GIS-models with fuzzy logic for Susceptibility Maps of debris flow using multiple types of parameters: A Case Study in Pinggu District of Beijing, China

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Abstract

Debris flow is one of the main causes of life loss and infrastructure damage in mountainous areas~~,~~. ~~this~~ This hazard ~~must~~ should be recognized in the early stage of land development planning. According to field investigation and expert experience, a scientific and effective quantitative susceptibility assessment model was established in Pinggu District of Beijing. This model is based on Geographic Information System (GIS), combining with grey relational, data-driven and fuzzy logic methods. The influence factors, which are divided into two categories and consistent with the system characteristics of debris flow gully, are selected, also a new important factor is proposed. ~~The inherent influence factors, which are divided into two categories, are selected in the model consistent with the system characteristics of debris flow gully and one new important factor are proposed.~~ The results of the 17 models are verified ~~by results~~using data published by the authority, and validated by two other indexes as well as Area Under Curve (AUC). Through the comparison and analysis of the results, we believe that the streamlining of factors and scientific classification should attract attention from other researchers to optimize a model. We also propose a good perspective to make better use of the watershed feature parameters. These parameters fit well with the watershed units. ~~a method to optimize is proposed, including reasonable application of field investigation and expert experience, simplification of factors and scientific classification.~~ With full use of insufficient data, scientific calculation, and reliable results, the final optimal susceptibility map could potentially help decision makers in determining regional-scale land use planning and debris flow hazard mitigation. ~~And the final optimal susceptibility map with full discussion has the potential help in determining regional-scale land use planning and debris flow hazard mitigation for decision makers, with full use of insufficient data, scientific calculation, and reliable results.~~ The model has advantages in economically backward areas with insufficient data in mountainous areas because of its simplicity, interpretability and engineering usefulness.

Key words: debris flow; susceptibility assessment; fuzzy logic; model optimization; hazard mitigation

1 Introduction

Debris flows are processes of rapid transport of water and soil materials in mountain watersheds, with sudden and destructive outbreaks(Di et al., 2019). Some debris flows can often cause devastating disasters and huge losses(Zhang et al., 2021) and seriously threaten the lives and properties of ~~the~~ people in the mountains, the safety of major projects, and restrict social and economic development (Iverson, 1997; Hungr et al., 2005; Hu et al., 2011; Takahashi, 2014; Wu et al., 2019). Mass movements in Beijing range in scale from shallow slope failures and rockfalls to catastrophic rock avalanches frequently mobilize to form debris flows, threatening the ecological environment of the mountainous area (Zhong et al., 2004). Especially, in recent years, due to the superposition of extreme rainstorm weather and human engineering activities, debris flow events have increased gradually(Li et al., 2021b). As the capital of China, Beijing also has strong influence and radiation at home and abroad, where geological disasters are widely concerned (Xie et al., 2004; Li et al., 2020b). With the deepening understanding of debris flow disaster and the updating of database, a new and more accurate evaluation is also very necessary. Therefore, it is of great significance to establish accurate and scientific debris flow susceptibility map.

Through previous studies, it can be summarized that the current research on debris flow mainly focuses on the following aspects: study on mechanism of debris flow, study on early warning and prediction of debris flow, study on numerical simulation of debris flow and study on debris flow hazard analysis. Especially, studies on debris flow hazard analysis have raised the attention of the researchers as soon as it appears(Dong et al., 2009). Communicating information about debris flow hazard analysis is a crucial component of preparedness and hazard mitigation (Chiou et al., 2015). Susceptibility assessment, an important part of a hazard assessment of geological processes, is more flexible(Li et al., 2021a). In the early days, the susceptibility assessment of debris flows was mainly qualitative research using geomorphological information (Guzzetti et al., 1999). In 1976, the United Nations commissioned the International Union of Engineering Geology to conduct a risk assessment of debris flows, which marked the beginning of research on the susceptibility assessment of debris flows as an important research direction for disaster prevention and prediction (Li et al., 2020b). Many methods and techniques have been proposed to evaluate debris flow susceptibility assessment based on different qualitative and quantitative approaches ~~and~~ along with geo-environmental information (Liu and Wang, 1995), Such as the analytic hierarchy process (Wu et al., 2016), logistic regression method (Regmi et al., 2013; Conoscenti et al., 2015), information value (Akbar and Ha, 2011; Melo et al., 2012), support vector machine(Pourghasemi et al., 2017), frequency ratio (FR) (Sun et al., 2018), certainty factor (CF) (Tsangaratos and Ilia, 2015), neural network (Lee et al., 2003; Liu et al., 2005) and Bayesian network algorithm (Liang et al., 2012; Tien Bui et al., 2012), etc. These methods have corresponding advantages and limitations for research subjects with different geological conditions. Generally speaking, it is easier to get satisfactory results by combining and comparing various methods (Meyer et al., 2014; Di Napoli et al., 2020; Fang et al., 2020). In summary, with the development of mathematical theory, the susceptibility assessment of debris flows has been extensively and quantitatively studied, and the research methods have also changed from single to comprehensive.

