Classification and susceptibility assessment of debris flow based on a semi-quantitative method combining of the fuzzy C-means algorithm, factor analysis and efficacy coefficient

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Abstract: The existence of debris flows not only destroys the facilities, but also seriously threatens human lives, especially in scenic areas. Therefore, the classification and susceptibility analysis of debris flow are particularly important. In this paper, 21 debris flow catchments located in Huangsongyu town ship, Pinggu District of Beijing, China were investigated. Besides field investigation, geographic information system, global positioning system and remote sensing technology were applied to determine the characteristics of debris flows. This article introduced clustering validity index to determine the clustering number, and the fuzzy C-means algorithm and factor analysis method were combined to classify 21 debris flow catchments in the study area. The results were divided into four types: scale-topography-human activity closely related, topography-human activity-matter source closely related, scale-matter source-geology closely related and topography-scale-matter source-human activity closely related debris flow. And 9 major factors screened from the classification result were selected for susceptibility analysis, using both the efficacy coefficient method and the combination weighting. Susceptibility results showed that the susceptibility of 2 debris flows catchments were high, 6 were moderate, and 13 were low. The assessment results were consistent with the field investigation. Finally, a comprehensive assessment including classification and susceptibility evaluation of debris flow was obtained, which was useful for risk mitigation and land use planning in the study area, and provided reference for the research on related issues in other areas.

Keywords Debris flow classification, Susceptibility, Fuzzy C-means algorithm, Factor analysis, Efficacy coefficient method

1 Introduction

Debris flow is a common geological disaster widely distributed across the world. Due to its sudden outbreak, it is often difficult to give real-time warning. Debris flow usually flows at a speed of 0.8-28 tn/s (Dieter et al., 1999; Clague et al., 1985), inflicting severe damage to lives and properties once it occurs. China is one of the worst affected areas prone to natural disasters. According to data, there are nearly 8,500 debris flows distributed across 29 provinces, with an area of approximately 4.3×106 km^2 (Ni et al., 2010). Every year, nearly one hundred counties are directly endangered by debris flow, and hundreds of people lose their lives, resulting in irreparable losses (Kang et al., 2004).

Debris flow susceptibility analysis (DFS), which expresses the likelihood of a debris flow occurring in an area with respect to its geomorphologic characteristics (Blais et al., 2016), is very important to mitigate, evaluate and control debris flow disasters (Chiou et al., 2015). Physical, empirical, and statistical approaches are used to analyze debris flow, which expresses the presumption of a debris flow occurring in an area with respect to its geomorphologic characteristics (Blais et al., 2016). Physical-based approaches (Carrara et al., 2008; Burton and Bathurst, 1998) are more applicable to analyze physical and mechanical factors in independent catchments. Empirical model belongs to qualitative evaluation and is too subjective to be convinced. Statistical analyses which are usually applied in the research of regional debris flow, belongs to quantitative evaluation and depends on the completeness and accuracy of data. For a study area with a limited number of debris flows, a semi-quantitative evaluation method is more appropriate. This analysis includes the extraction of evaluation factors, the determination of weight factors and the establishment of an evaluation model. Considering that the influencing factors of debris flow are complex, multiple evaluation indexes are generally involved, and linear correlations between different factors further complicate debris flow susceptibility analysis (Benda et al., 1990). However, the unreasonable selection of factors may cause the loss of important information and failure to obtain accurate evaluation results. One way to alleviate these problems is dimension reduction through exploratory factor analysis (Aguilar et al., 2000). Some researchers (Peggy et al., 1991; Ming et al., 2016) have used the principal component analysis method to conduct effective dimensionality reduction for selected factors and eliminate the correlation between factors. However, the coefficient of principal component after dimensionality reduction can be positive or negative, which is not ideal for the occurrence of debris flow. Factor analysis, in which the coefficients of the common factors are all positive, and the variables are more resolvable by rotation technology is applied in the current study.

To determine the influence of different factors on debris flow susceptibility, the weights of these factors should be assigned first. The combined weighting method, which possesses the advantages of subjective and objective weighting methods, was applied to assign factors with logical weights.

The efficiency coefficient method (ECM) is a comprehensive evaluation method based on multiple factors and is suitable for complex research objects, such as debris flow. The factors can be converted into measurable scores through the appropriate function and objectively reflect the situation of the evaluation object in the case of a large difference in the factor value. This research primarily focuses on the method, which is applied to the debris flow susceptibility evaluation based on the results of the weight analysis.

Debris flow classification plays a direct guiding role in disaster prevention and mitigation, and mature classification methods have been developed (Iverson et al., 1997; Brayshaw et al., 2009). However, a single classification standard cannot fully and accurately reflect the comprehensive characteristics of debris flow ditches, and base on different classification criteria, the same debris flow will belong to different types at the same time. The fuzzy C-means (FCM) method which is applicable to a wide variety of geostatistical data analysis (Bezdk et al., 1981), was applied to classify debris flow in this paper. Considering that the main influencing factors of different types of debris flow are also different, FA was carried out for each category to obtain major factors to define each type of debris flow.

In recent years, with the improvement of computer performance and the advance features in geographic information systems (GIS), global positioning systems (GPS) and remote sensing (RS) techniques, also known as "3S technology", has become very effective and useful especially to debris flow research (H. Gómez 2008; Glade T 2005; Conway SJ 2010). In particular, the application of GIS has greatly improved the ability of spatial data processing and analysis, such as slope direction analysis and flow direction calculation (Mhaske et al., 2010; Xu et al., 2013; Kritikos et al., 2015). Therefore, FA、FCM and ECM were used to classify and evaluate the susceptibility of debris flow in the current study, combining with "3S technology" and field investigation.

2 Study area

The research area is located around several scenic spots in Huangsongyu township, Pinggu district, Beijing. The village covers an area of 12.83 square kilometers, including 732 households, a total of 2043 people. And the Shilin gorge is the core scenic area of Huangsongyu geopark, attracting a large number of tourists all year round. The geographical location of the study area and 21 debris flow catchments are shown in Fig. 2. During our field investigation, some scenic spots have been closed down due to the threat of falling rocks, floods and debris flow, which were shown in Fig.3. And Fig.4 and Fig.5 show the situation of the other two scenic spots, respectively. Considering the sudden and rapid outbreak of debris flow and the large number of tourists and surrounding villagers in the scenic area, it is necessary to assess the susceptibility of debris flow.

The study area is located in the northwest of north China plain, which belongs to yanshan mountain range. Surrounded by high terrain, the central is flat, and the highest elevation of the territory is 1188m, the lowest is 174m. The Yanshanian and Indosinian periods in the study area were characterized by strong tectonic activity, which resulted in a series of large fold and fault structures. Due to long-term geological processes, the structure in the area is relatively complex. But the strata are relatively simple, except for a few Archean metamorphic rocks, the exposed strata are middle Proterozoic sedimentary strata and Quaternary sediments. The main lithology of the Archean age (Ar) is amphibious plagiarize gneiss and black cloud matinee. The Great Wall system (Ch) is the broadest strata in this area, and the main lithology is dark gray ferric dolomite, sacrilegious micritic dolomite, dolomite sandstone. The main lithology of jixian system (Jx) is dolomite. Quaternary system (Q) is dominated by sand, gravel and clay of residual and diluvial facies. The non-developed lithology of magmatite is mainly granite and quartz diorite.

