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Risk Assessment of Geological Hazards in the Alpine Gorge Region and Its Influencing Factors: A Case Study of Jiulong County, China

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Abstract: The mountainous areas in the western part of Sichuan Province are mostly Alpine Gorge regions with high mountains, steep slopes, complex topography and geomorphology, special climatic conditions, infertile soils, and fragile ecological environments. In this study, a geohazard risk assessment was carried out in the Alpine Gorge region to prevent geohazards from hindering socio-economic development, affecting the lives and safety of residents, and undermining sustainable development in the region. With the help of a geographic information system (GIS), the analysis of geohazard influence factors was carried out; eight indicators, such as elevation and slope aspect, were selected to construct the evaluation index system. Additionally, the time and space distribution pattern of each influence factor and geohazard was analyzed. Geologic hazards in the region are influenced mainly by precipitation and human engineering activities. The prediction and evaluation of geohazard risk in Jiulong County are based on the Information Value model (IV), the Logistic Regression model (LR), and the Random Forest model (RF). Comparing the Receiver operating characteristic (ROC) curves of the three models for the accuracy test, the results show that all three models are suitable for the Alpine Gorge region, and the Logistic Regression model has the highest accuracy. Based on the evaluation results, measures and countermeasures for geologic disaster prevention and mitigation are proposed in light of the reality of geologic disaster prevention and mitigation work in Jiulong County. The research results can guide the government's disaster prevention and mitigation work, provide a scientific basis for formulating regional geologic disaster prevention and control strategies, and ultimately promote the region's sustainable development.

Keywords: alpine gorge region; geological disasters; risk assessment; model accuracy; disaster prevention and mitigation

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1. Introduction

Geologic hazards are geodynamic activities or phenomena, such as landslides and mudslides, that are formed by the interaction of natural or human-made factors and cause a loss of human life and property and environmental damage [1,2]. Geohazard risk evaluation mainly studies the probability and distribution of the occurrence of geohazards due to the combination of multiple influencing factors in a certain area [3,4]. The Alpine Gorge region in southwestern China, with its abundant rainfall, steep topography, and active tectonic movements, is the most vulnerable area to mudslide disasters in China [5,6]. Geological hazards often have serious consequences, causing social and economic disruption, destroying the environment, and causing enormous losses of life and property, with serious implications for the sustainable development of the region [7–9]. In order to mitigate the losses resulting from geohazards, geohazard risk assessment emerged as a major area of interest for academics and a crucial component of global catastrophe prevention and mitigation plans [10–13]. However, the systematic analysis and research on the evaluation of the risk of geologic hazards in an Alpine Gorge region near Sichuan and Tibet and the factors affecting them are not thorough enough. Therefore, conducting a risk assessment of mountain geohazards in the Alpine Gorge region of Sichuan Province and an examination of the elements that influence them is extremely important, both theoretically and practically.

Currently, with the rapid development of geographic information system (GIS) technology, people have conducted much research on geohazard risk assessment and achieved fruitful results [14,15]. Scientific and accurate geohazard risk assessment is the key to the research of geohazard prevention and control. A large number of scholars carried out in-depth research and practice in this regard [16,17]. In terms of research content, the analysis of the key factors and the best combination of the main influencing factors in the formation of geohazards is relatively insufficient. From the perspective of research methods, the development trend of geohazard risk evaluation methods evolved from qualitative methods to quantitative methods [10]. The most popular ones are the Analytic Hierarchy Process (AHP) evaluation system [18–21], Information Value (IV) [22,23], Logistic Regression (LR) [24,25], Artificial Neural Networks (ANN) [26,27], Random Forest (RF) [28–30], and so on. All of the evaluation techniques described above have limitations and cannot fully capture the geographical pattern of geohazards in the Alpine Gorge region and their affecting factors. To directly represent the degree and severity of geological hazard risk in the research region and avoid natural catastrophes, many academics examine the geological hazard risk assessment through the comparison of various models [31,32] or improve a single model to achieve higher accuracy [33]. However, all of them have certain limitations, mainly focusing on a certain defined area as the main research subject and rarely studying a certain type of area from a macroscopic point of view. In order to meet the needs of sustainable development and environmental improvement in the future, future research should pay more attention to the difficult geological elements that are seldom studied at present, and this will be an important research trend [34,35].

In summary, this study takes Jiulong County, Sichuan Province, as the study area, analyzes the spatial and temporal distribution characteristics of geologic hazards in the Alpine Gorge region and their influencing factors by comparing three different models, and arrives at the best applicable model for evaluating the risk of geologic hazards in the Alpine Gorge region by comparing the Receiver operating characteristic (ROC) curves of the three algorithms. Finally, disaster prevention and mitigation countermeasures are proposed based on the evaluation results to develop effective disaster prevention strategies for local governments to ensure environmental safety and ultimately promote sustainable regional development.

2. Materials and Methods

2.1. Overview of the Study Area

Sichuan Province is located in the interior of southwest China, and Jiulong County belongs to Ganzi Tibetan Autonomous Prefecture of the Sichuan Province, which is located at the junction of the western Panxi region of Sichuan Province and the Tibetan Plateau, as shown in Figure 1. The river valleys in Jiulong County are mostly "V"-shaped valleys, typical of the southwest Alpine Gorge region. The area is characterized by high mountains, steep slopes, complex topography and geomorphology, special climatic conditions, infertile soil, and a fragile ecological environment. The terrain of this area has great undulation, showing a terrain high in the north and low in the south, with a big height difference, mainly divided into four major landforms: high mountains, very high mountains, mountains, and river valleys. The altitude of the high mountains in the north ranges from 4000 to 6000 m, with a maximum of 6010 m; the valleys are generally between 2000 and 3000 m. The extremely high mountains are mainly in the north, covered with snow and ice all year round.

