# SUSCEPTIBILITY ASSESSMENT OF RAINFALL-INDUCED DEBRIS FLOW IN THE LOWER REACHES OF YAJIANG RIVER BASED ON GIS AND CF COUPLING MODEL

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**KEY WORDS:** Rainfall debris flow, Analytic Hierarchy Process, Binary Logistic Regression, Random Forest, Certainty factor model, Susceptibility.

**ABSTRACT:**

The lower reaches of the Yajiang River are high in the east and low in the west, with abundant rainfall, and contain a large amount of hydropower resources that have not been exploited and utilized. Nonetheless, due to the unique geographical environment in southeast Tibet, rainfall debris flow is one of the frequent geological disasters in this area. In this research, 42 debris flow points were collected, ten disaster-causing factors were selected, and satellite elevation data were analyzed to evaluate the disaster susceptibility of the study area. The disaster-causing factors information is extracted from Arcgis. The certainty factor model (CF) was used to calculate the coefficient of certainty of 10 factors including fault distance, elevation, normalized difference vegetation index (NDVI), average annual rainfall, profile curvature, relief, silt content, TWI, SPI, and slope aspect. The Analytic Hierarchy Process (AHP), Binary Logistic Regression (LR), Random Forest (RF) and CF model were used to analyze and predict the possibility of debris flow occurrence. The results show that the accuracy of the CF-LR model is the highest under the verification of the ROC curve. In the prediction model, the high-risk areas of debris flow are mainly concentrated in the first half of the lower reaches of the Yajiang River and distributed along both sides of the river bank. After bringing the data of different annual rainfall into the model, it is found that the saturation critical value of debris flow water source in the study area is within the range of 600-700mm annual rainfall.

## 1. INTRODUCTION

Debris flow is a fluid mixture carrying water, sand and stones, which commonly erupts in the rainy season and has great explosive power and destructive power. Due to the influence of climate, environment and other factors, mudslides account for about 58 percent of the total geological disasters in Tibet, which critically affects the safety of local people and property. It occurs predominantly in the southeast of Tibet, and the time of occurrence is concentrated from May to September when the rainfall is high.

Southeast Tibet, with complex hydrological conditions, is the site of the great bend of the Yarlung Zangbo River. The lower reaches of the Yajiang River are characterized by large terrain drops, abundant rain and a narrow and deep valley, so it contains enormous water energy and can create more excellent value in agriculture, fishery, forestry and ecological environment protection. However, its steep terrain and massive flood also create good conditions for debris flow. It poses a potential threat to nearby engineering facilities.

In recent years, many methods have been proposed to study geological hazards. The qualitative analysis method represented by the Analytic Hierarchy Process (AHP) was first presented and widely used in geological disaster risk assessment. Research results showed that it can accurately predict the prediction of disaster risk distribution within ten years. Later, quantitative methods such as Fuzzy Comprehensive Analysis and Binary Logistic Regression combined with GIS have been widely applied in the geological disaster evaluation system, among which Binary Logistic Regression is the most outstanding method. Nowadays, with the rise of machine learning, Decision Tree, Random Forest, Convolutional Neural Network and other machine learning methods have been widely used in the research of debris flow risk prediction. Compared to the results of many previous studies, Random Forest stands out among other methods because of its high accuracy, low redundancy and fast learning speed. The certainty factor(CF) is a method to manage uncertainty in a rules-based expert system. It is a model developed by Shortliffe and Buchanan in the mid-1970s and widely used in medical diagnosis research in the early stage. Now it is generally used in the field of geological hazard risk assessment.

The selection of disaster factors is the basis for making a geological hazard susceptibility evaluation map. Considering the special hydrological and rainfall conditions near the Yajiang River, the topographic humidity index(TWI), the Standard Precipitation Index(SPI), profile curvature, average annual rainfall and other hydrologic-related disaster factors were selected. The certainty factor can calculate CF values of different categories of the same element. The southeast of Tibet is dominated by rainfall-type debris flow. By substituting CF values of annual rainfall of different categories, the susceptibility map of debris flow under different rainfall conditions can be obtained, so as to study the influence of annual rainfall on debris flow.

The specific flow chart of this paper is shown in Figure 1. Firstly, different analysis methods are used to study the susceptibility of debris flow. Secondly, the accuracy of different models was compared by the ROC curve. Then, the model with the highest accuracy is selected to make and analyze the debris flow disaster distribution map. Finally, combined with the susceptibility of debris flow under different annual rainfall, the threshold interval of debris flow rainfall in the study area is obtained. The three main purposes of this study are as follows:(1) The accuracy of CF-AHP, CF-LR and CF-RF coupled models for predicting debris flow was calculated; (2)

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To predict the distribution of debris flow susceptibility in the study area; (3) To analyze the susceptibility of debris flow under different annual rainfall intensity, and find the annual rainfall threshold.