The economy in mountainous areas is often backward, we cannot supervise and verify every basin due to ~~the~~ limited funds. The debris flow susceptibility assessment can give decision makers a basis for rational allocation of resources, and determine which gullies should be focused on. In other words, the study plays a link role for other studies. Recently, with the development of mathematical theory, computer technology, the application of 3S (Remote sensing, Geography information systems, Global positioning systems), the susceptibility assessment of debris flows has been extensively and quantitatively studied(Li et al., 2020a). As research progresses, debris flows are increasingly seen as an open system. There are many factors influencing the system and the combination of factors is non-linear and the interactions are chaotic. Therefore, it is very difficult to find a unified and standard evaluation model. At present, when the information is insufficient, ~~the~~ field investigation and experience of experts are necessary. However, the experience is often subjective and needs a lot of professional experience accumulation. It is very important to express the experience of experts objectively and understandably to serve decision makers. The application of fuzzy set theory in GIS environments is effective for similar problems(Luo and Dimitrakopoulos, 2003; Porwal et al., 2006).

The main objective of this paper is to propose a quantitative geographic information system (GIS)-based model. The results of expert experience scoring and site surveys are used as guidance and reference in the modelling process. We have tried to apply methods that can indicate the non-linearity of the debris flow system. Finally, the modelling process should respect the laws of geomorphological evolution and the geological basis. Otherwise, the result will tend to be simply data fitting(Porwal et al., 2006).

2 Study area

The study area is located on the northeast of Beijing, China (Fig. 1), with a total area of 948.24 square kilometers. The elevation of Pinggu is high in the northeast and low in the southwest. It is surrounded by mountains, accounts for about two-thirds of the total area, on three sides in the southeast and north. The central and southern parts are alluvial plains. The area, geologically, is the west extension of the famous Jixian section, whose bedrock is mainly Middle and Late Proterozoic dolomite(Lü et al., 2017). The administrative unit of Pinggu District is used as the study area boundary, mainly considering that geological hazards frequently influence human economic activities, so political factors must be taken into account. And within the administrative region, inconsistent decision-making can be effectively avoided.