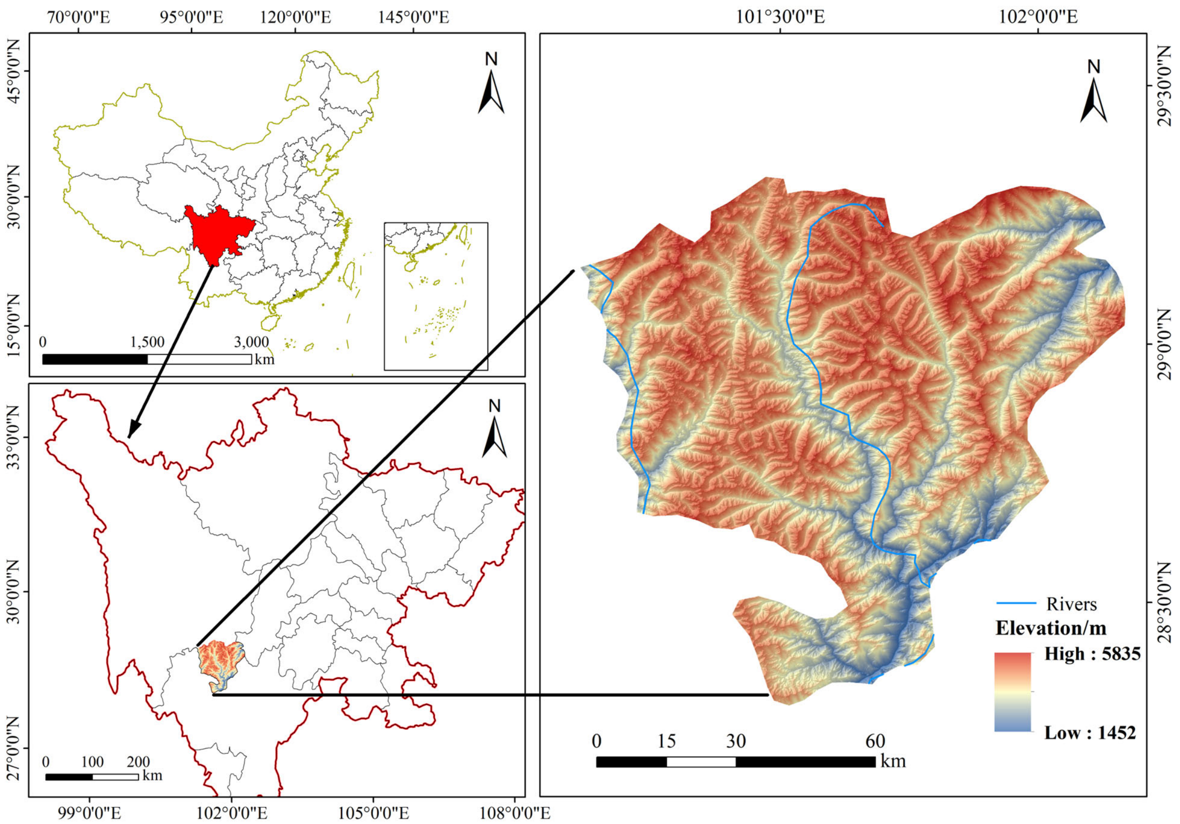

Figure 1. Geographic location of the study area in Jiulong County, Chengdu, China.

This area belongs to the continental plateau mountain monsoon climate; the summer rainfall is abundant, the climate is warm and cool, the winter is drier, the temperature is low, with a large temperature difference between day and night, and there are no obvious four seasons. The air temperature varies greatly with the altitude; the higher the altitude, the lower the temperature. From 1990 to 2019, the average annual temperature was 10.9 °C, the winter time was long, the frost-free period was short, and the average annual frost-free period was 182.2 days. There is an obvious dry rain season; the average annual precipitation is 918.57 mm. The light intensity is high, the sunshine is abundant, and the annual sunshine hours reach 1982.35 h. The rainy season extends from the middle of May to the end of September.

2.2. Data Acquisition and Preprocessing

Table 1 shows the data type and source. Based on the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) 30 M resolution digital elevation model, the spatial data analysis of the 499 geohazard hazardous sites was carried out to obtain the detailed distribution of the geohazardous sites. These data can be superimposed and modeled in the projection coordinate system. The meaning of NIR in Table 1 is Near Infrared.

Table 1. Data sources.