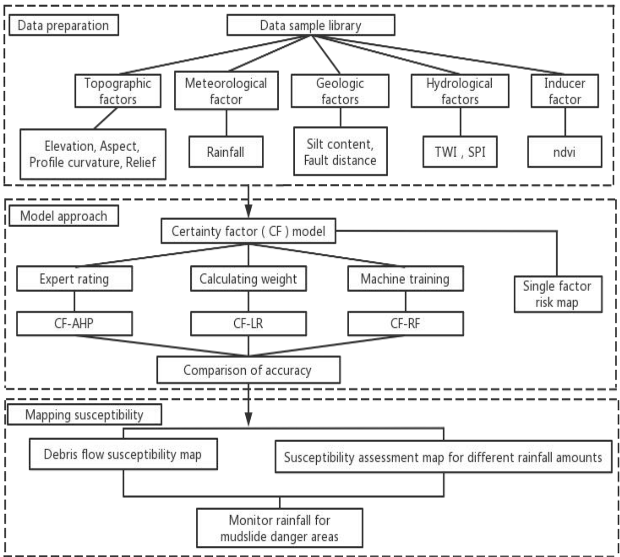


**Figure 1**. Flow chart of research method.

## 2. THE STUDY AREA

### 2.1 Research Scop

The research area is located in the southeast of Tibet, in a temperate monsoon climate with abundant rainfall and an average annual temperature of 8.7℃ without high temperature throughout the year. Yajiang flows from Lang County into Nyingchi City, from Modog County into India. The elevation ranges from 86 to 5110m.

The Yajiang River basin is prone to natural geological disasters, which will cause serious damage to the surrounding environment. For example, in 2010, an ice collapse occurred in India due to weather conditions, which subsequently triggered a massive mudslide disaster, causing continuous damage to 437 basic hydropower facilities. In 2013, flash floods and landslides caused by heavy rainfall in northwestern Himalayan State killed more than 6000 deaths. In this paper, the width of the two banks of the Yajiang River in southeast Tibet is 2 km as the study area. The area accounts for about 4309.5 ㎢, recorded 42 potential debris flow points. In order to calculate and verify the model, another 42 non-debris flow points in the study area were randomly selected. The assessment work was carried out through 84 debris flow sample points, as shown in figure2.

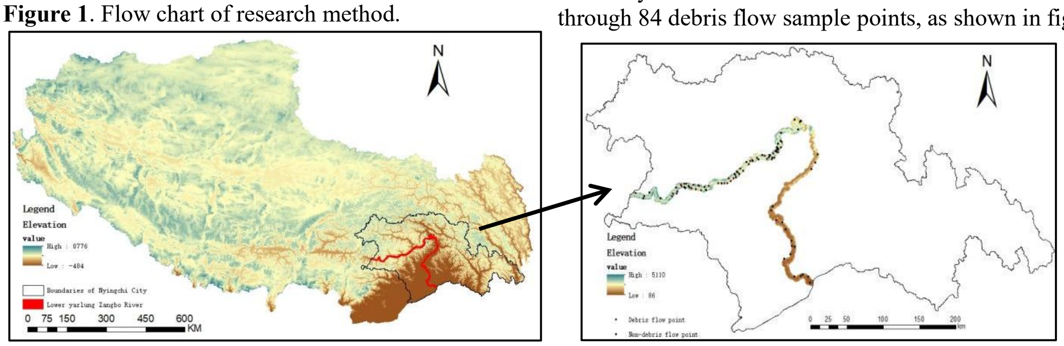


**Figure 2**. Scope of the study area.

### 2.2 Disaster-inducing factors

**2.2.1 Topographic factors**: The research area has a special plateau environment. The weathering degree of rocks, climatic conditions and natural environment are distinctive at different elevations. Slope aspect affects sunshine duration, vegetation growth and airflow direction. The profile curvature can better reflect the concavity of the overall topography than the slope. Refers to the difference between the highest elevation and the lowest elevation in a specific region, and the formula is:

$$H = h_{max} - h_{min} \qquad (1)$$

**2.2.2 Meteorological factors**: Most of the debris flows in southeast Tibet are rainfall type, and the outbreak time is concentrated in the rainfall season. Because the topographic geology and environmental conditions do not change much in a short period of time, the average annual rainfall is taken as the main factor in this study.

**2.2.3 Geological factors**: After weathering for a long time, the surface of some rocks becomes silty sand and melts into the soil. According to the content of silty sand in the soil, the weathering of surrounding rocks can be known. In addition, severely weathered rocks can be transformed into solid sources of debris flow under certain conditions. Therefore, the content of silt and sand is selected as the geological factor.

The seismic fault zone in southeast Tibet is active. The earthquake will seriously damage the mountain structure, damage the ecological environment, cause secondary geological disasters, is a natural disaster that cannot be predicted at present.

**2.2.4 Hydrological factors**: TWI and SPI are important hydrological factors commonly used in the study of geological hazards. The calculation is as follows:

$$TWI = ln(\alpha / tan(Slope)) \qquad (2)$$

$$SPI = \alpha \times tan(Slope) \qquad (3)$$

where α is the cumulative upslope area of a drainage basin through a point and tan(Slope) is the angle of the slope at the same point. α high index value indicates a great potential of water accumulated due to low slope angles.