The study area is characterized by a north temperate continental climate with distinct four seasons and large annual temperature difference. The coldest average January temperature is 6 ~ 8°C and the hottest July average temperature is 21.6°C. The annual precipitation is about 639.5mm, and the average monthly rainfall (1959-2017) is shown in Fig. 1. Precipitation is concentrated in the summer, accounting for 74.9% of the annual precipitation, which is generally concentrated in late July and early August, promoting debris flow.

3 Methodology

3.1 Fuzzy c-means clustering (FCM)

The fuzzy c-means method belongs to soft clustering, which is widely used at present. Its core idea is to map data points of multi-dimensional space to different clustering sets in the form of membership degree, so as seeks C cluster centers in such a manner that the intercluster associations are minimized and the intracluster associations are maximized (Bezdek et al., 1981). For every group, each point is assigned a membership degree between 0 and 1. The membership values indicate the probability of each point belonging to the different groups (Samuel et al., 2019). The steps of FCM algorithm are as follows (Fig.6):

(1) The membership matrix μ_{ij} is initialized with random Numbers between 0 and 1, which is used to represent membership degree of x_i to the cluster j. And it satisfies the constraint conditions:

$$\sum_{i=1}^{C} u_{ij} = 1, j = 1,2,......,n \tag{1}$$

Where C represents the number of clusters.

(2) Calculating clustering centers C_i and the formula is as follows (Hammah et al., 1998)

$$C_i = \sum_{j=1}^{n} u_{ij}^m x_j / \sum_{j-1}^{n} u_{ij}^m \tag{2}$$

where m controls the degree of fuzziness and m = 2 is deemed to be the best for most applications (Bezdek et al., 1981); X_j represents the j[th] sample.

(3) Determining the number of clustering centers

The clustering number C of FCM algorithm is not clearly given, which is one of the key factors affecting the clustering effect. So this paper combines the non-distance-based FCM clustering effectiveness index proposed by Chen and Pi (Chen et al., 2013) to determine the value of C. The exponent (Vcs) consists of compactness index and separation index. And the definition of compactness is as follows:

$$C_{ij} = \begin{cases} {u_{ij}}^2, u_{ij} \geq \dfrac{1}{c} \\ 0, u_{ij} < \dfrac{1}{c} \end{cases} \tag{3}$$

where C_{ij} is the compactness of the jth sample with the ith. When u_{ij} is greater than or equal to 1/c, it avoids the meaningless for too small . When u_{ij}<1/c, it indicates that the J sample is unlikely to belong to the i[th] class. When all samples clearly belong to a certain class, the compactness degree is the maximum. That is, the clustering result is compact. We define the whole compactness of sample data as following:

$$C = \sum_{i=1}^{c} \sum_{j=1}^{n} C_{ij} \tag{4}$$

The definition of separation index is as follows:

$$S_{ij} = \min\left(u_{ik}, u_{jk}\right), k = 1, 2, ..., n \quad (5)$$

That is, the minimum value of the membership degree of samples belonging to these two categories. When the division of the two categories is relatively clear, it indicates that the membership degree of samples belonging to a certain category must be greater than other values. Therefore, the better the clustering result is, the smaller S_{ij} should be. And the total separation is defined as:

$$S = \max_{i=1, j=1, i \neq j}^{c} S_{ij} \quad (6)$$

The smaller the dispersion is, the greater the difference between the two classes is and the better the clustering result is.

Based on this, the clustering effectiveness Vcs index is defined as follows:

$$V_{cs} = \frac{C}{S} \quad (7)$$

In conclusion, when C is larger and S value is smaller, Vcs is larger and the clustering effect is better.

（4）Calculating the value function J.

$$J = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^{2}\left(X_j, V_i\right) \quad (8)$$

where N is the total number of observations, and j is the fuzzy objective function; d^2 is the Euclidean distance between the i^{th} clustering center and the j^{th} data point (Wang, 2008);

The operation is stopped when J is less than a certain threshold.

（5）Calculating the new matrix U_{ij} and return to step 2

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{d_{ij}}{d_{kj}}\right)^{2/(m-1)}} \quad (9)$$

3.2 Factor analysis

FA is a multivariate statistical analysis method, which studies the internal dependence of variables and reduces some variables with intricate relations to a few comprehensive factors (Li et al., 2016). FA is the inferred decomposition of observed data into two matrices. One matrix represents a set of underlying unobserved characteristics of the subject which giverise to the observed characteristics and the other explains the relationship between the unobserved and observed characteristics (Max R 2018). And the mathematical formula can be expressed as follow:

$$X = AF + \varepsilon \quad (10)$$

Where X (x1,x2,..., xp) is the original factor，F (F1，F2，..., Fm) is the common factor ; A= (a_{kj}) p×m is factor load matrix，a_{kj} represents the load of the K original factor on the J common factor; ε =(ε_1，ε_2 ,…, ε_p) is a special factor.

The main calculation steps of factor analysis method can be divided into six steps:

1 Test the feasibility of FA of original evaluation index variables

In this paper, SPSS was used to provide Bartlett sphericity test to determine whether variables are suitable for FA.

2 Standardized calculation of original data

In order to eliminate the numerical differences of different variables in order of magnitude and dimension, the original data should be standardized. And this paper adopted the Z standardization method in SPSS software.

3 Construct a common factor F

In the study, the first m factors for which the cumulative variance contribution rate is no less than 85%, were selected as common factors to represent the original data.

4 Factor rotation

In this paper, varimax orthogonal rotation was used to realize factor rotation.

5 Calculating factor scores;

The most common method for calculating factor scores is the Thomson regression method (Max R 2018), and the formula is as follow:

$$F = A'R^{-1}X \tag{11}$$

where $A' R^{-1}$ is factor scoring coefficient matrix and A is the factor loading matrix after rotation.

6 Calculating weight

The product of factor score coefficient and variance contribution rate is the contribution of each factor in the sample, and the sum of the contribution of each factor divided by the contribution of all indexes is the weight of each factor. It is expressed by the formula:

$$\omega_i = \frac{\sum_{j=1}^{m} \beta_{ji} e_j}{\sum_{i=1}^{p} \sum_{j=1}^{m} \beta_{ji} e_j} \tag{12}$$

where β_{ji} is the coefficient score of each index in principal component F_j; i=1,2 ,..., p; j=1,2, ..., m; e is the contribution rate of factor variance.

3.3 Combination weighting method

Considering the defects of the current method for determining the weight of factors, the combination of analytic hierarchy process and factor analysis method is used to determine the weight of each influencing factor of debris flow.

3.3.1 Analytic hierarchy process (AHP)

Analytic hierarchy process (AHP) was first proposed by Saaty (1979), a famous American mathematician. It decomposes the factors related to decision-making into multiple layers, such as target layer, criterion layer and scheme layer. AHP is a subjective weighting method and has obvious advantages in determining the weight of each factor. The specific steps are as follows:

1 Establishing hierarchical structure model

The hierarchical structure is mainly divided into three layers: target layer, criterion layer and scheme layer.

2 Establishing the judgment matrix

For the same level, judgment matrix is established by pair-wise comparison. The formula is as follow:

$$A=\left(a_{ij}\right)_{n\times n},a_{ij}>0,a_{ij}=\frac{1}{a_{ji}},\left(i,j=1,2,...n\right) \tag{13}$$

where a_{ij} is the ratio of relative importance between element B_i and B_j, which is usually expressed by the scoring method from 1 to 9 (Saaty, 1977), as shown in table 2.