Data Type	Method for Data Acquisition	Data Format	Data Source
Geological hazard points	Spatialization of geological hazard points	Vector point data	Related government statistical reports
Elevation	Extracted using DEM	Raster data	Geospatial data cloud
Slope	Calculated using DEM	Raster data	Digital elevation model
Slope aspect	Calculated using DEM	Raster data	Geospatial data cloud
Terrain relief	Calculated using DEM	Raster data	Geospatial data cloud
Lithology	Vectorization from geological maps	Vector data	Geological map of Sichuan Province
Annual precipitation	Kriging interpolation from multiyear mean precipitation	Raster data	Sichuan Meteorological Bureau
NDVI	(NIR-Red)/(NIR+Red)	Raster data	Data Center of Resources and Environmental Sciences, Chinese Academy of Sciences
Land-use type	Interpreted by Landsat image remote sensing	Raster data	Data Center of Resources and Environmental Sciences, Chinese Academy of Sciences

2.3. Risk Assessment Model Construction

2.3.1. Selection of Evaluation Indexes

The development of geological disasters is affected by many factors, and different factors have different contributions to its development. Scientific selection of the evaluation index system is the key to regional geological hazard risk assessment. In view of the special topographic and geomorphic features of the study area, elevation, slope, slope aspect, NDVI, lithology, land-use type, average annual precipitation, and terrain relief were selected as the indicators for geohazard risk evaluation in Jiulong County from the perspective of the influencing geohazard factors in the Alpine Gorge region. The spatial distribution characteristics of each indicator are shown in Figure 2.

From among these eight indicators, elevation, slope, slope aspect, and topographic relief were chosen to characterize the influence of topographic and geomorphic features on geohazards, which affect geohazards by influencing the stability of regional rock and soil [12,36]. Stratigraphic lithology shows the fragility of rocks, and it can also impact the occurrence and evolution of geologic hazards [37]. Annual average precipitation is an important factor inducing the formation and development of regional geological disasters [38,39]. The region's NDIV and land use both indicate the extent to which human engineering operations disturbed the natural environment. Construction land use, in particular, has the potential to seriously undermine the region's geotechnical stability and result in geologic hazards [40].