**2.2.5 Inducer factors**: Vegetation coverage has the function of preventing soil erosion, especially in areas with high rainfall. But in the case of debris flow, vegetation can also become a solid source.

**2.2.6 The data source**: Elevation data were obtained from ASTGTM2 satellite images with an accuracy of 30 m. Debris flow sites were provided by geological disaster survey data of counties and cities in Tibet Autonomous Region. Other data were obtained from the Center for Resources and Environmental Science and Technology, Chinese Academy of Sciences.

## 3. MATERIALS AND METHODS

### 3.1 Certainty Factor model

The CF model can well calculate the CF values of different categories of the same factor, and the calculation formula is as follows:

$$CF = \begin{cases} \dfrac{PPa - PPs}{PPa * (1 - PPs)} & if \;\; PPa > PPs \\ \dfrac{PPa - PPs}{PPs * (1 - PPa)} & if \;\; PPa < PPs \end{cases} \quad (4)$$

Where PPa is the occurrence probability of debris flow points in different categories of single factor area, and PPs is the occurrence probability of debris flow points in the total study area. CF values range from -1 to 1, with the closer to 1 the more certain, and the closer to -1 the more uncertain.

The 10 disaster causing factors of 42 debris flow sample points in the study area were classified. The CF value is calculated by CF model, as shown in Table 1.

| Disaster factor | classification | Category area（㎢） | Debris flow point | The total number of（%） | CF |
|---|---|---|---|---|---|
| Fault distance | 0-2000 | 390.1167 | 3 | 7.14 | -0.2126 |
| | 2000-4000 | 787.4118 | 9 | 21.43 | 0.1488 |
| | 4000-6000 | 477.3636 | 6 | 14.29 | 0.2268 |
| | 6000-8000 | 434.9799 | 5 | 11.90 | 0.1536 |
| | 8000-10000 | 640.6857 | 4 | 9.52 | -0.3616 |
| | 10000-12000 | 256.8735 | 9 | 21.43 | 0.7289 |
| | 12000-14000 | 99.7353 | 6 | 14.29 | 0.8462 |
| Elevation | 2900-3100 | 657.1017 | 17 | 40.48 | 0.6294 |
| | 3100-3300 | 369.9387 | 7 | 16.67 | 0.4897 |
| | 3300-3500 | 296.8272 | 7 | 16.67 | 0.5925 |
| | 3500-3700 | 261.7623 | 4 | 9.52 | 0.3658 |
| | 3700-3900 | 213.7941 | 5 | 11.90 | 0.5890 |
| | 3900-4100 | 153.8442 | 2 | 4.76 | 0.2528 |
| NDVI | 0.2-0.4 | 259.7121 | 3 | 7.14 | 0.1578 |
| | 0.4-0.6 | 486.9963 | 11 | 26.19 | 0.5741 |
| | 0.6-0.8 | 1062.332 | 18 | 42.86 | 0.4290 |
| | 0.8-1 | 2428.728 | 10 | 23.81 | -0.5799 |
| Average annual rainfall | 600-700 | 1263.117 | 3 | 7.14 | -0.7581 |
| | 700-800 | 1779.83 | 22 | 52.38 | 0.2136 |
| | 800-900 | 1069.183 | 14 | 33.33 | 0.2582 |
| | 900-1000 | 183.0861 | 3 | 7.14 | 0.4092 |
| Profile curvature | 0-5 | 1071.729 | 13 | 30.95 | 0.1985 |
| | 5-10 | 1509.003 | 16 | 38.10 | 0.0816 |
| | 10-15 | 962.2728 | 7 | 16.67 | -0.2554 |
| | 15-20 | 471.6315 | 5 | 11.90 | 0.0815 |
| | 20-25 | 197.0577 | 1 | 2.38 | -0.4817 |
| Relief | 0-10 | 264.9465 | 7 | 16.67 | 0.6373 |
| | 10-20 | 535.6998 | 9 | 21.43 | 0.4240 |
| | 20-30 | 512.3988 | 5 | 11.90 | 0.0013 |
| | 30-40 | 586.0062 | 4 | 9.52 | -0.3017 |
| | 40-50 | 641.7855 | 6 | 14.29 | -0.0411 |
| | 50-60 | 595.4427 | 2 | 4.76 | -0.6576 |
| | 60-70 | 458.5059 | 4 | 9.52 | -0.1058 |
| | 70-80 | 301.1166 | 0 | 0.00 | -1.0000 |
| | 80-90 | 177.4665 | 3 | 7.14 | 0.4276 |