3 Consistency testing

The consistency test is divided into three steps:

(1) Calculate the consistency index（CI）(Saaty, 1977)and the expression is:

$$CI=\frac{\lambda_{\max}-n}{n-1} \tag{14}$$

Where λ_{max} is the largest eigenvalue of the judgement matrix A.

(2) Average random consistency RI;

RI is associated with the order of judgment matrix, and their relationship is shown in Table 3.

(3) Obtaining the test coefficient CR.

$$CR=\frac{CI}{RI} \tag{15}$$

If CR<0.1, judgment matrix has a good consistency with reasonable judgment. Otherwise, the judgment matrix needs to be revised until the consistency test is satisfied.

3.3.2 Combination weighting rule

The weight value obtained by AHP is set as ω^c_i, and the weight value obtained by FA is set as ω^y_i (Feng et al., 2010), as shown in Eq16.

$$\begin{cases} Min=\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\alpha r_{ij}\omega^{c}{}_{i}-\beta r_{ij}\omega^{y}{}_{i}\right) \\ \alpha+\beta=1 \end{cases} \tag{16}$$

Where α and β are weight coefficients calculated through AHP and factor analysis method, respectively; r_{ij} is the standardized value of the jth influencing factor of the i^{th} debris flow. And α and β are determined according to the following formula:

$$\begin{cases} \alpha = \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}^{2}\omega^{y}{}_{i}\left(\omega^{c}{}_{i} + \omega^{y}{}_{i}\right) / \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}^{2}\left(\omega^{c}{}_{i} + \omega^{y}{}_{i}\right)^{2} \\ \beta = \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}^{2}\omega^{c}{}_{i}\left(\omega^{c}{}_{i} + \omega^{y}{}_{i}\right) / \sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}^{2}\left(\omega^{c}{}_{i} + \omega^{y}{}_{i}\right)^{2} \end{cases} \tag{17}$$

And the combined weight（$\omega^{z}{}_{i}$） can be represented in Eq18:

$$\omega_i^z = \alpha\omega_i^c + \beta\omega_i^y \tag{18}$$

3.4 Efficiency coefficient method

Based on the principle of multi-objective programming, the efficiency coefficient method transforms each factor into a measurable evaluation score through the efficiency function, and combines the weight of factors to make a comprehensive evaluation. The specific steps are as follows:

1 Selecting evaluation factors

2 Determine the satisfactory value and the unallowable value

The satisfaction value is a value based on years of experience, while the unallowable value is the lowest or highest acceptable value of the evaluation index.

3 Calculating the single efficacy coefficient

The single efficacy coefficient was calculated by the corresponding efficacy function based on the sensitivity of each factor. And It is mainly divided into three variables: the extremely large variable (the higher the factor, the higher the efficiency coefficient), the infinitesimal variable (the smaller the index value, the larger the efficiency coefficient value) and the Interval variable (The value reach the highest in a certain interval). The specific formula is as follows:

$$\mathrm{g}_{1i} = \begin{cases} \dfrac{x_i - x_{ni}}{x_{yi} - x_{ni}} \times 40 + 60, x_i < x_{yi} \\ 100, x_i \geq x_{yi} \end{cases} \tag{19}$$

where g_{1i} is the single efficacy coefficient value of the i[th] extremely large factor; X_i is the actual value of the i[th] factor; X_{yi} is the satisfactory value of the i[th] factor; X_{ni} is the unallowable value of the i[th] factor.

The infinitesimal variable：

$$\mathrm{g}_{2i} = \begin{cases} \dfrac{x_i - x_{ni}}{x_{yi} - x_{ni}} \times 40 + 60, x_i > x_{yi} \\ 100, x_i \geq x_{yi} \end{cases} \tag{20}$$

The Interval variable：

$$\mathrm{g}_{3i} = \begin{cases} \left(1 - \dfrac{x_{\min} - x_i}{x_{\min} - x_{n\min}}\right) \times 40 + 60, x_i < x_{\min} \\ 100, x_{\min} < x_i < x_{\max} \\ \left(1 - \dfrac{x_i - x_{\max}}{x_{n\max} - x_{\max}}\right) \times 40 + 60, x_i > x_{\min} \end{cases} \tag{21}$$

4 Calculating the total efficiency coefficient

$$G = \sum_{i}^{m} \left(g_i \omega_i \right) \tag{22}$$

where G is the total efficacy coefficient, g_i is the single efficacy coefficient and ω_i is the weight of the i^{th} factor.

The flow chart for the method used for our classification and susceptibility analysis is shown in Fig. 8.

3.5 Influencing Factors

The topographical, geological and climatic factors play a critical role in the distribution and activities of debris flows (B. F. DI et al., 2008). Table 2 shows the influencing factors selected by researches in debris flow susceptibility assessment in recent years. Rainfall is one of the most pivotal external factors inducing debris flow disasters, but the meteorological data in our area are all from the same station, which cannot reflect the differences between each catchment. Therefore, rainfall was not included in this study. In addition, the frequency of debris flow and the size of soil particles are difficult to obtain accurately. The loose material volume reflects the lithological characteristics and fault length to some extent, so lithology and fault length were not taken into account. The basin area, main channel length, drainage density, average slop angle, average gradient of main channel, vegetation coverage, maximum elevation difference and curvature of the main channel, which were cited and available, were selected in this paper. As source conditions, the loose material volume and the loose material supply length ratio were also considered. As the study area is located in a tourist area with a relatively dense population, population density is selected as the factor of human activities. A total 13 influencing factors were selected based on the previous research findings to reflect the characteristics of the watershed. All these factors were acquired in our field survey or calculated in ArcGIS, as described below.

Basin area（F1）（km^2）

Basin area reflects the scale of debris flow. Generally, the larger the basin area is, the greater the risk of debris flow will be. It was obtained by geometric operations in ArcGIS and corrected by the remote sensing image in Google earth.

Main channel length（F2）（km）

Main channel length reflects the potential for increasing loose sources along the route. This value was measured from ArcGIS by combining RS technology and topographic map.

Drainage density（F3）（km/km^2）

Drainage density is the ratio of the total drainage length to the watershed area and it is an important index to describe the degree of ground being cut by gullies.

Average gradient of main channel（F4）

It is the ratio of the maximum elevation difference of main channel to its linear length. The larger the value, the better the hydrodynamic condition is. This value is obtained from the DEM.

Average slop angle（F5）（°）

As F5 increases, the erosion capacity and intensity of precipitation increase. The value was obtained by ArcGIS slope analysis tool.

Maximum elevation difference（F6）（m）

The difference between the maximum and minimum elevation values in the basin provides kinetic energy condition of disaster. This value is also obtained from the DEM.

Curvature of the main channel（F7）

F7 is the ratio of the main channel length to its linear length, which reflects the degree of channel blockage.

The loose material volume （F8）（×104m^3）

The loose material is one of fundamental factors triggering debris flows. This factor is obtained through field investigation with tape and laser rangefinder. And the thickness was obtained by field estimation and trench test.

The loose material supply length ratio （F9）

F9 is the ratio of loose material length along a channel to total channel length, which reflects the successive supplied sediments. It was obtained through field survey and RS technology.

Vegetation coverage（F10）

The lower the vegetation coverage will be, the more serious the soil erosion. It was estimated from field survey and SPOT5 imaging.