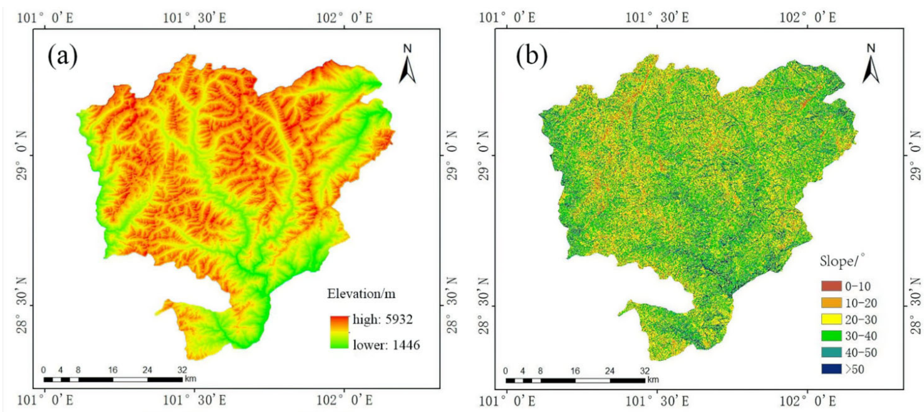

Figure 2. *Cont.*

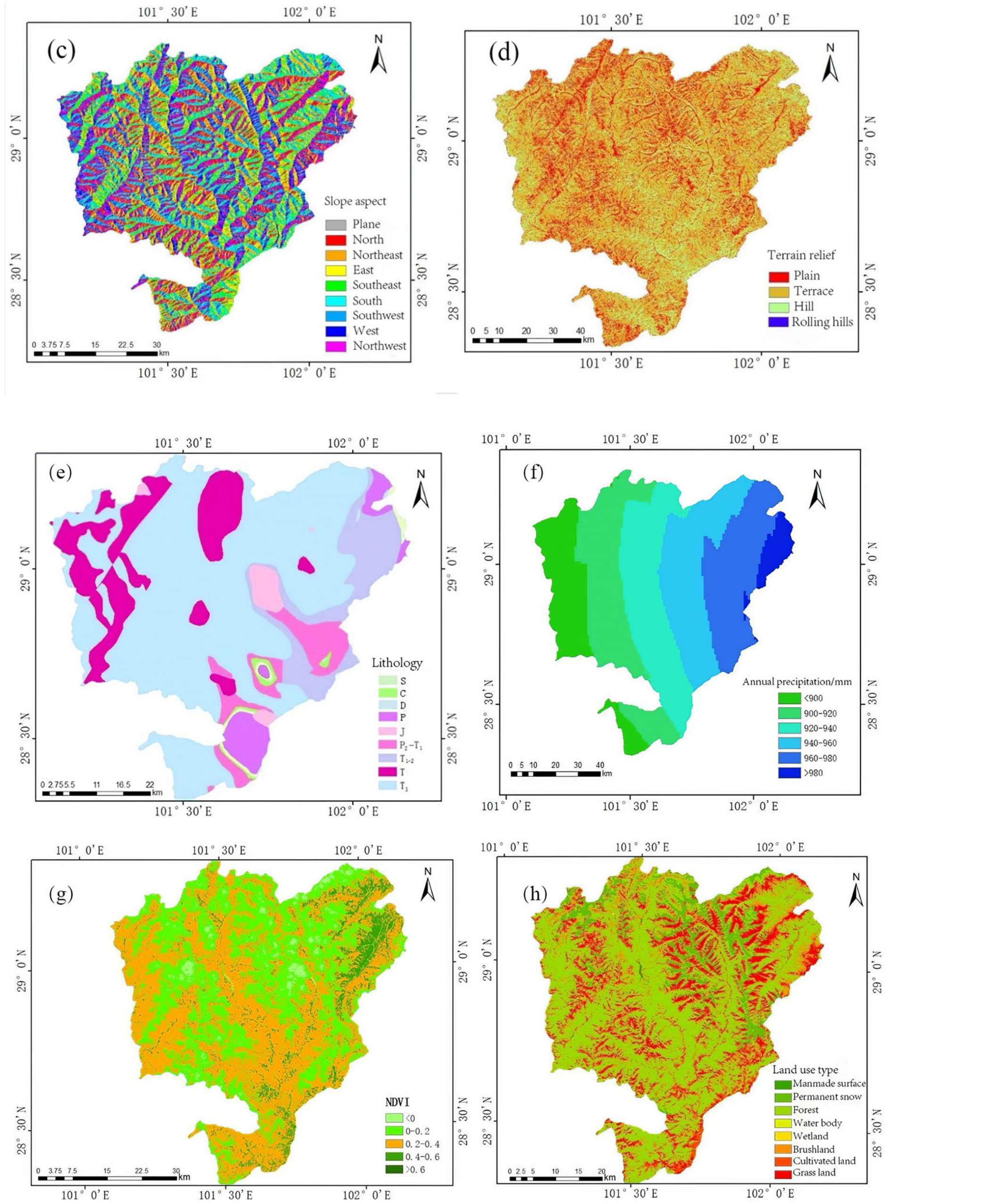

Figure 2. Spatial distribution of geological hazard risk assessment indexes. ((**a**) elevation, (**b**) slope, (**c**) slope aspect, (**d**) terrain relief, (**e**) lithology, (**f**) average annual precipitation, (**g**) NDIV, (**h**) land-use type).

2.3.2. Evaluation Factor Correlation Analysis

In this paper, based on the selected evaluation factors, the evaluation study of geological hazard risks in Jiulong County is conducted to avoid the data redundancy phenomenon between the evaluation factors due to too much similarity, which leads to the failure of the model. Based on this, it is necessary to test the independence of each evaluation factor. In the evaluation of hazards, multicollinearity can be a good test of the degree of association between the factors [41]. Multicollinearity can indicate the correlation between factors, i.e., the phenomenon that the change of one variable causes the change of another variable. Multicollinearity improves the model prediction accuracy by calculating the correlation between the evaluation factors and removing the evaluation factors with excessive correlation, and the variance inflation factor (VIF) is commonly used in the literature to test the multicollinearity of geohazard evaluation factors [42,43].

Using Statistical Product and Service Solutions (SPSS), the VIF was calculated, the correlation among the evaluation factors was analyzed, and the selected evaluation factors were analyzed by collinearity test. When the VIF value is greater than 10, it indicates that the index has a high collinear relationship.

$$VIF = 1/(1 - R_i^2) \tag{1}$$

In Formula (1), the coefficient is the complex correlation coefficient of the first independent variable to the other independent variables. The VIF values of each evaluation factor in Jiulong County are shown in Table 2. It can be seen from the table that the VIF values of the evaluation factors are all less than 10, which meets the requirements of the collinearity test. Therefore, all eight evaluation factors are applied to the risk assessment of geological disasters in Jiulong County.

Table 2. Evaluation factor collinearity test.

Evaluation Factors	Significance	VIF
Elevation	0.000	1.511
Slope	0.611	1.615
Slope aspect	0.175	1.102
Terrain relief	0.307	1.602
Lithology	0.000	1.264
Annual precipitation	0.139	1.571
NDVI	0.359	1.238
Land-use type	0.440	1.075

2.4. Hazard Evaluation Methods

2.4.1. Information Value

IV is simple to calculate, highly accurate, and widely used in the risk evaluation of landslides and other geohazards. The informativeness model is used to reflect the degree of contribution of each evaluation unit to the development of geohazards by analyzing the actual situation of the study area and converting the measured values of the influencing factors reflecting the occurrence of geohazards into informativeness values, which are used as quantitative indicators of vulnerability zoning [44,45].

For a geohazard event Y, X_i are the influencing factors that induce geohazards, *i* is the geohazard hazard indicator (i = 1, 2, 3,..., n), and $I(X_i, Y)$ is the value of the amount of geohazard information provided by each evaluation indicator. The steps of the IV calculation are as follows: (1) Calculate the informativeness value $I(X_i, Y)$ for each evaluation indicator X_i

$$\mathrm{I}(\mathrm{X}_i, \mathrm{Y}) = \ln\left(\frac{N_i/N}{S_i/S}\right) \tag{2}$$

In Equation (2): N is the total number of geohazard hazard sites developed in the study area; S is the total area of the study area; N_i is the number of geohazard hazard sites developed of a certain category distributed within the evaluation unit indicator X_i; S_i is the study area of the evaluation indicator X_i contained in the zone. (2) Calculate the total information I_i: In Equation (3): n is the number of causative factors.

$$\mathrm{I}_\mathrm{i} = \mathrm{I}(\mathrm{X}_\mathrm{i}, \mathrm{Y}) = \sum_{i=1}^{n} \ln\left(\frac{N_i/N}{S_i/S}\right) \tag{3}$$

The eight evaluation indexes selected by the research institute were counted, analyzed, and calculated by the GIS system to obtain the total Information Value of geological hazards in Jiulong County. When the value of information is greater than 0, it means that the disaster-causing factor is favorable to the development of geological hazards, and vice versa means that it is unfavorable to the development of geological hazards. The greater the value of information, the more dangerous the area.