| | | | | | |
|---|---|---|---|---|---|
| | 90-100 | 236.2662 | 2 | 4.76 | -0.1325 |
| Silt content | 10-20 | 335.1366 | 3 | 7.14 | -0.0822 |
| | 20-30 | 2598.244 | 27 | 64.29 | 0.0628 |
| | 30-40 | 963.4104 | 12 | 28.57 | 0.2197 |
| TWI | <0 | 1262.587 | 10 | 23.81 | -0.1888 |
| | 0-2 | 1247.879 | 10 | 23.81 | -0.1792 |
| | 2-4 | 943.4673 | 5 | 11.90 | -0.4587 |
| | 4-6 | 350.8659 | 2 | 4.76 | -0.4175 |
| | 6-8 | 141.7248 | 3 | 7.14 | 0.5449 |
| | 8-10 | 173.4723 | 5 | 11.90 | 0.6684 |
| | 10-12 | 130.9842 | 6 | 14.29 | 0.7950 |
| | 12-14 | 28.9854 | 1 | 2.38 | 0.7246 |
| | >14 | 29.5353 | 0 | 0.00 | -1.0000 |
| SPI | <-8 | 414.8919 | 5 | 11.90 | 0.1932 |
| | -8,-4 | 872.6598 | 8 | 19.05 | -0.0599 |
| | -4,0 | 877.1535 | 12 | 28.57 | 0.2904 |
| | 0-4 | 1930.46 | 15 | 35.71 | -0.2043 |
| | 4-8 | 203.0436 | 2 | 4.76 | 0.0107 |
| Aspect | north | 532.7046 | 6 | 14.29 | 0.1360 |
| | northeast | 513.9783 | 3 | 7.14 | -0.4035 |
| | east | 484.9236 | 2 | 4.76 | -0.5792 |
| | southeast | 543.9105 | 5 | 11.90 | -0.0573 |
| | south | 543.357 | 7 | 16.67 | 0.2459 |
| | southwest | 559.8576 | 5 | 11.90 | -0.0844 |
| | west | 539.8083 | 4 | 9.52 | -0.2415 |
| | northwest | 580.2552 | 10 | 23.81 | 0.4388 |
| | plain | 10.7055 | 0 | 0.00 | -1.0000 |

**Table 1**. CF values of 10 disaster-causing factor classification levels.

### 3.2 CF-AHP

The Analytic Hierarchy Process (AHP) is an evaluation method combining qualitative and quantitative methods, which decomposes the elements related to decision-making into levels of objectives, criteria and schemes, etc. The core is to rely on experts to score the disaster-causing factors and calculate the results after the evaluation matrix passes the consistency test]. The factor weight w can be calculated by AHP. Each factor w multiplied by the corresponding CF value was added to obtain the debris flow occurrence coefficient φ of the grid cell. If φ>0, debris flow may occur. The larger φ is, the greater the possibility is. If φ< 0, no debris flow will occur. Finally, 84 debris flow points in the sample database were used to verify the accuracy.

In order to judge the rationality of factor scoring, formula (5) is obtained by converting Aw=λw and then $\lambda_{max}$ is calculated. According to Formula (6), CI can be obtained. The smaller the CI value is, the more reliable the weight is. When CR<0.1, the matrix passes the consistency test.

$$\lambda_{max} = \sum_{i=1}^{n} \frac{[Aw]_i}{nw_i} \text{ (i=1,2,....n)} \tag{5}$$

$$CI = (\lambda - n)/(n - 1) \tag{6}$$

$$CR = \frac{CI}{RI} \tag{7}$$

where A is the constructed judgment matrix, w is the weight, n is the number of indicators, and RI can be obtained by consulting the table.

The disaster factors are divided into two layers. In the first criterion layer, A1 is terrain, A2 is solid source, and A3 is a water source. The matrix is shown in Table 2, CR=0.058<0.1, passing the consistency test. The second criterion layer is divided into three matrices, as shown in Table 3, which are B1 elevation, B2 slope aspect, B3 profile curvature and B4 relief; C1 fault distance, C2 silt content, C3 NDVI; D1 rainfall, D2 TWI, D3 SPI. CR was 0.033, 0.0582 and 0.089, respectively.

| | A1 | A2 | A3 |
|---|---|---|---|
| A1 | 1 | 1/2 | 1/4 |
| A2 | 2 | 1 | 1/2 |
| A3 | 4 | 2 | 1 |

**Table 2.** Judgment matrix of the first criterion layer.

| | B1 | B2 | B3 | B4 |
|---|---|---|---|---|
| B1 | 1 | 2 | 1/4 | 1/3 |
| B2 | 1/2 | 1 | 1/6 | 1/4 |
| B3 | 4 | 6 | 1 | 3 |
| B4 | 3 | 4 | 1/3 | 1 |

| | C1 | C2 | C3 |
|---|---|---|---|
| C1 | 1 | 1/4 | 1/2 |
| C2 | 4 | 1 | 2 |
| C3 | 2 | 1/2 | 1 |

| | D1 | D2 | D3 |
|---|---|---|---|
| D1 | 1 | 3 | 5 |
| D2 | 1/3 | 1 | 2 |
| D3 | 1/5 | 1/2 | 1 |

**Table 3**. Judgment matrix of the second criterion layer.

### 3.3 CF-LR

The binary logistic regression model is an algorithm that expresses or predicts trends with a linear relationship based on statistics. 70% of the sample points, including 29 groups of debris flow points and 29 groups of non-debris flow points, were randomly selected to construct the model. The remaining 30% of debris flow was used to validate the model. The calculated CF value was used to replace the data of 10 disaster causing factors of debris flow and was used as the independent variables of the model. Whether debris flow occurs (" 1 "means debris flow occurs," 0 "means no debris flow occurs) is used as the dependent variable of the model, and the results are shown in Table 4.