Population density（F11）（quantity/km^2）

With the development of social economy, human activities have gradually become an important factor affecting debris flow. Population density reflects the intensity of human activities, which is estimated according to the number of buildings through field survey and RS technology.

Roundness（F12）

Roundness is the morphological statistical element of gully, and the plane shape of gully variates from its developmental stage. F12 is the ratio of the length of main channel of debris flow to its area.

The most volume of once flow（F13）（×104m^3）

Liu (1993) selected F13 as the main factor in the risk assessment of debris flow, which is one of the important factors to evaluate the degree of debris flow hazard.

4 Result

4.1 Fuzzy c-means clustering analysis

The curve of clustering effectiveness index Vcs with the number of clustering centers is shown in Fig. 9 and the optimal number of clustering of evaluation units is 4. Based on the basic data of 21 debris flows, the FCM was carried out and set the fuzzy weighted index m=2. And results were shown in table 5.

Thus 21 debris flows in the study area are divided into 4 categories. The data of each catchment belonging to the same category have certain internal similarity and vary greatly among different categories. In other words, data of different influencing factors have different effects on different types of debris flows, which provide a favorable basis for us to analyze the main influencing factors of debris flows, and also points out the direction for monitoring and prevention of debris flows.

4.2 Factor analysis

Based on the clustering results of 21 debris flows, FA was used to analyze each type of debris flow. Table 2, table 3, table 4 and table 5 are the results of the first, second, third and fourth categories, respectively.

As shown in table 2, in the first category, the accumulative contribution rate of the first three factors (C1, C2 and C3) reaches 86.40%, which retain most information of the 13 original variables. For the first group, the load values of the main factors 1, 2 and 3 are relatively large in the basin area, the most volume of once flow, the maximum elevation difference, the main channel length and curvature of the main channel, population density and drainage density, respectively. Similarly, in the second type, the load values of the main factors 1, 2 and 3 are relatively large in the basin area, the main channel length and population density, loose material volume and drainage density, maximum elevation difference, respectively. In the third category, the load values of the main factors 1, 2 and 3 are relatively large in the basin area, main channel length, the most volume of once flow, loose material volume and the loose material supply length ratio and vegetation coverage, respectively. And In the fourth category, the load values of the main factors 1, 2 and 3 are relatively large in main channel length, drainage density, loose material volume, the most volume of once flow and the loose material supply length ratio and population density, respectively.

Among the 13 factors, the basin area and the most volume of once flow reflect the scale of debris flow eruption. The main channel length, drainage density, average gradient of main channel, the average slope, maximum elevation difference, curvature of the main channel, roundness reflect the topographical condition. The loose material volume and the loose material supply length ratio are the material sources for debris flow. Vegetation coverage reflects geomorphologic condition. Population density reflects the impact of human activities on nature to some extent. Therefore, four types of debris flows can be named according to the results of FCM and FA.

The first category can be defined as debris flow closely related to scale-topography-human activities. Considering the situation, monitoring and control of basic material sources is recommended. Similarly, the second, third, and fourth categories can be defined as topography-human activities-provenance, scale-provenance-topography topography-scale-provenance-human activities, respectively. In the same way, corresponding prevention measures can be proposed according to the characteristics of each type of debris flow.

4.3 Weights of major factors

Based on FA of each category of debris flow in the previous section, the main influencing factors were obtained. However, the repeatability of evaluation information should be reduced. Average slop angle and average gradient of main channel are both indicators of potential energy, so the average gradient of main channel is omitted. Similarly, curvature of the main channel, the loose material supply length ratio and roundness were omitted. So 9 factors, including basin area F1, main channel length F2, drainage density F3, average slop angle F5, maximum elevation difference F6, the loose material volume F8, vegetation coverage F10, population density F11 and the most volume of once flow F13 were selected. On the other hand, a reduction in the number of indicators facilitates the allocation of weight values.

4.3.1 Subjective weights

Analytic hierarchy process（AHP）was applied to calculate the subjective weight in this paper. The hierarchical structure (Fig. 10) was constructed, and the 1-9 scale method was used to grade each factor. The judgment matrices A-A ' (Table 10) and B-B' (Table 11) were constructed and the consistency test was conducted, respectively. The weight values of each factor are shown in table 12.

4.3.2 Objective weights

FA was applied to calculate the objective weight in this paper. The weight values of each factor are shown in table 13.

4.3.3 Combination weights

After the subjective weight and objective weight are obtained, the respective distribution coefficients are solved according to eq1 and the final combined weight values of each factor are shown in table 14, $\alpha=0.70$，$\beta=0.30$, F8>F13>F11>F1>F2=F6>F10>F3>F5.

4.4 The efficacy coefficient of factors

Among the 9 factors, basin area, main channel length, drainage density, maximum elevation difference, the loose material volume, the most volume of once flow and population density are all extremely large variables. Vegetation coverage is the infinitesimal variable. And Average slop angle is an interval variable. Table 15 shows the efficacy coefficient scores of 21 debris flows after combined with weight calculation.

4.5 Susceptibility assessment of debris flow

Taking the total efficiency coefficient of each catchment as the evaluation standard (the larger the value is, the higher the possibility of debris flow), FCM was conducted for 21debris flow in the study area. The result showed that the susceptibility of debris flow was divided into three grades: high (H), moderate (m) and low (L). Combined with the classification of each debris flow mentioned above, the final results were shown in the table 16.

As shown in table 16, susceptibility for the 10^{th} and 13^{th} catchments was high and both of them belong to the debris flow with close relationship between topography, human activities and provenance. Susceptibility for 6 catchments, including the 1^{st}, 4^{th}, 6^{th}, 17^{th}, 20^{th} and 21^{th}, had medium susceptibility. The other 13 had low susceptibility.

Normative scoring, k-means clustering algorithm and hierarchical cluster were determined to validate susceptibility analysis methods used in this paper.

Based on the field investigation, the 10th catchment is located in Huangsongyu national

Mining Park, where a large amount of slag has been accumulated. With low vegetation coverage and steep terrain, the gully was in its prime, which directly threatened the safety of villagers and tourists. What's more, there are several warning boards of natural disaster and corresponding monitoring equipment in the scenic spot（as shown in Fig.5. And the 13th catchment is located Lishugou village scenic spot. Part of the pedestrian passageway was built, but a lot of stones were piled up in the trench and the road was broken and steep（as shown in Fig.6）. However, there is no obvious accumulation of loose materials in the catchments with low susceptibility. The gully was in its old stage with high vegetation coverage and little human interference. The quantitative comprehensive evaluation results of debris flow susceptibility are shown in table 17, which are divided into two levels: low (L) and moderate (M). Among them , the susceptibility of the 10th and the 13th catchments were moderate and the others were low.

The K-means algorithm (K) (Hartigan et al.,1978) and Hierarchical cluster (H) (Kimes et al., 2017) were used for the classification of our data to measure the classification performance in this paper. And the results were shown in table 17. The susceptibility results obtained by K and FCM are exactly the same. The susceptibility assessment of 17^{th} and 21^{th} were high based on H and moderate from FCM and K. However, such minor differences are acceptable. On the other hand, the susceptibility results obtained by FCM and normative scoring are different. This is mainly because the number of categories is different and the level was generally higher obtained by FCM. In addition, it can be seen from the tree graph（Fig.11）obtained by Hierarchical cluster, that the clustering results are more reasonable to be divided into three categories, which is consistent with the Vcs. Therefore, the susceptibility model established in this paper is suitable and reasonable.