2.4.2. Logistic Regression

LR is a regression analysis model for dichotomous variables, where the dependent variable is a dichotomous variable, and the independent variables can be either continuous or discontinuous variables [46]. LR is widely used in geohazard risk assessment because of its nonlinear characteristics and clear physical significance [47,48]. The dependent variable of binary Logistic Regression is dichotomous, and the outcome of the dependent variable can only be "yes" or "no", usually expressed as "1" or "0". The result of the dependent variable can only be "yes" or "no", which is generally indicated by "1" or "0". In the prediction and evaluation of geologic hazard risk, a value of "1" means that a geologic hazard occurs, and a value of "0" means that no hazard occurs [49]. The probability of a disaster occurring is p, and the function $f(p)$ is set to perform a logical transformation:

$$f(p) = \ln \frac{p}{1-p} \tag{4}$$

$$ln\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_1 + \cdots\cdots + \beta_i x_i \tag{5}$$

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_1 + \cdots\cdots + \beta_i x_i \tag{6}$$

In Equations (5) and (6): $\beta 0$, $\beta 1$, $\beta 2$,..., βi are Logistic Regression coefficients; z is the geohazard sensitivity function, which is related to the geoenvironmental factor Xi and is linear. The probability of geohazard occurrence is obtained by bringing in the above equation:

$$p = \frac{1}{1+e^{-z}} \tag{7}$$

In Equation (7): p is the probability of occurrence of geohazards, taking the value range [0, 1], and the regional geohazard risk prediction can be obtained through GIS calculation and analysis.

2.4.3. Random Forest

Random Forest is an ensemble learning method, constructing multiple decision trees through different data subsets and voting on the results of multiple decision trees to obtain the output of the Random Forest [50]. RF is a common integrated machine learning model in the current geohazard risk assessment research, based on the data iteration, which can significantly reduce the amount of computation. RF is a combined model from the combination of each decision tree, which utilizes Bootstrap for sampling. N samples are extracted from the original training set to form a training set, and the sample size of each sample is the same as that of the original training set. The unsampled samples are called out-of-bag (OOB), which can be used to assess the reliability of the model, called OOB estimation [51]. Assuming that the sample has a total of M features, set a feature number P less than or equal to M and randomly select P features from it as the split feature set. Create a decision tree and out-of-band data, respectively. Compose the generated decision tree into a Random Forest and then perform classification prediction or regression analysis. Geological hazard risk assessment is used for classification prediction, and finally, each record is voted according to various classification results to finalize its classification [52]. It is important to avoid subjectivity in parameter setting when constructing a Random Forest model and to improve the predictive ability of the model by constructing different training sets so that the variability among its classification models increases [53].

3. Results

3.1. Characteristics of the Temporal Distribution of Geologic Hazards

Figure 3 represents the distribution of the number of geologic hazards by month in Jiulong County during the period from 1999 to 2020, where yellow, blue, and red correspond to debris flows, collapses, and landslides, respectively. Statistics show that when the annual rainfall is less than 920 mm, the proportion of earthquake disasters is 22.85%. When the annual rainfall is greater than 920 mm and less than 940 mm, the proportion of earthquake disasters is 41.08%. When the annual rainfall is greater than 940 mm, the proportion of earthquake disasters is 36.7%. In recent years, precipitation has played an important role in geological disasters. As one of the important inducements of regional geological disasters, its influence on geological disasters in Jiulong County is mainly based on the dividing line of annual rainfall 920 mm. Years greater than this value are more prone to geological disasters. Moreover, the occurrence of geological disasters has a certain fluctuation. During the period from May to August every year, geological disasters have an overall increasing trend, which is positively related to the monthly rainfall. The increase in precipitation destabilizes the slopes and increases the possibility of geologic hazards. The possibility of geohazards is higher in areas with relatively high rainfall because rainfall causes rainwater to erode the geotechnical body, which increases the gravitational force on the material on the slope, leading to an increase in the downward force. At the same time, the water content also increases, the geotechnical body becomes softer, the shear strength becomes lower, and the stability decreases and, ultimately, induces geohazards.

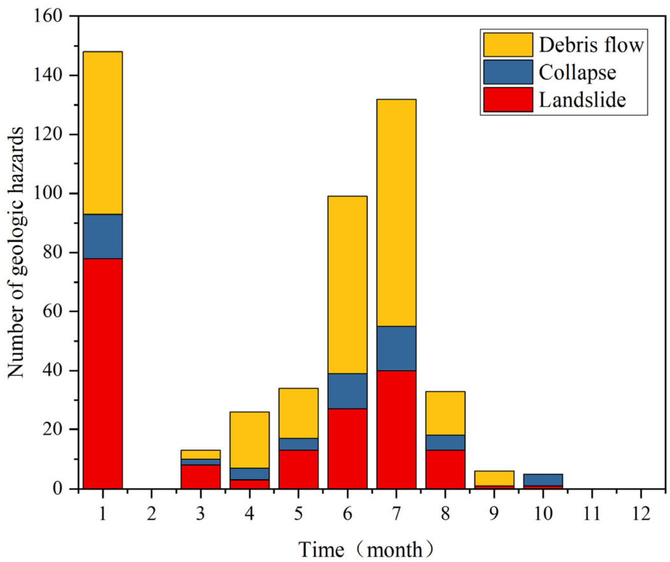

Figure 3. Monthly distribution of the number of geologic hazards developed in Jiulong County between 1999 and 2020.

3.2. Characteristics of the Spatial Distribution of Geologic Hazards

The interplay of elements, including the natural environment and human activity, affects the formation of geologic hazards. Due to the complex geological conditions in the whole study area, geologic hazards are characterized by a large number and wide distribution. As analyzed in Figure 2, the geologic hazard sites in Jiulong County are mainly distributed between elevations of 2000 and 2800 m, slopes between 10 and 30°, and slope aspects due east and southeast.

