred in the Yili River Valley. There are about 66 large and large landslide events, concentrated in Xinyuan County;most of the debris flow disasters are concentrated in Kizilsu Kirgiz Autonomous Prefecture, southwest of Kashgar, south of Changji Hui Autonomous Prefecture, and northern Bayingoleng Mongolia Autonomous Prefecture. And other areas. There are about 59 large and large debris flow events;about 30 large and large collapse events.

3.2. Data Source and Preprocessing

The data used in this study are information from Xinjiang, including DEM data, land use, fault structure, lithology, roads, historical disaster points and hidden danger points. First of all, because the data sources are different, and considering that the calculation of area, length, etc. will be involved in the experiment, the Albert equal area projection is uniformly used.

(1)Digital elevation model. The digital elevation model data can not only obtain the terrain factors(such as slope, angle, slope curvature)in specific regions, but also the hydrological parameters. The evaluation process will involve spatial superposition operations, so the thematic data needs to be rasterized. According to the choice of grid size at different scales. The study compared the digital elevation models generated by two data sources, namely the global elevation model from ASTER and the 20m accuracy contour line provided by Georgia. The minimum raster accuracy of the landslide range prediction software Flow-R for the regional range is 50m;the elevation accuracy of the ASTERGDEM data is lower;the ASTER data is more affected by the original format when interpolating the 50In raster, and the 20m accuracy contour is better. Therefore, the digital elevation model used in this study was obtained by interpolation of contours with a precision of 20m, and the grid size was 50m.

(2)Water network and road network. Water network data comes from the digital elevation model and is processed by the software ILWIS. Here the water network does not only refer to the river area, but generally refers to the area where the terrain is gully. Disasters such as debris flow occur in gullies. In this paper, when the catchment range is set to 0. 5km, a water network is formed. Statistics show that roads in steep areas have contributed greatly to landslide disasters.

Rely on the Arc GIS platform to convert and resample thematic data and DEM.

3.3. Implementation of Wireless Sensors

The architecture of the automatic monitoring and early warning system for geological disasters based on wireless sensor networks is mainly composed of wireless sensor network gateways, backbone networks, and user networks.

WSN is composed of sensor nodes in AdHoc mode. The backbone network mainly refers to GSM, Internet and satellite networks. The gateway realizes transparent interconnection between the sensor network and the backbone network. Sensor nodes deployed inside the monitoring area must be able to self-organize into a network in a wireless AdHoc manner. At the same time, the environmental information collected by each sensor node is transmitted to the gateway through multi-hop routing. After various sensor data is transmitted to the gateway, it is then transmitted to the user network through the backbone network.

The background management software consists of 3 parts, namely:WSN, transmission network and background management software. WSN collects data in the monitoring area, and transmits various sensor data to the background management software through the transmission network. The background management software analyzes, processes, and stores these data in order to obtain relevant information about WSN(raindrops, soil moisture content, nodes Displacement), and monitor the operation and environmental conditions of the WSN. In addition, the background management software informs WSN through the transmission network in order to complete specific tasks. The main tasks of developing background management software are database design, data processing engine design, background component design and user graphical interface design. Node-level programming is performed on the Tiny OS operating system. nesC language is an extension of C language, so use nesC language for programming. When writing nesC programs, the core work is to write various components, and then connect the components according to some specifications. Management machine level programming is programmed in a C#environment. The front-end system software is mainly composed of 5 modules:parameter setting module, data acquisition module, data processing module, output module and data management module.

3.4. Landslide Monitoring

For a long time, early warning of landslides has been a difficult problem, and monitoring is an important physical premise for early warning. This research group began to install monitoring signs in the danger zone of mountain slides from March 2017. In order to grasp the deformation dynamics of mountain sliding. From the monitoring results, the landslide is generally stable. The maximum cumulative displacement of the surface monitoring point is nearly 50mm. It is located in the upper part of the landslide. No major deformation occurred.

4. Discussion

4.1. Numerical Simulation Analysis of Landslide Stability

The current mathematical model methods for landslide stability analysis can be divided into two categories, one is the rigid body limit equilibrium method based on limit equilibrium theory, and the other is the numerical analysis method. The finite element method is used in the research of this subject. In the typical position of the landslide, four calculation profiles were selected for the stability calculation of the landslide body under saturated and anhydrous conditions.

