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Assessing Debris Flow Susceptibility in Mountainous Area of Beijing, China Using a Combination Weighting and an Improved Fuzzy *C*-means Algorithm

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Susceptibility analysis is important in any study of debris flows. This paper presents a model for debris flow susceptibility analysis using a combination weighting and an improved fuzzy C-means algorithm. Twelve factors of influence were acquired by 3S technologies. Analytic hierarchy process (AHP) and entropy method were performed to obtain subjective and objective weighting of the factors, respectively. Game theory was carried out to determine the combination weighting since it provides analytical tools to model interactions among factors. An improved fuzzy C-means clustering analysis was applied to determine the susceptibility level of debris flows. This method is based on a particle swarm optimization algorithm, which is an evolutionary algorithm that can achieve global optimization, and is not sensitive to the initial cluster centers. Results showed that the susceptibility levels for one of the debris flow catchments was high, four were moderate, and five were low. Our quantitative assessments based on these nonlinear methods were consistent with field investigations.

1. Introduction

Debris flows are important geomorphic agents in mountainous area of Beijing. Susceptibility assessment represents an important criterion for engineers to understand the overall situation of the debris flow. Physical, empirical, and statistical approaches are widely used to evaluate debris flow susceptibility (Montgomery and Dietrich (1994); Carrara et al. (2008)). Although physical approaches are highly suited to susceptibility analyses, data for the factors used in these approaches cannot be obtained for large-scale debris flows (Dong et al. (2009)). Discriminant analysis and logistic regression are widely used as statistical tools in susceptibility analysis (Carrara et al. (2008)). Statistical approaches assume that the factors that caused debris flows are the same as those that will generate debris flows in the future. However, the availability of data should be ascertained before carrying out such an approach, since such data are difficult to obtain for most of China.

This paper aims to determine debris flow susceptibility using a combination weighting and an improved fuzzy C-means clustering. We used a geographic information system (GIS), a global positioning system (GPS) and remote sensing (RS), collectively known as the ‘3S technologies’, to determine factors of influence. Analytic hierarchy process (AHP) and entropy method were performed to obtain subjective and objective weighting of the factors, respectively. A combination weighting method based on game theory was carried out to obtain a more rational factor weight. Susceptibility analysis was conducted with these weighted factors using a fuzzy C-means (FCM) algorithm. The FCM algorithm is a method used for clustering which allows data to belong to two or more clusters. This method is applicable to a wide variety of geostatistical data analysis problems (Bezdek et al. (1984)). Therefore, we used the FCM algorithm for sorting debris flow catchments with similar characteristics into clusters. However, the FCM method cannot be guaranteed to reach a global optimum, and the initial cluster centers greatly influence the clustering results. To overcome these disadvantages, Kennedy and Eberhart (1995) proposed the particle swarm optimization (PSO) algorithm to simulate the phenomenon of biological predation. The PSO algorithm is useful because it is simple to program (Poli et al. (2007)). We used this algorithm to remedy the defect in the FCM algorithm. Hence, we carried out a susceptibility analysis of debris flows based on a combination weighting and a PSO-enhanced FCM clustering algorithm.

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2. Study area

Ten catchments were investigated for susceptibility analysis, which were Dawa (*DW*), Lamadong (*LMD*), Lamanan (*LMN*), and Duitaizi (*DTZ*) from Miyun district, Nanjiao (*NJ*), Beijiao (*BJ*), and Xiqu (*XQ*) from Fangshan district, Damo (*DM*), Longmiao (*LM*), Donghe (*DH*) from Mentougou district. Geographical settings to the 10 debris flow catchments investigated are shown in Fig. 1.

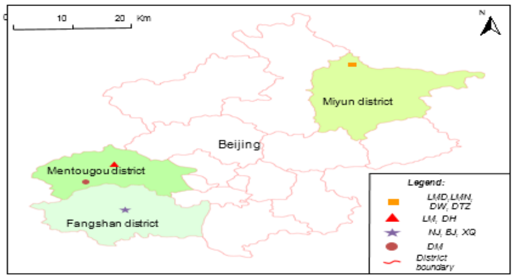

Figure 1: Geographical settings to the 10 debris flow catchments

Based on the field investigation, many kinds of loose materials, such as collapse deposits and landslides, are distributed in the debris flow catchments. For example, collapse deposits in main channel of Dawa gully were shown in Fig. 2. There are lots of crushed stone in main channel of Nanjiao (Fig. 3).