| | Regression coefficient | Standard error | Chi-square value | Degree freedom |
|---|---|---|---|---|
| Fault distance | 2.217 | 1.746 | 1.612 | 1 |
| Elevation | 3.991 | 2.619 | 2.322 | 1 |
| NDVI | -0.282 | 1.067 | 0.07 | 1 |
| Average annual rainfall | -1.779 | 1.863 | 0.912 | 1 |
| Aspect | 0.917 | 1.574 | 0.339 | 1 |
| Profile curvature | 0.062 | 2.633 | 0.001 | 1 |
| Relief | 2.259 | 1.231 | 3.367 | 1 |
| Silt content | 0.292 | 5.683 | 0.003 | 1 |
| TWI | 3.088 | 2.195 | 1.98 | 1 |
| SPI | -4.016 | 2.269 | 3.132 | 1 |
| constant | -0.885 | 1.556 | 0.324 | 1 |

**Table 4**. Binary regression analysis table.

Therefore, the occurrence probability of debris flow in the cell can be expressed as follows:

$$Y = 2.217\,x1 + 3.991\,x2 - 0.282\,x3 - 1.779\,x4 + 0.917\,x5 + 0.062\,x6 + 2.259\,x7 + 0.292\,x8 + 3.088\,x9 - 4.016\,x10 - 0.885 \tag{8}$$

### 3.4 CF-RF

Random Forest (RF) is a non-parametric statistical technique based on regression or classification of decision tree set (forest). The workflow flow chart is shown in Figure 3. The importance of features is obtained by using 70% debris flow sample points. The remaining 30% verifies model accuracy.

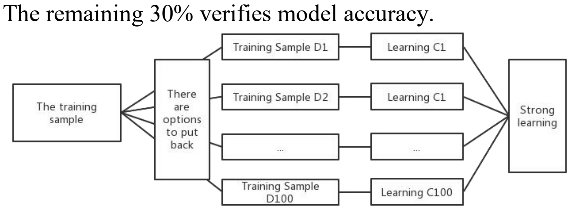


**Figure 3**. Schematic diagram of random forest.

## 4. RESULTS AND DISCUSSION

### 4.1 Comparison of model accuracy

In the AHP, the weight of the disaster factor is obtained by multiplying the weight of the first criterion layer and the second criterion layer. The characteristic importance of disaster-causing factors was obtained after data training in Random Forest, and the specific parameters are shown in Figure 4.

Receiver operating characteristics (ROC) graphs are useful for organizing classifiers and visualizing their performance. Subsequently, the accuracy of the three models was calculated by the ROC curve, as shown in Figure 5. According to the AUC area, the accuracy of the CF-LR coupling model reaches 0.911, followed by the CF-RF coupling model and CF-LR coupling model.

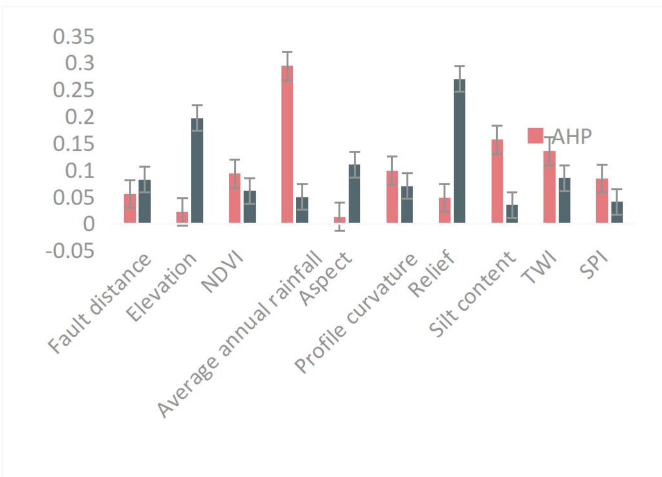

**Figure 4**. AHP calculated weight and RF characteristic importance value.

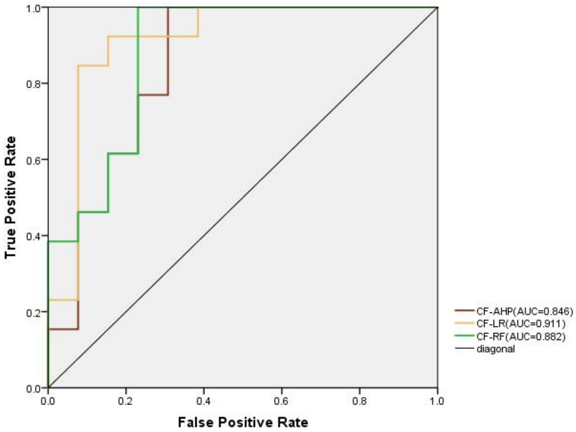


**Figure 5.** ROC curve verification of the three models.

## 4.2 Debris flow susceptibility map of the study area

GIS can well collect, analyze and process complex spatio-temporal data and provide good help in processing geological disaster information. The calculated CF value is used to assign values to the raster graph, as shown in Figure 6. The CF-LR coupling model is used to make the debris flow disaster susceptibility distribution map. The evaluation chart of debris flow susceptibility in the lower reaches of the Yajiang River is shown in Figure 7.