4.2. Finite Element(FEM)Analysis of Landslide Stability

This calculation uses ANSYS version 6. 0, adopts nonlinear analysis in structural statics, and selects a plane four-node element and Drucker-Prager constitutive model. During the calculation of the profile, the calculated profile was selected to be more than 3 times the area ofthe landslide. A total of 1659 units and 1873 nodes were divided. The grid was encrypted at the landslide surface, slope top, and slope foot. The level was applied at the bottom and rear boundaries of the calculated profile Constraints on direction and vertical direction. The physical and mechanical parameters of rock and soil are shown in Table 2. The parameters in the brackets in the table are the parameters when the slope is dry. Geomechanical physical and mechanical index analysis of the stress on the profile and the other three profiles shows that the stress of the landslide body under both water-free and saturated conditions is mostly compressive stress, and the direction is down the landslide. The value is not large, there are few places where tensile stress appears, it usually appears on the top of the trailing edge of the calculated section, and sometimes the tensile stress appears on the landslide surface, but the value of the tensile stress is very small. Generally speaking, tensile stress is likely to be caused on the landslide surface, the top of the trailing edge of the calculated slope surface, the upper part of the subgrade landslide, and the joint between the fill and the original soil. From the calculation of displacement, the landslide displacement in the two conditions mainly occurs in the landslide body. The displacement at this part is significantly larger than other parts. The direction is vertically downward or downward along the landslide direction. The displacement value is not very large. Change between 5~12cm.

Table 2. Physical and mechanical indexes of rock and soil under profile conditions

Rock formation	Modulus of elasticity / M Pa	Poisson's ratio	Cohesion / k Pa	Internal friction angle / ( )	Density/ (Kg. m-3)
Fill	7. 35	0. 37	28. 68	16. 52	1. 91
Silty clay	5. 82	0. 33	26. 72	15. 63	1. 89
Pebbly	7. 96	0. 42	32. 31	8. 69	1. 93
Clay layer	8. 11	0. 35	50. 26	19. 41	2. 05

4.3. Geological Environmental Conditions

Geological environment conditions mainly include several aspects such as topography, faults, lithology types and vegetation coverage. Different geological environmental conditions affect the landslide in different ways and magnitudes.

Elevation can affect precipitation, groundwater runoff, vegetation coverage, changes in stress values on slopes, and the range of human activity. Due to the difference in distance from the water vapor source, there will be a large deviation in the content of water vapor and the intensity of transportation in the influence of the direction, height, slope and local topographical factors of the mountain range. At a large scale, elevation is the main factor affecting precipitation, and there is an inverse correlation between elevation and precipitation, that is, as the elevation increases, the precipitation decreases. The change of surface runoff is similar to the elevation. For large scale, the runoff decreases with the increase of elevation. For example, the Lancang and Nujiang basins have obvious anti-correlation. On the other hand, the distribution of vegetation and elevation, precipitation, slope, aspect and elevation are interdependent. Elevation is a gradient characteristic that determines the distribution of vegetation. At different elevations, there are obvious differences in vegetation types and vegetation diversity. In low-altitude water-rich areas, vegetation growth is good and vegetation is rich and diverse. In high-altitude areas, vegetation is single. Most are hardy vegetation. The elevation can control the stress value of the slope body, and the stress value will increase with the increase of the slope height. Finally, the intensity of human activity is different at different elevation ranges. Relatively high altitude areas, the population is concentrated, and the surrounding natural environment is strongly transformed. At high altitudes, the population is scarce and materials are scarce. All in all, elevation affects the distribution of these factors to varying degrees, and these factors are important inducers that affect the occurrence of landslides.

According to the DEM chart, it is reclassified into 8 grade types as shown in Figure 1 below, which shows a wave-like decline as the elevation increases. The relative density of points and areas with elevations below 500m are relatively high, and these areas have been disturbed by the erosion of rivers and human activities. The point relative density and area relative density are small peaks within 1500-2000m, and the slopes in these areas have formed steep slopes. As the elevation increases, the landslide point density and area density decrease. The higher the elevation, the deeper the groundwater is buried, the human activity is weak, and the slope is stable.