3.3. Analysis of Factors Affecting the Occurrence of Geologic Hazards

Analyzing the causes of geologic disasters can clarify the spatial distribution characteristics of geologic disasters, reduce the losses of geologic disasters, promote sustainable development in the region, and provide a basis for successful disaster prevention and mitigation. The influencing factors of geohazards in the Alpine Gorge region are mainly divided into two aspects, including natural factors and human activity factors. For example, heavy rainfall, as an important natural factor, is the main cause of geohazards such as landslides, avalanches, and mudslides, which, in turn, lead to serious casualties and economic losses; at the same time, since heavy rainfall occurs mostly in May–August, May–August is also the most frequent period of geohazards. From the viewpoint of human activity factors, engineering construction, slope excavation, mining, and other human engineering activities will have a certain impact on the topography and geomorphology. Engineering construction will increase the burden of the slope body, make the slope body lose its original stability, and under the combined influence of various factors, lead to slope instability, thus inducing geological disasters.

Table 3 describes the construction time of hydropower plants in Jiulong County, average annual energy production, etc. The mainstream section of Jiulong River adopts the "one reservoir, five stages" gradient development program, which consists of Xigu Reservoir, Wuyiqiao, Shaping, Pianqiao, and Jiangbian Hydropower Station from top to bottom, and the first-grade tributary of Taca River on the left bank, which consists of two graded hydropower stations, namely, Xieka Hydropower Station and Taca Hydropower Station, from top to bottom. These hydropower plants generate an average of about 150 Billion kwH per year, guaranteeing sustainable development in the region. The water system of the basin is developed in the form of feathers, and the rock layer along the river is strongly weathered, cut, and broken. The stability of the bank slopes is poor, coupled with the frequent development of hydropower along the coast as well as the construction of large- and medium-sized projects, the basin suffers from landslides, avalanches, mudslides, and other geologic hazards, which are becoming more and more serious.

Table 3. Development of hydropower plant construction in Jiulong County.

Hydropower Station	Building Time	Elevation	Mean Annual Energy Production
Xigu	2010–2013	2860 m	10.55 Billion kW·h
Wuyiqiao	2008–2009	2200 m	6.24 Billion kW·h
Shaping	2005–2008	2187 m	7.80 Billion kW·h
Pianqiao	2005–2008	2005 m	10.91 Billion kW·h
Jiangbian	2008–2011	1797 m	110.43 Billion kW·h
Xieka	2009–2014	3168 m	5.18 Billion kW·h
Taka	2008–2010	2657 m	4.96 Billion kW·h

Data sources: Large Dam Safety Supervision Center, National Energy Administration.

Figure 4 indicates that the annual number of geological disasters that occurred in Jiulong County from 1999 to 2020 will be a disaster year every few years. The number of geological disasters in Jiulong County was higher in 2005, 2008, and 2012, during which several hydropower stations began to be constructed. It can be visualized that in the early stages of hydropower plant construction, geohazards increased to a certain extent. The frequent development of hydropower projects in the Alpine Gorge region makes geologic disasters in the region inevitable, and it is indispensable to analyze the factors affecting geologic disasters in the Alpine Gorge region to guarantee a stable power supply every year, promote economic development, and facilitate the sustainable development of the region.

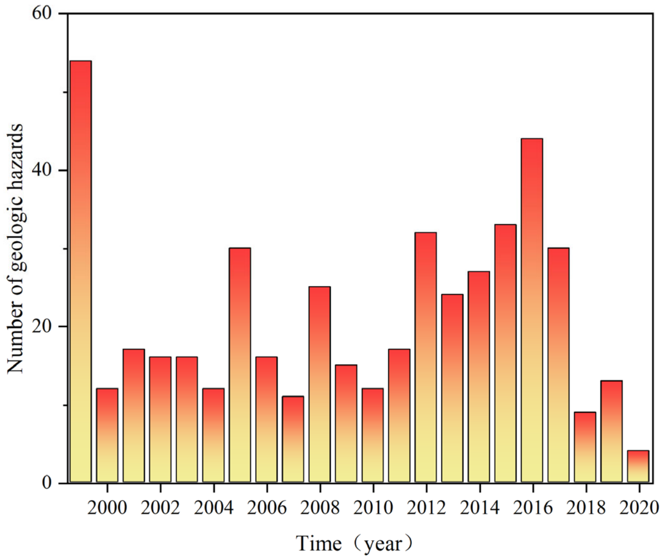

Figure 4. Distribution of the number of geologic hazards in Jiulong County, 1999–2020.

4. Discussion

4.1. Verification of the Accuracy of Geohazard Evaluations

The Receiver operating characteristic curves are a common method for verifying the accuracy of geologic hazard-prone areas. Drawing the ROC curve does not need to select the classification threshold, which avoids the interference of too many human factors on the accuracy verification and has better objectivity [54,55].

4.2. Comparison of Evaluation Results of Different Models

Based on the features of their individual research domains, many academics selected appropriate assessment models and subsequently assessed the geohazard risk in the area. Nonetheless, the range of applicability for various assessment frameworks varies. Next, we mainly compare the relationship between the distribution of geohazard sites and the risk zoning of the following three models. Table 4 divides the risk level into five levels, the area and percentage occupied by the three different modeling methods in different risk levels, and the relationship between the distribution of geohazard sites and the risk level zoning.