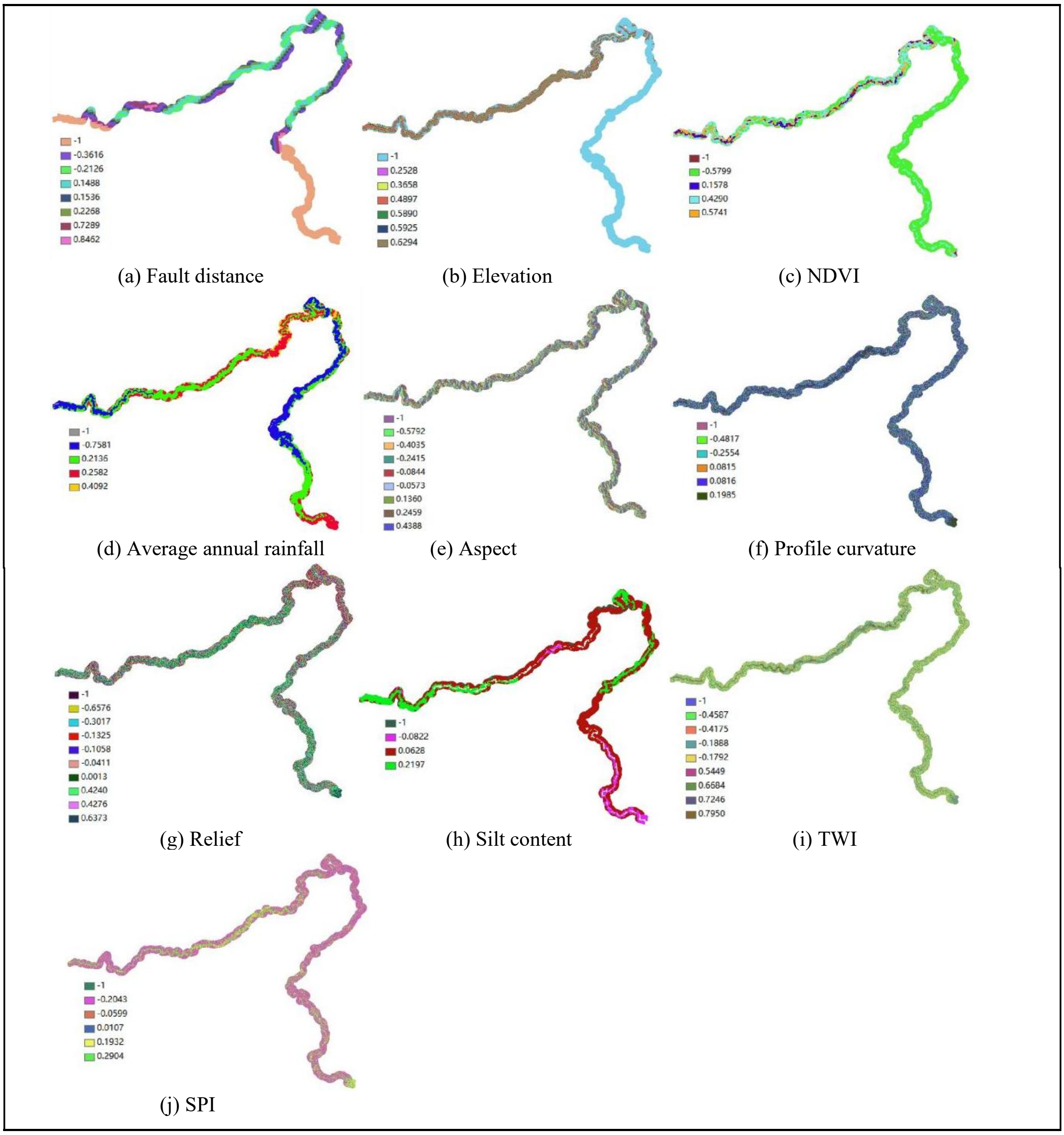


**Figure 6**. CF value raster layer.

The susceptibility was divided into four categories by equal interval classification: low susceptibility area, mild susceptibility area, moderate susceptibility area and high susceptibility area. It can be seen from FIG. 7 that most of the study area belongs to the low risk area of debris flow, accounting for 65.55% of the total study area. mild, moderate and high risk areas accounted for 11.58%, 10.39% and 12.48% respectively. With the Grand Canyon as the boundary point, the areas prone to debris flow are basically distributed on both sides of the upstream river bank of the Grand Canyon, and a small amount of them are distributed downstream.

The high susceptibility areas are mainly concentrated in the "n" shaped watershed that just flowed into Nyingchi. The current in this water is fast and complex, as shown in Figure 8. At continuous turns, rapid water flow will also increase the hidden danger of debris flow, as shown in FIG. 9 and FIG. 10.