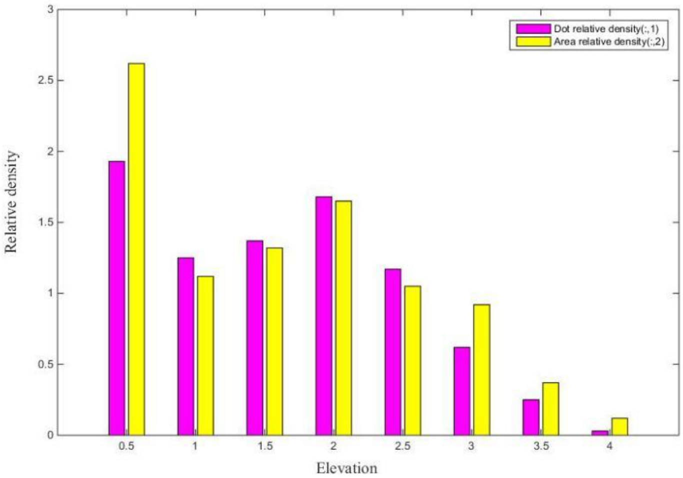

Figure 1. Relationship between landslide disaster density and elevation grade

4.4. Landslide Warning

The spatial identification method is usually used to determine the danger area of landslide occurrence or potential occurrence, and to issue early warning information. It is highly subjective and cannot accurately determine the stability of the landslide body and the dangerous period of the landslide, which brings hidden dangers to local residents'safety. The landslide state early-warning method mainly focuses on the change signs of the landslide body in a critical state. The relevant early-warning indicators are determined through various methods, and the threshold value is determined based on the change of the landslide body's early-warning value in different critical states, and the warning information is issued based on this. Through the establishment of models, empirical formulas and data statistics, the following warning indicators are determined:

(1)Daily rainfall

Select the A5 sensor in the area where the displacement of the landslide is more serious as the criterion. Observe the relationship between the landslide sliding distance and rainfall during the period of frequent rainfall from June 19, 2018 to July 19, 2019, as shown in Figure 2. It can be found that there is a strong positive correlation between the landslide displacement value and the daily rainfall, and the displacement value has a lag of 2 to 3 days relative to the change in rainfall.

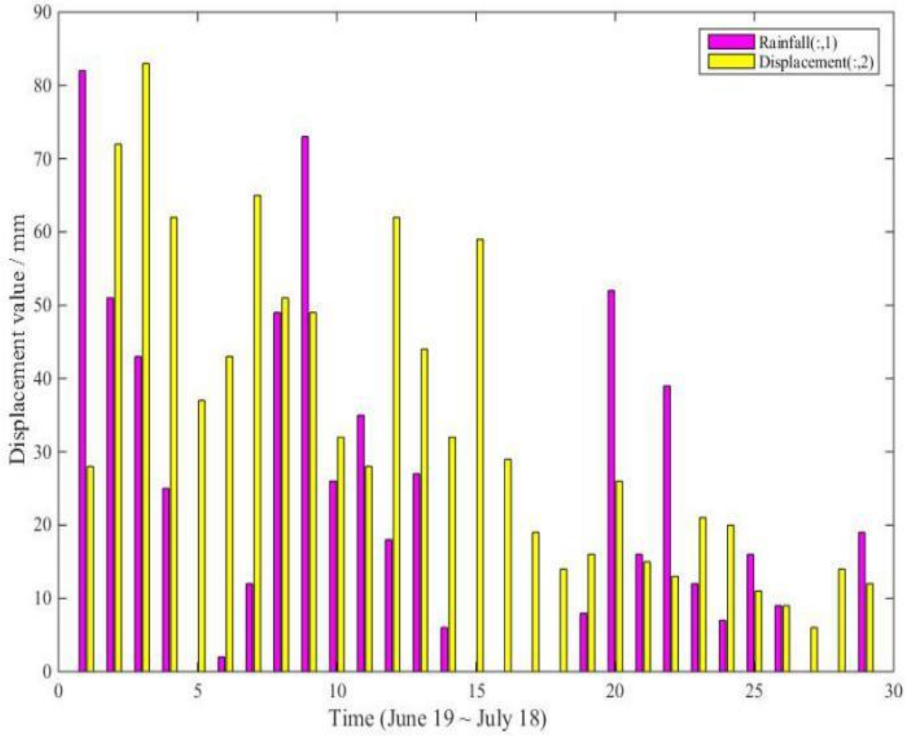

Figure 2. Image of relationship between landslide displacement and daily rainfall

(2) Sliding rate

Rainfall changes significantly with the seasons. Corresponding to rainfall, the changes in landslide displacement are mainly concentrated in June to July. It is generally believed that when the landslide body is in a relatively stable state, seasonal precipitation will have little effect on it, and the state of the landslide body will not change drastically. When the landslide body is in the critical state of occurrence, the displacement value and displacement rate will follow the seasonal rainfall. The changes in characteristics and their obvious changes, deformation phenomena and signs can be used as early warning criteria for landslide conditions. The following figure 3 shows the displacement cumulative curve and daily displacement curve of the A5 sensor from June to July 2018:

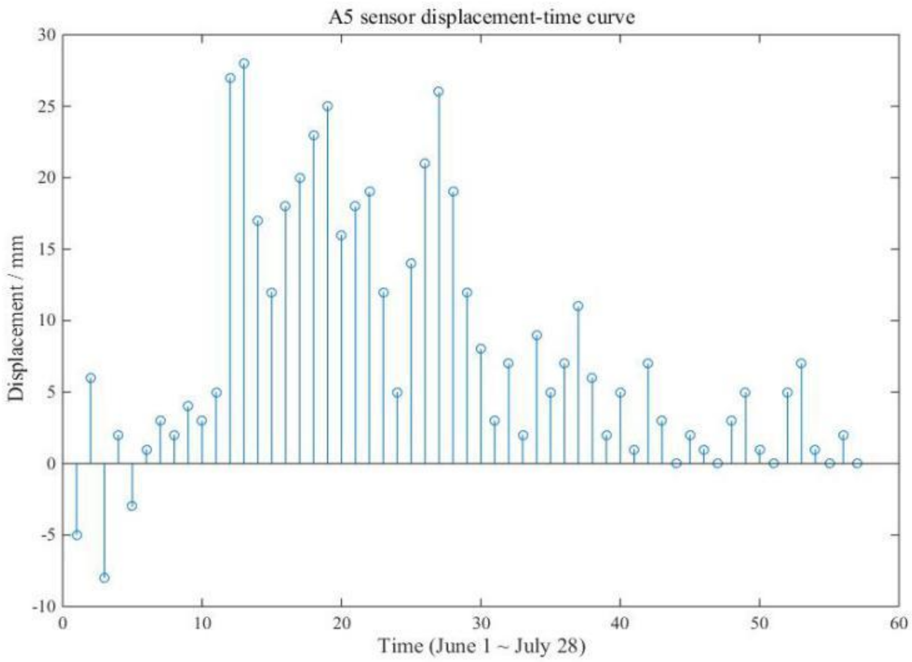

Figure 3. Diurnal change curve of A5 sensor displacement

Based on the selection method of the above-mentioned landslide state early-warning indicators and the monitoring curve change law, the following early-warning criteria can be summarized:

1)The displacement of the landslide body changes significantly with the season, and the sliding rate exceeds 100mm/month;

2)The daily sliding rate increases suddenly and sharply, and the value is greater than 10mm for more than 10 consecutive days. Red warning information is issued when both of the above criteria are met, and orange warning information is issued when one of the criteria is met. From this, orange warning information can be released for the study area in June 2018, and red warning information can be released for the period from June 12 to June 23.

(3)Cumulative displacement

By studying the monitoring data and analyzing the change of the cumulative displacement of multiple landslide bodies in the critical state, the following conclusions are obtained:The cumulative displacement values of different landslides in the critical state are different, and the differences are obvious. The size of the cumulative displacement value alone cannot Accurately release early warning information. In order to show the characteristics of the landslide body, the cumulative displacement value is compared with the length of the landslide body in the sliding direction, and the percentage is used to determine the change of the landslide body. Generally, the displacement ratio in the critical state is between 0. 4%and 0. 8%. between. The main landslide body in the study area is about 70m wide and 90m high, and the length of the landslide body is about 50m in the sliding direction. According to the above conclusions, it can be calculated that when the cumulative displacement of the landslide is between 0. 2 and 0. 4m, the landslide is in a critical state. Early warning information, when the cumulative displacement value of the landslide is greater than 0. 4m, the landslide is in a dangerous state, and red warning information is issued. Therefore, from June 21, 2018, the cumulative landslide displacement value reached 0. 2m, and orange warning information should be issued. From July 8, 2018, the cumulative displacement value of the landslide reached 0. 4m, and red warning information should be issued.