Table 4. Relationship between the distribution of geologic hazard sites and hazard zoning.

Modeling Approach	Risk Level	Area (km^2)	Area Proportion	Number of Disaster Points	Percentage of Disaster Points
Information Value	Low risk	2350.69	34.72%	0	0
	Medium–low risk	2037.27	30.09%	1	0.20%
	Medium risk	1018.63	15.03%	16	3.21%
	Medium–high risk	940.28	13.89%	88	17.64%
	High risk	423.13	6.25%	394	78.96%
Logistic Regression	Low risk	2187.15	32.31%	0	0
	Medium–low risk	2269.17	33.52%	2	0.41%
	Medium risk	1214.65	17.94%	35	7.01%
	Medium–high risk	747.54	11.04%	105	21.04%
	High risk	351.51	5.19%	357	71.54%
Random Forest	Low risk	3342.30	49.37%	0	0
	Medium–low risk	1264.83	18.68%	14	2.81%
	Medium risk	916.46	13.54%	36	7.21%
	Medium–high risk	689.94	10.19%	119	23.85%
	High risk	556.46	8.22%	327	66.13%

Through the zoning classification by GIS using the natural breakpoint method, the area of hazardous zones of the three models is roughly the same. None of the low hazardous zones has the distribution of hidden hazard points, and the number and surface density of hidden hazard points in the high hazardous zones are the largest. Moreover, with the increase in the degree of danger, the number and surface density of geohazard development increases, but the area of danger zoning decreases, and the results are in line with the actual distribution law of hidden hazard points. The area of high-risk zone accounts for about 6% of the total area in Jiulong County, of which the distribution of geologic hazard sites accounts for about 70%. Among them, the distribution of LR zoning and geologic hazard sites is shown in Figure 5. On the left side, the risk class zones of the Logistic Regression model are shown, and on the right side, the distribution of hazard sites is labeled on the left side, and it is easy to find that the number and density of sites in the high-risk area are the largest. According to the geographic terrain, the terrain is high in the north and low in the south, with many "V"-shaped valleys, which is typical of the Alpine Gorge region. The high-risk area is more in the south than in the north and in the center than in the east and west, and it is concentrated in populated areas such as rivers and highways. High-risk areas are more in the south than in the north, more in the center than in the east and west, and are mainly concentrated in densely populated areas such as rivers and highways.

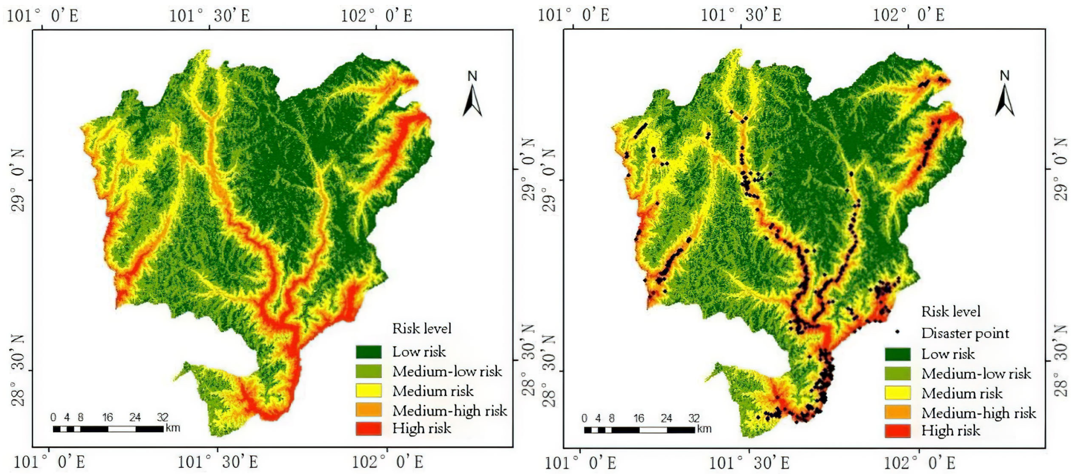

Figure 5. LR model zoning and distribution of geologic hazard sites.

The ROC curves of different models are shown in Figure 6; the area under the curve of the IV model, LR model, and RF model is 0.901, 0.914, and 0.875, respectively, which indicates that the results of the geohazard risk assessment of the three models are accurate and reliable in this region, and the LR model has the largest area under the curve, which is the most suitable model to be used for geohazard risk assessment in the Alpine Gorge region.

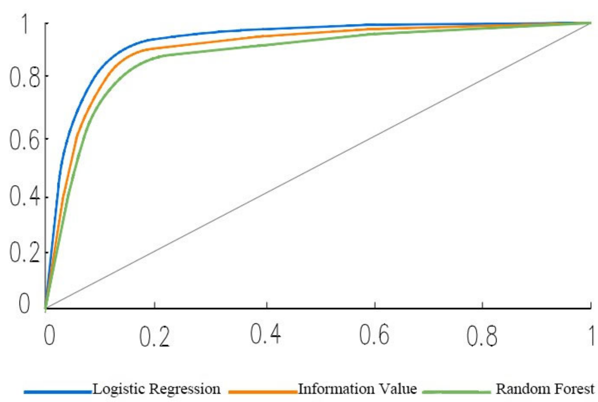

Figure 6. Evaluation of model ROC curves.