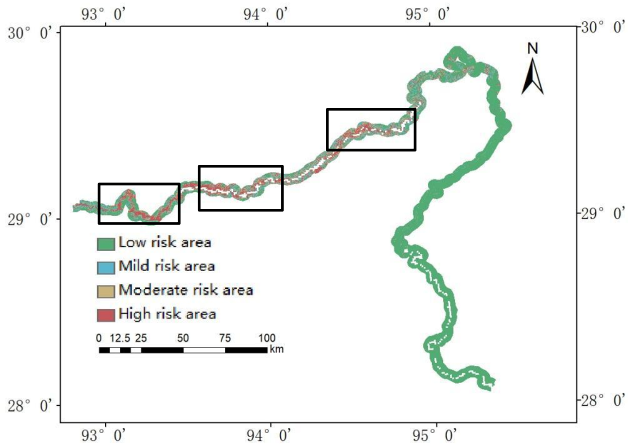


**Figure 7**. Susceptibility map of rainfall-type debris flow in the study area.

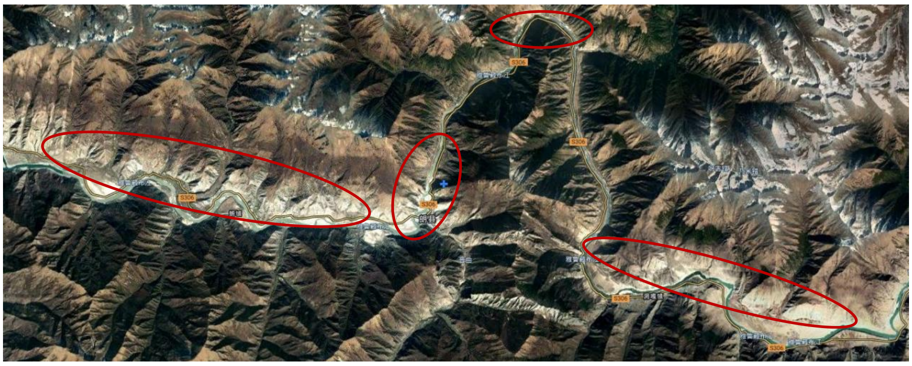

**Figure 8**. "n" shape watershed.

**Figure 9**. The first river bends continuously.

**Figure 10**. The second river bends continuously.

### 4.3 Disaster factor analysis

FIG. 11 is the floating point diagram of CF value obtained from Table 2. The ordinate of the point is the CF value of each category. It can be seen from the figure that the classification of each disaster-causing factor with the greatest impact on debris flow is respectively. It can be seen from the figure that each disaster-causing factor has the greatest impact on debris flow in the following categories: 1000-14000m (classification 7) of fault distance, 2900-3100m (classification 1) of elevation, 0.4-0.6 (classification 2) of NDVI, 900-1000mm (classification 4) of annual rainfall, 0-5 (classification 1) of profile curvature,0-10 (classification 1) of relief, 30-40 (classification 3) of silt, 10-12 (classification 7)of TWI, -4-0 (classification 3) of SPI, and northwest (classification 8) of slope aspect. FIG. 12 is the average CF of each factor corresponding to 42 debris flow points. It can be seen from the figure that elevation, fault distance, NDVI and rainfall have a greater possible influence on debris flow.