5 Discussion

The accuracy of the debris flow classification directly affects the development of prevention and control measures. Based on different criteria, such as genetic classification, outbreak frequency, material composition, the same debris flow can belong to multiple categories at the same time, which does not reasonably reflect its multiple characteristics. In addition, the traditional classification standard has some hysteresis to prevent debris flow. Considering that different types of debris flow have different main influencing factors, the FCM and FA were combined in this study to refine and summarize the importance of various factors to improve the accuracy of the classification. FCM is different from traditional rigid division and it is based on the distance function to make the maximum correlation between the same kind of data and the minimum correlation between different kinds of data (Samuel et al., 2019). The clustering effectiveness Vcs was introduced to effectively solve the problem of determining the number of clusters, and the clustering analysis was carried out on the basic data of 21 debris flows. FA is a primary exploratory tool for dimension reduction and visualization (Verde et al., 2018). The main influencing factors of each category are obtained by FA, which not only realizes effective dimensionality reduction but also eliminates the linear relationship between factors. The results showed that different kinds of debris flows obtained by the FCM had different major influencing factors. In other words, data for different influencing factors have different effects on different types of debris flows, which demonstrate the advantages of the FCM when combined with the factor analysis. According to different main influencing factors, the development characteristics of debris flows can be reclassified. It also provided an effective basis for us to study the origin and classification of debris flow and point out the direction for monitoring and controlling disasters.

The reasonable selection of evaluation factors is the premise of accurate evaluation of debris flow susceptibility. In this paper, 13 factors were preliminarily selected based on previous experience and field investigation conditions. And secondary screening was carried out based on FA analysis results, which enhanced rationality of screening. The determination of the factor weight is crucial to accurately evaluate the susceptibility of the debris flow (Zhang et al., 2013). FA is a common objective evaluation method in statistical analysis that determines the weight of factors according to the internal correlation and patterns of data. However, the objective method cannot reflect the relative significance of each influencing factor and may create misleading information. The AHP can make full use of expert experience and achievements in the corresponding fields to evaluate the influencing factors, which is a subjective method. However, different researchers have different preferences for major factors, which have a negative impact on the results. Therefore, combination weighting, which combines the advantages of the FA and AHP, is superior to the other methods alone when trying to obtain a more scientific and reasonable evaluation result.

The efficiency coefficient method is different from other evaluation systems. By determining the satisfaction value of each factor as the upper limit and the unallowable value as the lower limit, the satisfaction degree is calculated through the corresponding efficiency function, and the final comprehensive score was obtained based on the weight evaluation. This method not only considers the relative importance of different factors but also determines the value based on the susceptibility to debris flow. Therefore, the efficiency coefficient method can objectively evaluate complicated research objects, such as debris flow, with this form of classification that conforms to people's logical thinking. However, the evaluation method adopted in this paper also has limitations: (1) Fuzzy c-means clustering is not applicable to the evaluation of a single debris flow gully; (2) Factor analysis method is not applicable when the sample data is too small; (3) The tools used in field investigation are too simple and some data, such as the loose material supply length ratio, are not accurate enough; (4) Rainfall variations were not considered between different debris flow.

6 Conclusions

Classification and susceptibility analysis are of great significance for the early warning and prevention of debris flow. Based on field investigation and "3S technology", an improved FCM and FA method were used to establish classification model and obtain the main influencing factors of different types of debris flow in the current study. And the ECM was used for the susceptibility analysis based on the combination weights of major factors.

In this paper, 21 debris flows in Beijing were divided into 4 categories. Nine major factors screened from the classification results were determined for susceptibility analysis using both the ECM and combination weighting, and the susceptibility assessment was divided into 3 levels, which has been validated with normative scoring, the K-means algorithm and hierarchical clustering. An effective scientific classification and susceptibility assessment results of debris flow were obtained, which provides a theoretical basis for formulating disaster prevention, reduction plans and measures for debris flow. Therefore, a semi-quantitative evaluation method which combines fuzzy mathematics, multivariate statistical analysis and geological environment, is suitable for risk assessment for a study area with a limited number of samples. Different methods have their own advantages and disadvantages, and some methods are complementary to a certain extent, so it is desirable to enhance the rationality of the application through the combination of multiple methods.

Data availability

The data used to support the findings of this study are included within the article.

Author contribution:

Zhu Liang was responsible for the writing and graphic production of the manuscript. Changming Wang was responsible for the revision of the manuscript. Songling Han was responsible for the part of the calculation. Kaleem Ullah Jan Khan was responsible for the translation. Yiao Liu was responsible for the reference proofreading.

Competing interests:

The authors declare that they have no conflict of interest.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (Grant No. 4197020250 and 41572257).

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Table 1 The random average consistency index

n	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54

Table 2 Definition of comparative importance

1	Two decision factors (e.g., indicators) are equally important
3	One decision factor is more important
5	One decision factor is strongly more importan
7	One decision factor is very strongly more important
9	One decision factor is extremely more important
2,4,6,8	Intermediate values
Reciprocals	If a ij is the judgment value when i is compared to j. Then $U_{ji} = 1/U_{ij}$ is the judgment value when j is compared to i

Table 3 Factors frequently used in susceptibility ananlysis of debris flow

Factors	Lin (2002)	Chang (2006)	Chang (2007)	Lu (2007)	Meng (2010)	Zhang (2011)	Zhang (2013)	Shi (2016)	Niu (2014)	Time
Rainfall intensity		√	√							2
Daily rainfall			√			√	√			3
Cumulative rainfall		√	√							2
Main channel length		√	√		√	√		√	√	6
Average slope angle	√	√	√		√		√	√	√	7
Drainage density		√	√		√	√	√	√	√	7
Soil particle size		√	√							2
Basin area	√	√	√	√	√	√		√	√	8
Average gradient of main channel	√			√		√	√	√	√	6
Frequency	√				√	√				3
Loose material volume					√		√	√	√	4
Vegetation coverage	√			√	√		√		√	5
Population density						√				1
Lithology	√								√	2
Maximum elevation difference					√	√		√	√	4
Curvature of the main channel						√	√	√	√	4
Fault length	√									1

Table 4 The values for the 13 factors of the 21 debris flow catchments

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13
1	1.887	1.721	2.51	0.48	25.88	639	1.09	1.04	0.36	0.5	28	0.74	2.41
2	0.907	0.984	1.85	0.7	26.77	579	1.09	0.706	0.65	0.5	8	0.68	0.49
3	0.292	0.321	1.71	0.24	25.27	371	1.22	0.167	0.33	0.45	90	0.82	0.05
4	2.057	2.296	2.05	0.44	27.17	752	1.1	1.615	0.74	0.55	27	0.62	2.33
5	1.547	1.728	1.6	0.42	25.44	610	1.18	0.956	0.41	0.45	25	0.58	1.62
6	2.77	3.113	2.16	0.32	25	745	1.15	1.616	0.77	0.65	6	0.61	5.95