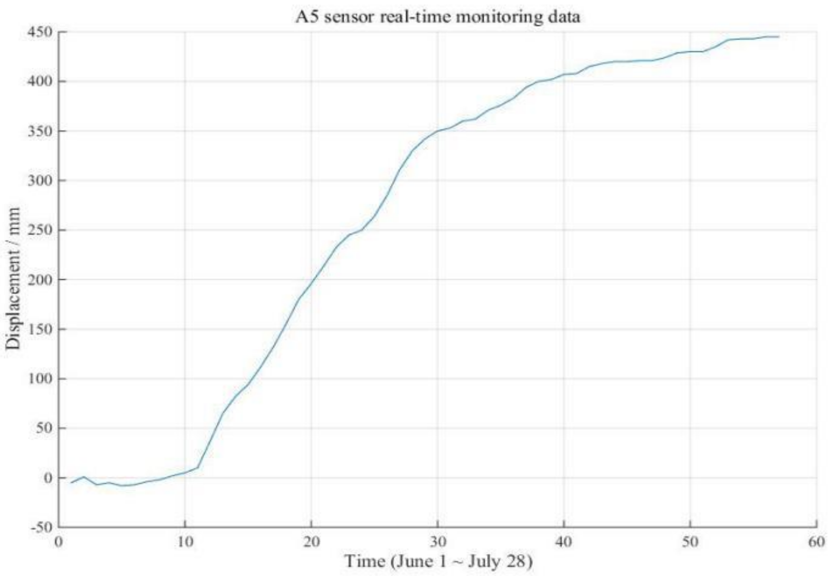

Figure 4. A5 sensor cumulative displacement curve

5. Conclusion

China has a vast area and frequent geological disasters, and increasingly serious geological disasters threaten the lives and property of the people at all times. In the past two or three decades, domestic and foreign scholars have done a lot of work on geological disaster monitoring. Because of its ability to realize remote automatic monitoring, wireless sensor technology has the characteristics of dynamic network flexibility, adapting to changes in the physical network at any time, low cost and reliability. It is more and more used in geological disaster monitoring.

This paper fully absorbs the core idea of Logistic, and solves the problem of sample quantification in the process of evaluation and prediction of large regions. Based on the comprehensive advantages of GIS technology and Logistic method, a risk assessment model is established. Taking Xinjiang landslide disaster as an example, the danger of landslide disaster is evaluated. The results show that the integration of GIS technology and statistical methods is of feasibility and practical significance for the research on the assessment of geological disaster risk in large regions. As a preliminary research result, there are still some problems in the model design that need to be improved. For example, the formation mechanism of geological hazards is not a linear system. Try to introduce a nonlinear model to optimize the existing results. Research on proper grid division.

This article concludes that the analysis of the landslide disaster in Xinjiang shows that when the cumulative landslide displacement is between 0. 2 and 0. 4m, the landslide is in a critical state, and an orange warning message is issued. When the cumulative landslide displacement value is greater than 0. 4m, the landslide is in danger. Status, release red warning information. Therefore, from June 21, 2018, the cumulative landslide displacement value reached 0. 2m, and orange warning information should be issued. From July 8, 2018, the cumulative displacement value of the landslide reached 0. 4m, and red warning information should be issued.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] Dingde Xu, Li Peng, Shaoquan Liu. Influences of Risk Perception and Sense of Place on Landslide Disaster Preparedness in Southwestern China. International Journal of Disaster Risk Science, 2018, 9(2):1-14.

[2] Ari J. Posner, Konstantine P. Georgakakos. Soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador. Landslides, 2015, 12(6):1179-1196.

[3] Peng Ling, Xu Suning, Peng Junhuan. Regional Landslide Risk Assessment Using Multi-Source Remote Sensing Data. Journal of Jilin University, 2016, 46(1):175-186.

[4] W. Sai, X. Suning, P. Ling. A rapid extraction of landslide disaster information research based on GF-1 image. Proceedings of SPIE - The International Society for Optical Engineering, 2015, 9669(1):307-314.

[5] H Tjahjono, S Suripin, K Kismartini. Structuring the Environment of Landslide-Prone Disaster and Its Mitigation in The District of Banyumanik. Iop Conference, 2018, 145(1):012082.

[6] H Habil, E Yuliza, M M Munir. Instrumentation system design and laboratory scale simulation of landslide disaster mitigation. Journal of Physics Conference, 2016, 739(1):012056.

[7] LI Xishuang, LIU Baohua, LIU Lejun. Prediction for Potential Landslide Zones Using Seismic Amplitude in Liwan Gas Field, Northern South China Sea. Journal of Ocean University of China, 2017(6):1035-1042.

[8] Alessandro Messeri, Marco Morabito, Gianni Messeri. Weather-Related Flood and Landslide Damage: A Risk Index for Italian Regions. Plos One, 2015, 10(12):e0144468.

[9] Pei Zuan, Yong Huang. Prediction of Sliding Slope Displacement Based on Intelligent Algorithm. Wireless Personal Communications, 2018, 102(3):1-17.