Figure 2: Collapse deposits in main channel of Dawa gully. Figure 3: Crushed stone in main channel of Nanjiao

Maximum elevation difference of these ten debris flow catchments range from 0.32 km to 1.1 km. Average gradients of main channels are between 0.052 and 0.268. Annual precipitation is between 400 and 800mm. Due to intense human activity, the natural vegetation has been subjected to severe damage, with the irrational deforestation and reclamation.

3. Methods

Subjective weights were determined by AHP, meanwhile objective weights were acquired by entropy method. A combination weighting method based on game theory was performed to get a more rational weight. Finally a PSO-enhanced FCM is introduced for assessing debris flow susceptibility.

3.1 Determination of weight

3.1.1 Analytic hierarchy process

AHP is performed in the following steps: (1) divide a complex problem into the component factors; (2) arrange these factors in a hierarchy order; (3) construct a pair-wise comparison matrix; (4) Comparison values can be determined from human judgments on the relative importance of each factor with respect to another factor within the same level. Comparisons were made through a scale of 1–9 based on Saaty's (1977) scaling method. In AHP, the consistency ratio (CR) is utilized to judge the consistent degree of the comparison matrix, which is defined as (Saaty (1977)).

$$\mathrm{CR}=\mathrm{CI}/\mathrm{RI} \tag{1}$$

where RI represents the random consistency index, which depends on the dimension of the comparison matrix (Saaty (1980)). The consistency index (CI) for the comparison matrix with the largest eigenvalue $\lambda_{\max}$ can be estimated by (Saaty (1977)).

$$\mathrm{CI}=\left(\lambda_{\max}-N\right)/(N-1), \tag{2}$$

where $\lambda_{\max}$ is the largest eigenvalue and *N* is the dimension of the comparison matrix.

Smaller CR results in a more rational assessment. The value of 0.1 is small enough according to Satty (1980). The weights of all factors within the subcriterion level for the goal level can be determined as follows. Assume that the criterion level involves *v* factors which include C_1, C_2, …, C_v; and their weights for the goal level are c_1, c_2, …, c_v, respectively. Assume also that the subcriterion level includes *n* factors, specifically D_1, D_2, …, D_n and that their weights with respect to C_j (j = 1, 2, …, v) are d_{1j}, d_{2j}, …, d_{nj}, respectively. When D_i (i = 1, 2, …, n) has no relationship with C_j, then d_{ij} is equal to 0. The weights of all factors within the subcriterion level d_1, d_2, …, d_n, with respect to the goal level, can be determined according to Eq. (3),

$$d_i = \sum_{j=1}^{v} d_{ij} c_j \tag{3}$$

3.1.2 Entropy weight

Debris flows, as systems with a certain turbulence degree, are influenced by numerous factors with degrees of influence. Entropy weight method involves the following steps: Suppose C_{ij} to be the *j*th factor of the *i*th debris flow catchment. The entropy of the *j*th (j = 1, 2, …n) factor can be determined by Eq. (4):

$$H_j = -K\sum_{j=1}^{n} f_{ij} Inf_{ij} \text{ , } \quad f_{ij} = r_{ij} \Big/ \sum_{j=1}^{n} r_{ij} \quad K = 1 \big/ \mathrm{Inn} \tag{4}$$

r_{ij} is the value of the *j*th normalized factor of the *i*th debris flow catchment.