7	1.223	1.098	1.96	0.58	23.51	584	1.12	0.7	0.61	0.6	9	0.77	0.66
8	0.445	0.898	2.07	0.49	19.8	386	1.19	0.463	0.69	0.65	23	0.66	0.18
9	0.34	0.396	1.25	1.06	25.81	381	1.12	0.29	0.73	0.6	16	0.71	0.06
10	6.65	3.539	1.98	0.27	22.46	856	1.08	18.457	0.48	0.52	102	0.68	5.04
11	0.388	0.965	2.57	0.37	22.56	508	1.11	0.397	0.75	0.55	105	0.43	0.19
12	0.713	0.787	2.74	0.63	22.35	366	1.16	0.564	0.62	0.55	145	0.72	0.21
13	6.319	4.539	2.13	0.22	22.89	828	1.12	5.549	0.35	0.6	22	0.6	6.75
14	0.664	1.036	1.61	0.54	25.31	550	1.13	0.956	0.66	0.7	62	0.48	0.29
15	0.492	0.51	1.3	0.77	25.66	368	1.09	0.13	0.68	0.6	230	0.71	0.07
16	1.093	1.564	1.95	0.41	24.55	568	1.22	1.027	0.72	0.65	30	0.59	0.75
17	5.312	4.564	1.55	0.18	24.78	743	1.03	6.443	0.31	0.62	14	0.43	4.04
18	0.85	1.289	2.04	0.47	20.99	571	1.07	1.196	0.74	0.6	120	0.53	0.6
19	0.425	0.901	2.17	0.56	22.49	479	1.09	0.451	0.62	0.55	165	0.66	0.22
20	1.71	2.334	1.77	0.26	17.27	583	1.05	1.313	0.71	0.55	182	0.5	3.59
21	3.804	3.32	1.57	0.25	18.46	668	1.2	0.4317	0.58	0.65	66	0.49	6.31

Table 5 Clustering results of 21 debris flows debris flows

Category	Catchment
I	1、2、5、7、14、16、21
II	4、6、10、13、17、
III	11、18、19、20
IV	3、8、9、12、15

Table 6 The factor load matrix after rotation and contribution ratios for the first category

Factor	C1	C2	C3
F1	0.960	0.258	0.094
F2	0.876	0.46	0.092
F3	-0.101	-0.465	0.589
F4	-0.611	-0.739	-0.17
F5	-0.832	-0.356	0.349
F6	0.902	0.053	0.422
F7	0.239	0.737	-0.164
F8	-0.776	0.2	0.569
F9	-0.272	0.102	-0.891
F10	-0.017	0.492	-0.683
F11	0.306	0.798	-0.193
F12	-0.077	-0.869	0.316
F13	0.938	0.311	0.084
Contribution rate (%)	51.686	24.245	10.469
Accumulative contribution (%)	51.686	75.931	86.399

Table 7 The factor load matrix after rotation and contribution ratios for the second category

Factor	C1	C2	C3

F1	0.850	0.497	-0.154
F2	0.937	-0.130	-0.301
F3	-0.203	0.090	0.961
F4	-0.944	0.073	0.303
F5	-0.853	-0.467	-0.208
F6	0.485	0.801	0.301
F7	-0.103	-0.230	0.968
F8	0.389	0.869	-0.148
F9	-0.808	-0.143	0.500
F10	0.280	-0.925	0.108
F11	0.075	0.980	-0.002
F12	-0.247	0.632	0.735
F13	0.690	-0.105	0.595
Contribution rate (%)	45.350	31.221	20.737
Accumulative contribution (%)	45.350	76.572	97.309

Table 8 The factor load matrix after rotation and contribution ratios for the third category

Factor	C1	C2	C3
F1	0.986	0.161	-0.043
F2	0.966	0.218	-0.136
F3	-0.931	0.318	-0.181
F4	-0.590	-0.739	0.325
F5	-0.981	-0.171	0.094
F6	0.806	0.415	0.423
F7	-0.965	0.128	-0.230
F8	0.882	0.142	0.450
F9	0.044	0.938	0.343
F10	0.042	0.054	0.998
F11	0.705	-0.571	-0.421
F12	-0.044	-0.996	0.075
F13	0.949	0.160	-0.273
Contribution rate (%)	61.553	24.036	14.411
Accumulative contribution (%)	61.553	85.589	100

Table 9 The factor load matrix after rotation and contribution ratios for the fourth category

Factor	C1	C2	C3
F1	0.749	0.239	0.610
F2	0.937	0.258	-0.110
F3	0.913	-0.314	0.184
F4	-0.249	0.875	0.068
F5	-0.900	-0.002	0.374
F6	0.051	0.293	-0.953

F7	0.328	-0.840	-0.431
F8	0.918	0.105	-0.123
F9	0.216	0.971	-0.093
F10	0.302	0.873	-0.305
F11	-0.068	0.053	0.919
F12	-0.455	-0.844	0.219
F13	0.994	0.090	0.037
Contribution rate (%)	44.768	30.086	19.917
Accumulative contribution (%)	44.768	74.854	94.771

Table 10 Comparison matrix elements for geology condition

Geology	F1	F2	F6	F5	F3	CI	RI	CR
F1	1.00	2.00	2.00	3.00	3.00			
F2	0.50	1.00	1.00	3.00	3.00			
F6	0.50	1.00	1.00	3.00	3.00			
F5	0.33	0.33	0.33	1.00	1.00			
F3	0.33	0.33	0.33	1.00	1.00	0.0024	0.52	0.0045

CR=0.0045<0.1, met the conformance inspection requirements.

Table 11 Comparison matrix elements of the criterion level factors

middle leve	Topography	Geology	Trigger condition	CI	RI	CR
Topography	1.00	1.50	2.00			
Geology	0.67	1.00	1.50			
Trigger condition	0.50	0.67	1.00	0.02	1.12	0.02

CR=0.02<0.1, met the conformance inspection requirements.

Table 12 The weighted values of the factors obtained by AHP

Factor	F1	F2	F3	F5	F6	F8	F10	F11	F13
Weight	0.11	0.07	0.03	0.03	0.07	0.28	0.06	0.17	0.18

Table 13 The weighted values of the factors obtained by factor analysis

Factor	F1	F2	F3	F5	F6	F8	F10	F11	F13
Weight	0.15	0.17	0.05	0.01	0.17	0.08	0.07	0.14	0.16

Table 14 The combined weighted values of the factors

Factor	F1	F2	F3	F5	F6	F8	F10	F11	F13
Combination Weight	0.12	0.10	0.04	0.03	0.10	0.22	0.06	0.16	0.17

Table 15 The efficacy coefficient scores of 21 debris flows

	F1	F2	F3	F5	F6	F8	F10	F11	F13	Total score
1	13.56	12.89	8.53	7.30	8.29	2.26	3.57	10.29	5.84	72.53
2	13.40	10.90	7.78	6.61	7.79	2.26	2.90	9.72	5.84	67.19
3	13.14	10.44	7.31	5.98	6.08	2.26	2.76	12.08	6.35	66.39
4	13.83	12.81	8.66	7.84	9.22	2.26	3.10	10.26	5.33	73.31