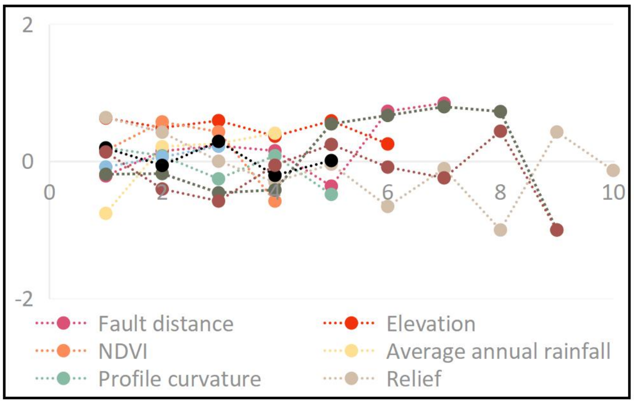


**Figure 11.** CF value floating-point diagram.

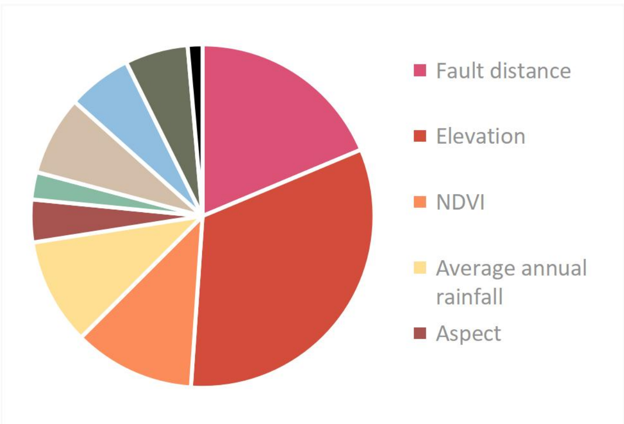


**Figure 12**. Average CF value.

### 4.4 Studies of different amounts of rainfall

Rainfall is the only factor that can influence the debris flow in a short time. The study of rainfall can improve the prevention of debris flow. The influence of annual rainfall on the study area was studied by bringing CF values of different annual rainfall into the model. CF value of 600-700mm rainfall in grade A is -0.7581, that of 700-800mm rainfall in grade B is 0.2136, that of 800-900mm rainfall in grade C is 0.2582, and that of 900-1000mm rainfall in grade D is 0.4092. The susceptibility of debris flow at different gears is obtained through grid calculation and processing, as shown in Figure 13. The results showed that when the annual rainfall was in the range of 600-1000mm, the proportion of low-prone areas increased with the annual rainfall, while the proportion of high-prone areas decreased with the annual rainfall.

The occurrence conditions of low, mild, moderate and high debris flow were assigned 1, 2, 3, and 4 respectively. The distribution area of each susceptible area was divided by the total area of the study area to obtain the proportion of different susceptible areas. The susceptibility index of the study area in each case of A, B, C and D =1*proportion of low susceptibility area +2*proportion of mild susceptibility area +3*Proportion of moderate susceptibility area +4*proportion of high susceptibility area. The relationship between the susceptibility index and the occurrence threshold of debris flow is shown in Figure 14.

The vulnerability value is higher in grade A, but the number of landslides suddenly increases in grade B. This may be due to the influence of geographical environment and geological factors in the study area; when the annual rainfall reaches 600-700mm, it is at the critical point of debris flow outbreak. After that, due to drainage difficulties or sufficient water sources, solid source movement is driven in some areas, and then a debris flow disaster breaks out.

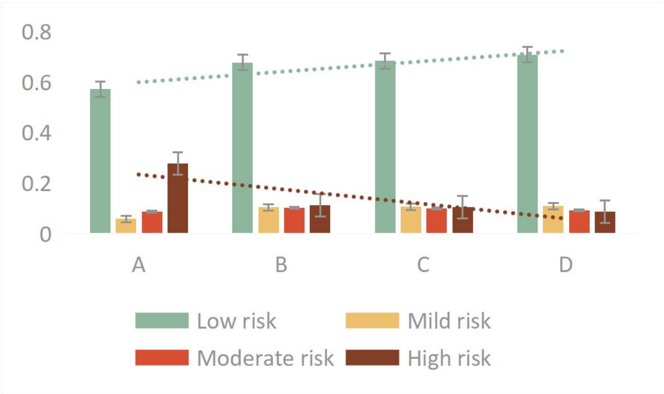


**Figure 13**. Comparison of vulnerable areas under four grades of annual rainfall.

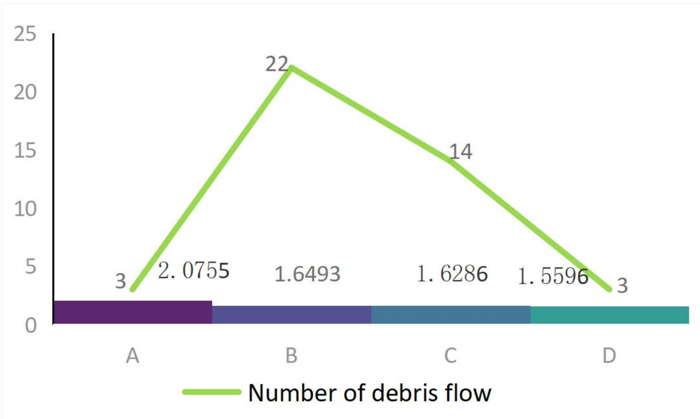


**Figure 14**. Susceptibility index and debris flow initiation diagram in the study area.

## 5. CONCLUSION

By establishing a 1:1 database of debris flow points and non-debris flow samples (70% randomly selected as the research database, and the remaining points as the verification database) and collecting disaster factor information, the evaluation of CF-AHP, CF-LR and CF-RF coupling models is relatively accurate, but the accuracy of CF-LR model is up to 0.911.

The study concluded that debris flows are most likely to erupt in the study area under these geological and geomorphic conditions: 1000-14,000m away from the fault; altitude between 2900 and 3100m; NDVI in 0.4 to 0.6; the profile curvature ranges from 0 to 5; the fluctuation is 0-10; silt sand content in 30%-40%; TWI in 10 to 12; SPI in the - 4-0; the slope aspect is located in the northwest range.

In GIS, based on the CF-LR model calculation, the proportion of low-risk areas in the study area is as high as 65.55%. The proportion of high risk areas is only 12.48%. The remaining mild and moderate risk areas accounted for a small proportion. The danger zone is mainly distributed in the Grand Canyon and the watershed before it, and is concentrated within 1 km on both sides of the river bank.

Four levels of rainfall CF values were respectively brought into the model, and the analysis showed that the annual rainfall threshold of debris flow in the study area was within the range of 600-700mm, and the debris flow erupted intensively when the rainfall reached 700-800mm. After the rainfall of 800 mm, the proportion of low-prone areas gradually increased, while the proportion of high-prone areas gradually decreased.

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