Then weights w_j can then be calculated according to these entropy values, as shown in Eq. (5):

$$w_j = \frac{1 - H_j}{\sum_{j=1}^{n} 1 - H_j} \text{ .} \tag{5}$$

3.1.3 Combination weighting based on Game theory

Game theory was used to construct a combination weighting optimality model (Myerson, (1991)). This method involves the following steps: If we define a set of weight vectors $\boldsymbol{U}\big| = \{\boldsymbol{u}_1, \boldsymbol{u}_2, ..., \boldsymbol{u}_n\}$, then a linear combination of $\boldsymbol{U}$ can be written as:

$$\boldsymbol{U} = \sum_{k=1}^{n} \alpha_k \boldsymbol{u}_k^{\mathrm{T}} \qquad (\alpha_k > 0) \text{,} \tag{6}$$

where α_k is the weight coefficient and $\boldsymbol{u}_k$ is a weight vector from the set.

Determine the optimized U^* from all possible linear combinations. According to differential properties of the matrix, the optimal first derivative condition as follow:

$$\sum_{j=1}^{n} \alpha_j \times \boldsymbol{u}_i \times \boldsymbol{u}_j^{\mathrm{T}} = \boldsymbol{u}_i \times \boldsymbol{u}_i^{\mathrm{T}} \quad (i = 1, 2, ..., n) \text{,} \tag{7}$$

solve equation to get $(\alpha_1, \alpha_2, \ldots, \alpha_n)$, and then normalize $(\alpha_1, \alpha_2, \ldots, \alpha_n)$ to get $\alpha_k^*(k = 1, 2, \ldots, n)$. Finally we can acquire the combination weighting:

$$\boldsymbol{u}^* = \sum_{k=1}^{n} \alpha_k^* \cdot \boldsymbol{u}_k^{\mathrm{T}} \text{ .} \tag{8}$$

3.2 A PSO-enhanced FCM clustering algorithm

3.2.1 Fuzzy C-means algorithm

The FCM clustering algorithm assumes that the whole data population can be grouped into *C* fuzzy clusters, where each cluster is specified by its center V_i (i = *1*, *2*,...,*c*) and an association of data points specified by their membership grade (Bezdek (1981)). According to a nonlinear function of the distances of data points from the cluster centers, membership grades are defined as:

$$u_{ij} = \frac{1}{d^2(X_j, V_i)} \left[\sum_{i=1}^{C} \left(\frac{1}{d^2(X_j, V_i)} \right) \right]^{-1} \text{, } \quad V_i = \sum_{j=1}^{n} u_{ij}^m x_j \Big/ \sum_{j=1}^{n} u_{ij}^m \text{,} \tag{9}$$

where *C* is the number of cluster centers; X_j denotes the *j*th observation; V_i denotes the *i*th cluster center; $d(X_j, V_i)$ is the distance between observation X_j and cluster center V_i; u_{ij} represents the membership grade of the *j*th observation to the *i*th set; and *m* is the fuzziness index. Iterative minimization of an objective function *J* was defined in terms of the weighted distances of the data points from the cluster centers:

$$J = \sum_{j=1}^{N}\sum_{i=1}^{C} u_{ij}^{m} d^{2}\left(X_j, V_i\right), \tag{10}$$

where N is the total number of observations. The FCM method cannot be guaranteed to reach a global optimum. Hence, a PSO was introduced to overcome these disadvantages.

3.2.2 Particle swarm optimization algorithm

PSO is a metaheuristic designed by Kennedy and Eberhart (1995) with inspiration from swarming theory. A particle i in a D-dimensional space is represented by its position and velocity which can be described as $X_i = (x_{i1}, x_{i2}, \dots x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \dots v_{iD})$, respectively (Lin et al. (2015)). The personal best position of each particle and the global best position of the entire swarm are represented as $P_i = (p_{i1}, p_{i2}, \dots p_{iD})$ and $P_g = (p_{g1}, p_{g2}, \dots p_{gD})$, respectively. The position and velocity of a particle i can be updated by:

$$v_{id} = wv_{id} + \mu_1 r_1 (p_{id} - x_{id}) + \mu_2 r_2 (p_{gd} - x_{id}), \tag{11}$$

$$x_{id} = x_{id} + v_{id}, \tag{12}$$

where d is the dimension of searching space, w is the inertia weight ranging from 0.4 to 0.9, μ_1 and μ_2 are positive constants ($\mu_1 = \mu_2 = 2$), and r_1 and r_2 are two random numbers in the range [0, 1]. A linearly decreasing inertia weight w by starting at $w_{max} = 0.9$ and ending at $w_{min} = 0.4$ is used to control this kind of balance.

$$w = w_{max} - t \times \frac{w_{max} - w_{min}}{t_{max}}, \tag{13}$$

where t is the current iteration number and t_{max} is the total number of iterations.