5	13.52	12.07	8.27	7.31	8.05	2.26	2.65	10.21	6.35	70.67
6	13.83	16.57	9.20	8.61	9.16	2.06	3.21	9.66	4.32	76.62
7	13.40	11.07	8.02	6.71	7.83	1.92	3.01	9.75	4.82	66.54
8	13.28	10.57	7.42	6.53	6.21	1.59	3.12	10.15	4.32	63.19
9	13.20	10.45	7.34	6.05	6.17	2.26	2.28	9.95	4.82	62.52
10	21.88	15.62	12.18	9.01	10.07	1.83	3.03	12.42	5.64	91.67
11	13.25	10.58	7.38	6.59	7.21	1.84	3.64	12.51	5.33	68.33
12	13.33	10.60	7.63	6.42	6.04	1.82	3.80	13.66	5.33	68.64
13	15.71	17.40	11.92	9.95	9.84	1.87	3.18	10.12	4.82	84.82
14	13.52	10.69	7.59	6.66	7.56	2.26	2.65	11.27	3.81	65.99
15	13.13	10.46	7.46	6.16	6.06	2.26	2.34	16.10	4.82	68.78
16	13.55	11.17	7.92	7.15	7.70	2.02	3.00	10.35	4.32	67.18
17	16.14	14.58	11.15	9.97	9.14	2.04	2.59	9.89	4.62	80.13
18	13.63	11.01	7.73	6.89	7.73	1.69	3.09	12.94	4.82	69.54
19	13.28	10.61	7.41	6.53	6.97	1.83	3.22	14.23	5.33	69.42
20	13.69	14.12	8.39	7.88	7.83	1.35	2.82	14.72	5.33	76.12
21	4.60	15.57	12.25	14.93	14.59	0.34	3.89	9.90	4.87	80.94

Table 16 The qualitative description and susceptibility class for each debris flow catchment

Catchment	Category	Susceptibilit level
1	I	M
2	I	L
3	IV	L
4	II	M
5	I	L
6	II	M
7	I	L
8	IV	L
9	IV	L
10	II	H
11	III	L
12	IV	L
13	II	H
14	I	L
15	IV	L
16	I	L
17	II	M
18	III	L
19	III	L
20	III	M
21	I	M

Table 17 Comparison of susceptibility analyses based on different algorithms

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
K	M	L	L	M	L	M	L	L	L	H	L	L	H	L	L	L	M	L	L	M	M
Hierarchical	M	L	L	M	L	M	L	L	L	H	L	L	H	L	L	L	H	L	L	M	H
FCM	M	L	L	M	L	M	L	L	L	H	L	L	H	L	L	L	M	L	L	M	M

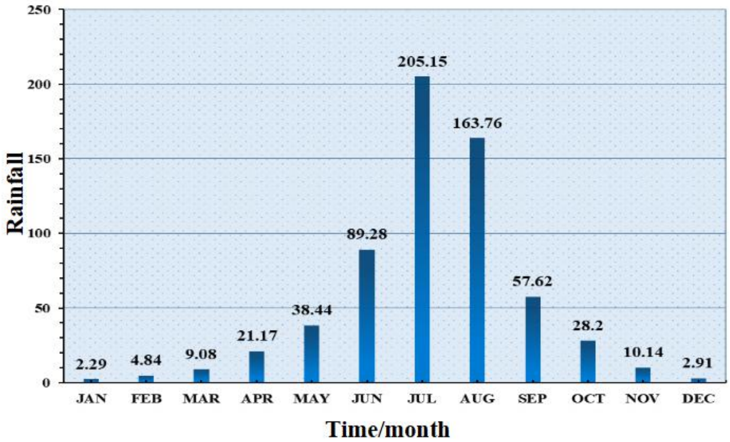

Fig1. Average monthly rainfall data (from 1959 to2017) for Pinggu district

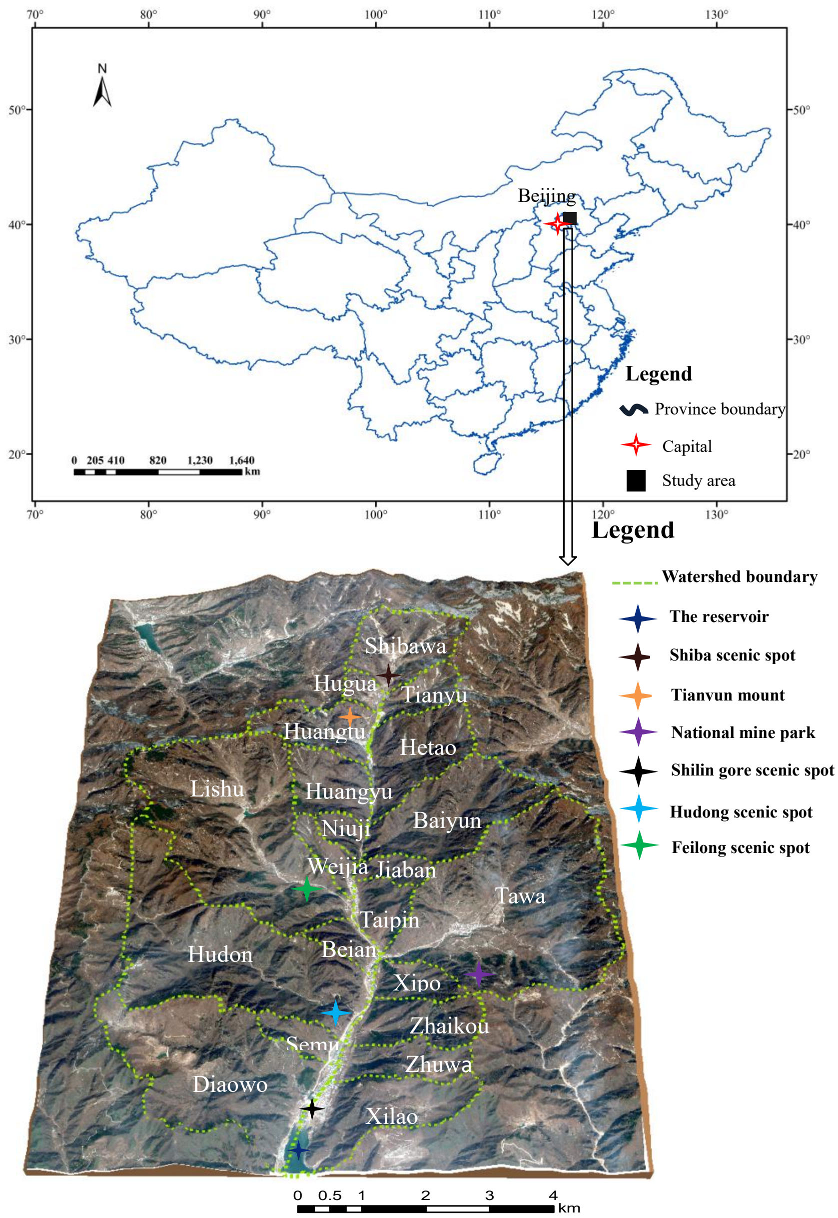

Fig.2 Geographical positions of the Huangsongyu scenic region and the investigated 21 debris flow catchments

Fig.3 Shilin gore scenic spot. **a** some scenic spots have been closed, **b** the scenic area was heavily blocked by rockfill, **c** threatening object of debris flow

Fig.4 Huangsongyu national mining park. d sign for debris flow hazard area, e debris flow monitoring instrument, f loose slag accumulated in formation area, g excavator mining

Fig.5 Lishu scenic spot. h stream sediments, i road cracks, g debirs flow deposit.