4.3. Strategy for the Development of Geohazardous Priority Areas

The purpose of the risk assessment of geologic hazards in the Alpine Gorge region is the prevention and control of geologic hazards, clarification of the factors affecting geologic hazards, provision of a theoretical basis for prevention and control, improvement of the comprehensive disaster prevention and mitigation capacity, and ultimately, promotion of sustainable development in the region.

Combined with the actual situation in Jiulong County, an emergency shelter is planned in each township. For high-risk areas to avoid geological disasters in time, it is also recommended to reduce the loss through relocation. Additionally, protective measures can be conducted in advance, early warning can be emphasized, and the source of danger can be eliminated; for other hazardous areas, through monitoring and early warning as well as the planning of the emergency shelter, disaster reduction can also be achieved. Based on GIS technology, according to the results of risk prediction and evaluation, the emergency refuge sites in Jiulong County are selected. There are three principles governing the location and layout of emergency shelters: accessibility—emergency shelters should be as close as possible to residential areas, roads, and towns and should be within reach when danger occurs; scientific—the selection of emergency refuge sites should avoid medium- and high-risk areas to prevent secondary disasters; safety—the service area of emergency refuge should be set according to the number of residents to meet the refuge needs of residents and ensure the safety of residents. Moreover, an emergency command center should be set up near the emergency refuge, the public and relevant departments should receive early notification and warning in a timely manner, and disaster prevention and reduction in the region should be improved through the provision of necessary rescue and evacuation guidelines. The proposed layout of the emergency refuge is shown in Figure 7.

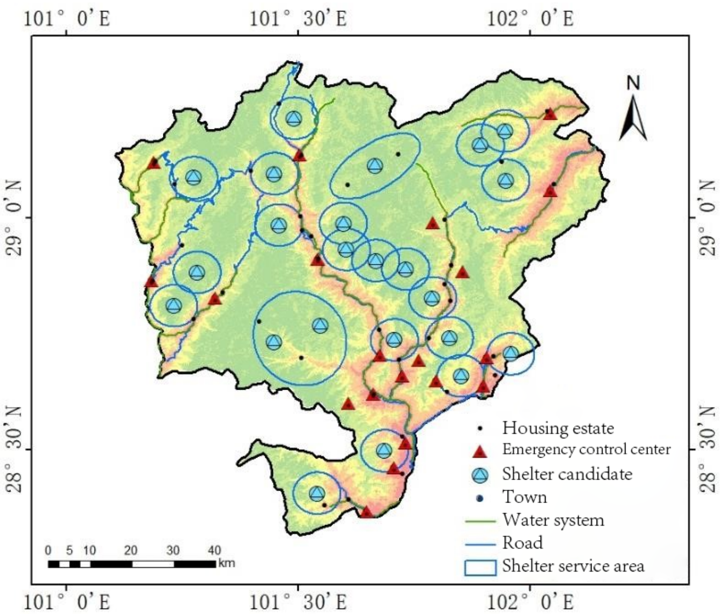

Figure 7. Jiulong County emergency shelter planning recommendations.

5. Conclusions and Recommendations

5.1. Conclusions

The temporal and spatial distribution and influencing factors of geohazard risk in the Alpine Gorge region are analyzed based on three different models and validated for comparison. The main conclusions are as follows.

1. The Alpine Gorge region experiences geological disasters as a result of human activity and the environment working together. The natural environment is mainly reflected in the fact that the development of disasters coincides with the cycle of precipitation,

which is mainly concentrated in May–August. Human activities together are mainly reflected in the fact that the years of heavy disasters often correspond to the early stage of hydropower project construction in the Alpine Gorge region. Precipitation and human engineering activities are the main factors inducing geohazards in the Alpine Gorge region.

2. Geological hazard sites in Jiulong County are mainly distributed between elevations of 2000 and 2800 m, with slopes between 10 and 30° and slope aspects due east and southeast. The high-risk areas are more in the south than in the north, more in the center than in the east and west, and are mainly concentrated in densely populated areas such as rivers and highways.
3. The IV model, LR model, and RF model can be applied in the risk assessment of Alpine Canyon. The LR model was verified by the ROC curve to be the most accurate and more suitable for the Alpine Gorge region.

5.2. Recommendations

The western part of Sichuan Province is characterized by complex geological conditions, high mountains and steep slopes, complex topography and geomorphology, special climatic conditions, infertile soil, and a fragile ecological environment. The frequent occurrence of geologic disasters and severe disaster situations seriously hinder social and economic development and affect the life and safety of residents, and the development of geologic disaster risk assessment is a need for the sustainable development of the region. Future studies should focus more on the challenging geological elements that are currently understudied. Additionally, to conduct research appropriate for particular global regions, data fusion, processing, and association mining must be investigated to enhance and compare the accuracy of various models.

This study can improve the scientific nature of the government's geohazard prevention and control strategy formulation, and the specific recommendations are as follows: local governments should formulate targeted regional sustainable development strategies around the core areas with large geohazards; additionally, the government needs to pay more attention to ecological and environmental issues, avoid the impact of human engineering activities on the sustainable development of energy resources in the region, strengthen the awareness of geohazard prevention, and improve preventive capabilities in the development of hydroelectricity and the construction of large- and medium-sized projects. Moreover, the government should improve preventive capacity and increase the frequency of emergency drills during the rainfall season to improve the residents' awareness of geologic disaster prevention and emergency response. In the case of disasters, timely forecasts and warnings of geologic disasters will be made to reduce the possible hazards caused by geologic disasters.

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