A fusion algorithm based on FCM and PSO is adopted: the position of each particle corresponds to the clustering result, each particle has a velocity V to change its position, and a fitness value f to evaluate the fitness of the position. In this study, the fitness value of each particle is represented by the accumulated distance between the centers of C cluster centers and their data points, which is computed by Eq. (10).

4. Susceptibility analysis of debris flows

4.1 Determination of factors of influence

The mostly likely factors for debris flow susceptibility are geological, topographical, hydrologic, meteorological, and vegetation conditions. Roundness was also considered as a morphological condition. Population density was included as a factor of influence in our research. Twelve factors of influence were selected, they are: loose material supply length ratio ($C1$); loose material volume per square kilometer ($\times 10^4 m^3/km^2$) ($C2$); maximum elevation difference of a catchment (km) ($C3$); average gradient of the main channel ($C4$); drainage density (km/km^2) ($C5$); basin area (km^2) ($C6$); total drainage length (km) ($C7$); drainage frequency ($C8$); maximum daily rainfall (mm) ($C9$); population density ($C10$); the ratio of vegetation area ($C11$); roundness ($C12$). All these factors were acquired by 3S technologies. A digital elevation model (DEM) was built using ArcGIS to obtain factors related to elevation. Positions of the watershed boundary and drainages were obtained by RS images. Loose material volume per square kilometer, loose material supply length ratio, and the ratio of vegetation area were acquired with a ruler and laser rangefinder during our field survey.

4.2 Combination weights and assessing debris flow susceptibility

As stated in Sect. 3.1.1, AHP structure diagram can be determined as Fig.4. Table 1 shows the comparison values of criterion level factors which have contributions toward the goal level. For example, a pair-wise comparison value of 2 in topographical condition versus geological condition represents the opinion of the respondent that topographical condition is important than geological condition. The weights of the subcriterion level factors can be determined. The geological condition includes $C1$ and $C2$. $C2$ is slightly more important than $C1$. Therefore, the weights of $C1$ and $C2$ in the geological condition are 0.33 and 0.67, respectively.

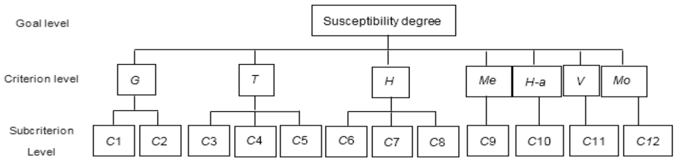

Figure 4: Hierarchical structure of the AHP method for debris flow susceptibility

Table 1: Comparison matrix elements of the criterion level factors

	G	*T*	*H*	*Me*	*H-a*	*V*	*Mo*
G	1	1/2	1/2	1/3	1/2	1	1/2
T	2	1	1	1/2	1	2	1
H	2	1	1	1/2	1	2	1
Me	3	2	2	1	2	3	2
H-a	2	1	1	1/2	1	2	1
V	1	1/2	1/2	1/3	1/2	1	1/2
Mo	2	1	1	1/2	1	2	1

Note: *G*, *T*, *H*, *Me*, *H-a*, *V*, and *Mo* is the abbreviation of Geological, Topographical, Hydrologic, Meteorological, Human activity, Vegetation, and Morphological.