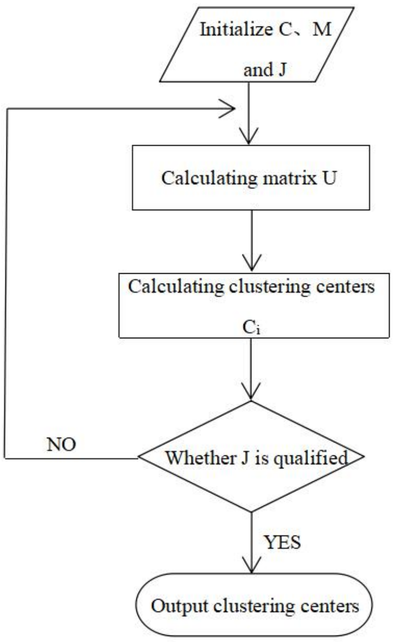

Fig.6 A flowchart of FCM

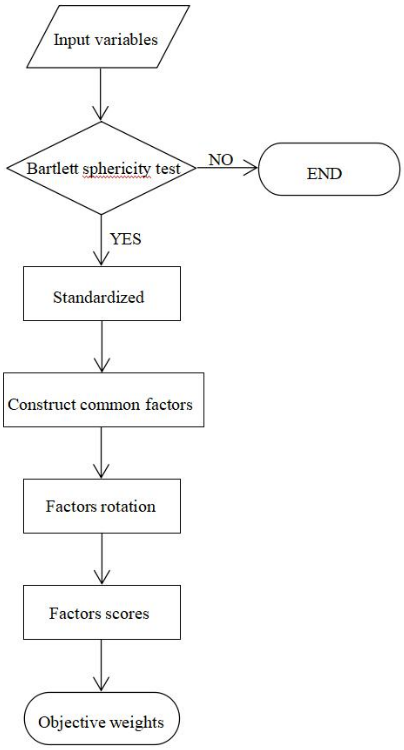

Fig.7 A flowchart of FA

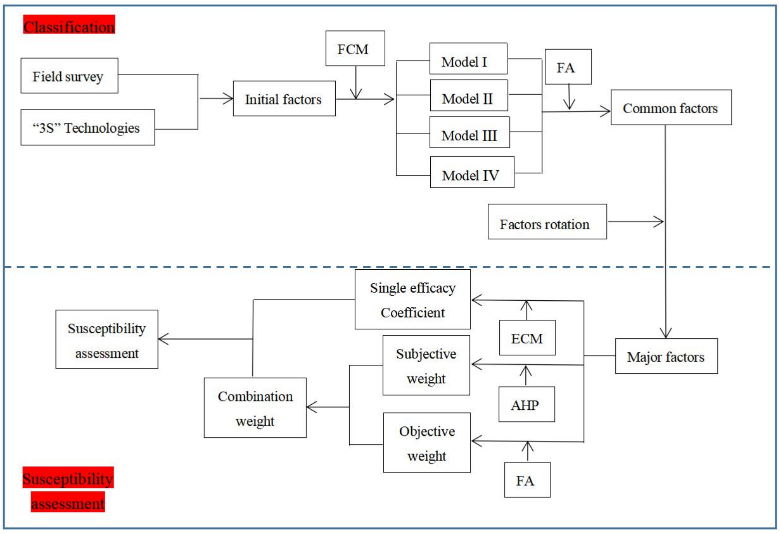

Fig.8 Flow chart used for classification and susceptibility assessment.

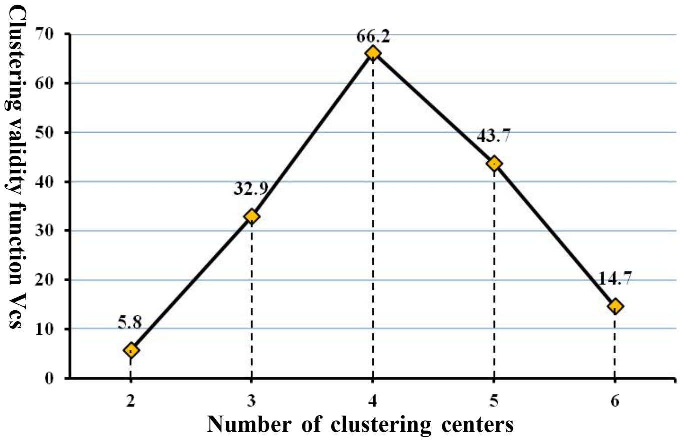

Fig.9 Clustering validity function Vcs

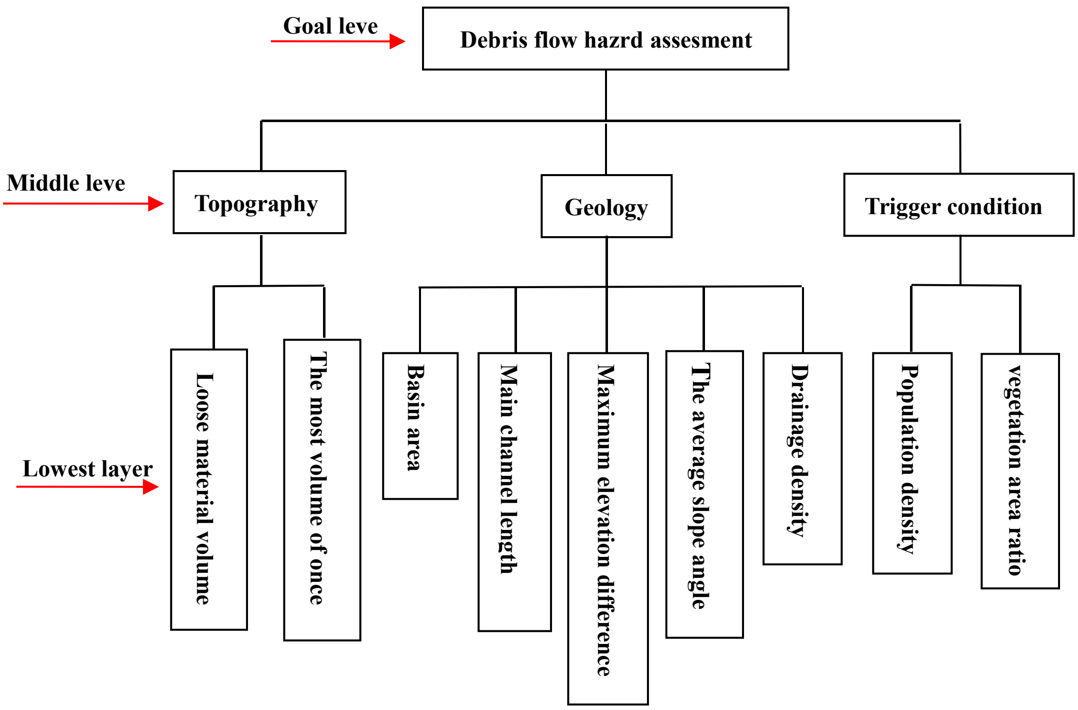

Fig.10 Hierarchical structure for debris flow susceptibility analysis

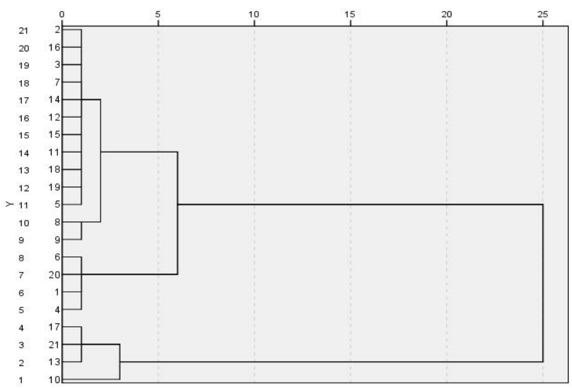

Fig.11 Tree diagram obtained by Hierarchical cluster.