[10] Abolfazl Jaafari. LiDAR-supported prediction of slope failures using an integrated ensemble weights-of-evidence and analytical hierarchy process. Environmental Earth Sciences, 2018, 77(2):42.

[11] Marcos Barreto de Mendonca, Adriana Sobreira Valois. Disaster education for landslide risk reduction: an experience in a public school in Rio de Janeiro State, Brazil. Natural Hazards, 2017, 89(1):351-365.

[12] Joko Sidik Purnomo, Yusep Muslih Purwana, Niken Silmi Surjandari. Analysis of slope slip surface case study landslide road segment Purwantoro-Nawangan/Bts Jatim Km 89+400. Journal of Physics Conference, 2017, 795(1):012069.

[13] Y. Chen, Tianbin Li, Y. Wei. Mechanism of gorge-type landslide disaster chain and its hazard evaluation. Chinese Journal of Rock Mechanics & Engineering, 2016, 35(s2):4073-4081.

[14] Chi-Wen Chen, Takashi Oguchi, Yuichi S. Hayakawa. Relationship between landslide size and rainfall conditions in Taiwan. Landslides, 2017, 14(3):1235-1240.

[15] Q. Xue, M. Zhang. Monitoring, early warning and deformation characteristics of yantu'an landslide in Yan'an. Northwestern Geology, 2018, 51(2):220-226.

[16] D. B. Kirschbaum, T. Stanley, J. Simmons. A dynamic landslide hazard assessment system for Central America and Hispaniola. Natural Hazards & Earth System Sciences Discussions, 2015, 15(10):2847-2882.

[17] Haoyuan Hong, Biswajeet Pradhan, Maher Ibrahim. Improving the accuracy of landslide susceptibility model using a novel region-partitioning approach. Landslides, 2018(1):1-20.

[18] N. Liu, L. Hu, G. Chen. Automatic monitoring and result analysis of primary school landslide in three gorges reservoir area. Journal of Geomatics, 2018, 43(4):41-44.

[19] C. -H. Zhang, M. -Z. Chen, R. -B. Zheng. Landslide hazard risk assessment and zoning of Huadu district of guangzhou based on "3S" technique and logistic regress-weighted SVM model. Journal of Ecology & Rural Environment, 2015, 31(6):955-962.

[20] Tian Qinghuai, Lin Jinhui, Wei Shengli. Measures and effects of comprehensive control of landslide:A case study of Yejialu slope of Jiande City, Zhejiang Province. Science of Soil & Water Conservation, 2015, 13(2):118-121.

[21] Christos Chalkias, Christos Polykretis, Maria Ferentinou. Integrating Expert Knowledge with Statistical Analysis for Landslide Susceptibility Assessment at Regional Scale. Geosciences, 2016, 6(1):14.

[22] Jorge Alán Salinas-Jasso, Luis G. Ramos-Zuñiga, Juan C. Montalvo Arrieta. Regional landslide hazard assessment from seismically induced displacements in Monterrey Metropolitan Area, Northeastern Mexico. Bulletin of Engineering Geology & the Environment, 2019, 78(2):1127-1141.

[23] J. C. Robbins, M. G. Petterson. Landslide inventory development in a data sparse region: spatial and temporal characteristics of landslides in Papua New Guinea. Natural Hazards & Earth System Sciences Discussions, 2015, 3(8):4871-4917.

[24] P. T. Ghazvinei, J. Zandi, J. Ariffin. Approaches for delineating landslide hazard areas using receiver operating characteristic in an advanced calibrating precision soil erosion model. Natural Hazards & Earth System Sciences Discussions, 2015, 3(10):6321-6349.

[25] Stefano Luigi Gariano, Olga Petrucci, Guido Rianna. Impacts of past and future land changes on landslides in southern Italy. Regional Environmental Change, 2017, 18(2):437–449.

[26] Hsiao-Wei Chung, Cheng-Chien Liu, I-Fan Cheng. Rapid Response to a Typhoon-Induced Flood with an SAR-Derived Map of Inundated Areas: Case Study and Validation. Remote Sensing, 2015, 7(9):11954-11973.

[27] Jewgenij Torizin, Michael Fuchs, Adnan Alam Awan. Statistical landslide susceptibility assessment of the Mansehra and Torghar districts, Khyber Pakhtunkhwa Province, Pakistan. Natural Hazards, 2017, 89(4):757-784.

[28] A Latypov, N Zharkova, I Nuriyev. Landslide hazard assessment in city under construction Innopolis (Russia). IOP Conference Series Earth and Environmental Science, 2016, 33(1):012042.