Table 2: Comparison matrix elements of C3–C5 for topographical condition

	*C*3	*C*4	*C*5
*C*3	1	1/3	1/2
*C*4	3	1	2
*C*5	2	1/2	1

Table 3: Comparison matrix elements of C6–C8 for hydrologic condition

	*C*6	*C*7	*C*8
*C*6	1	2	3
*C*7	1/2	1	2
*C*8	1/3	1/2	1

Objective weights of the factors were determined by using the entropy method. Then the method introduced in Sect. 3.1.3 was used to determine combination weights. The subjective, objective, and combination weights of factors *C*1 to *C*12 are shown in Table 4

Table 4: The subjective, objective, and combination weights of factors C1 to C12

	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10	*C*11	*C*12
subjective	0.029	0.059	0.034	0.113	0.062	0.113	0.062	0.034	0.209	0.113	0.059	0.113
objective	0.084	0.096	0.073	0.084	0.074	0.095	0.092	0.078	0.089	0.081	0.077	0.078
combination	0.032	0.062	0.032	0.110	0.061	0.111	0.062	0.032	0.207	0.110	0.061	0.110

Susceptibility analysis of debris flows was carried out with a PSO-enhanced FCM method based on factors and their weights. Our classification for the ten debris flow catchments based on the susceptibility analysis is shown in Table 5

Table 5: The factors and the susceptibility results of 10 debris flow catchments

	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10	*C*11	*C*12	Result
DW	0.35	1.28	0.54	0.14	3.90	2.13	7.5	3.29	362.8	70.0	30	0.68	*L*
LMD	0.26	0.38	0.35	0.12	3.54	1.43	4.5	3.49	362.8	130.0	40	0.62	*L*
	*C*1	*C*2	*C*3	*C*4	*C*5	*C*6	*C*7	*C*8	*C*9	*C*10	*C*11	*C*12	Result
LMN	0.24	1.19	0.32	0.09	2.37	2.51	6.6	2.79	362.8	240.0	35	0.66	*L*
DTZ	0.40	0.61	0.43	0.07	2.55	3.69	9.3	2.17	362.8	90.0	28	0.67	*M*
NJ	0.10	1.77	1.10	0.05	1.91	24.34	29.5	0.62	460.0	250.0	15	0.81	*H*
BJ	0.10	0.51	0.77	0.07	3.66	9.96	11.0	1.34	385.3	100.0	20	0.43	*M*
XQ	0.50	7.80	0.91	0.14	3.35	7.26	13.2	1.24	409.2	80.0	18	0.56	*M*
DM	0.70	5.71	0.86	0.23	1.20	4.87	9.6	1.64	224.8	130.0	25	0.65	*M*
LM	0.05	0.17	1.09	0.27	1.83	3.95	6.7	1.01	190.7	170.0	10	0.67	*L*
DH	0.08	0.37	1.03	0.09	1.32	5.58	8.5	0.90	190.7	160.0	9	0.78	*L*

Note: *DW*, *LMD*, *LMN*, *DTZ*, *NJ*, *BJ*, *XQ*, *DM*, *LM*, and *DH* is the abbreviation of Dawa, Lamadong, Lamanan, Duitaizi, Nanjiao, Beijiao, Xiqu, Damo, Longmiao, and Donghe. *H*, *M*, *L* is the abbreviation of high, moderate, low.

5. Discussion and conclusions

Ten debris flow catchments located in mountainous area of Beijing, China, were investigated. Twelve factors factors reflect various geological, topographical, hydrologic, meteorological, morphological, human activity, and vegetation conditions of a catchment. AHP and entropy method were performed to obtain subjective and objective weighting of the factors, respectively. The combination weighting method based on game theory was used to get a more rational weight. Weights of factors (from *C*1 to *C*12) were determined to be 0.032, 0.062, 0.032, 0.110, 0.061, 0.111, 0.062, 0.032, 0.207, 0.110, 0.061, and 0.110 respectively.

A susceptibility analysis for debris flows was carried out with a PSO-enhanced FCM clustering algorithm based on these factors and their weights. Results showed that the debris flow susceptibility of the Nanjiao catchment was high, the Duitaizi, Beijiao, Xiqu, and Damo catchments had moderate susceptibility, while the other five had low values.

The limitation of the analysis method used in this study is susceptibility of a single debris flow catchment cannot be assessed with this method. On a final note, the results of our susceptibility analysis, identified debris flow catchments with high susceptibility that should be flagged for environmental management.

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