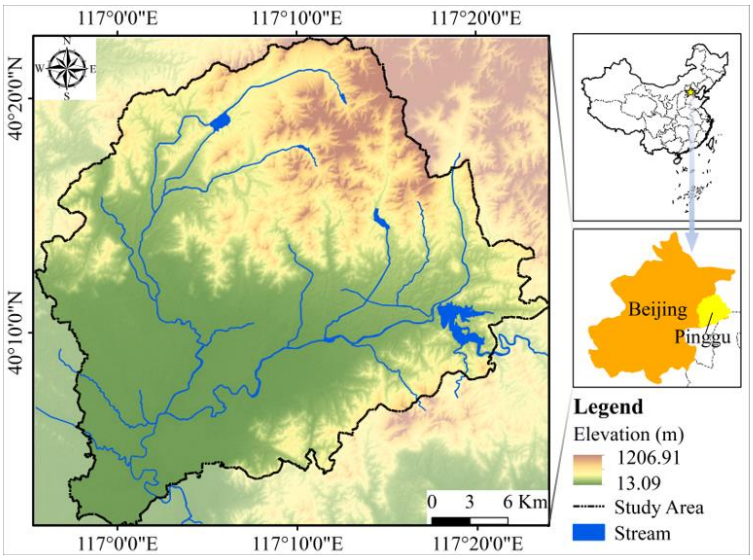

Fig. 1 Study area

3. Data and Methodology

In this study, the susceptibility assessment of debris flow hazard was based on the drainage basin unit. In ~~a debris flow susceptibility assessment~~such a model, hydro-logical response unit can fully represent the hydrological process of hillside and will make the results more meaningful(Khan et al., 2013; Khan et al., 2016; Zou et al., 2019). First, drainage networks were extracted from the ASTER-DEM by using the ArcGIS ArcHydro Toolbox and regions without obvious watershed characteristics were directly deleted. Then for each drainage basin, 19 controlling and triggering factors divided into two types were calculated. In addition, for these factors have different characteristics, different methods were used to calculate the fuzzy membership for different type factors. Field investigation is generally required in geological hazard surveys. If these data are applied to the model, it can help with the model building and reduce the time for model training~~If the data from the field investigation is applied to the model, it can help the model building and reduce the time for model training~~. The weights derived from the grey relational analysis method used in the following section (section 3.4.1) are based on the data from the field investigation. While geology and geomorphology factors are independent of watershed characteristics, it is suitable to use statistical methods to determine the objective weight. Finally, the debris flow susceptibility index (DFSI) map was derived by overlaying the factor thematic layers with fuzzy logic method. The workflow of debris flow susceptibility assessment is showed in Fig.2. First, a DEM map of the Pinggu area was downloaded. Then, the basin units were generated from the DEM map using the ArcHydro tool. The derived results were analyzed and units that did not fit the characteristics of the watershed were removed. During the analysis, the field investigation data and Google images were referenced. After that, the controlling and triggering factors for the remaining 135 catchments were counted. For the fuzzy memberships, watershed characteristic parameters were determined by grey correlation, ~~and~~ the geological and geomorphological factors were determined by the frequency ratio (FR) method and the cosine amplitude method.

Finally, the individual layers were overlaid by fuzzy logic operations to obtain the final map. As there were different combinations of factors, 17 results were derived. Three indexes (AUC, AR and RR) were used to evaluate advantages and disadvantages of these results.

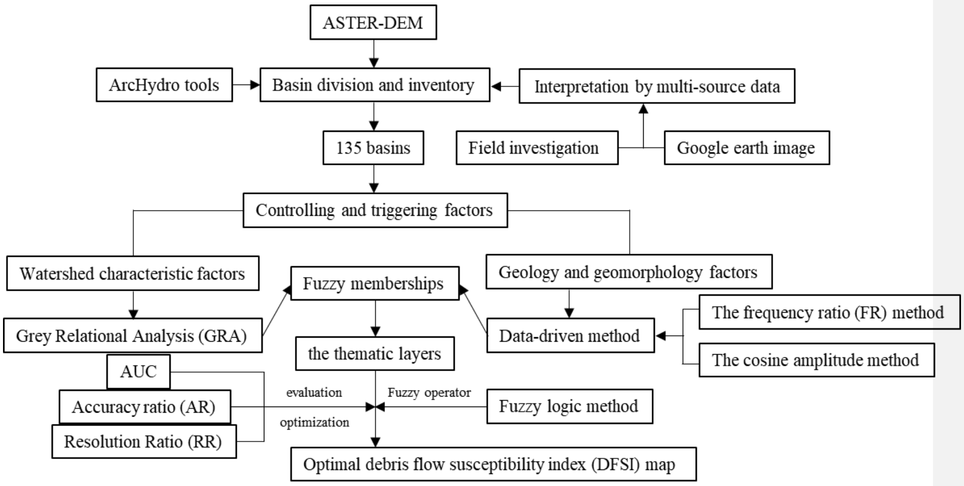

Fig.2 Workflow of debris flow susceptibility assessment

3.1 Debris flow basin division and inventory

There are many geological hazard points in mountainous area, so it is not realistic to monitor them completely by professional teams. According to the monitoring and preventing staff and the villagers, the detailed field investigation (Fig.3) for the evidence collection of debris flows will be carried out at the reported disaster point, aiming at record the loose material, delineating the basin and exploring other important information of the debris flow gullies. Moreover, field investigation is also very important for model modification. Then based on the Hydrology module in ArcGIS 10.2, the research object can be determined. Compared with grid unit and slope unit, hydrological response unit for susceptibility of debris flow has greater advantages(Li et al., 2021b; Zou et al., 2019). Finally, ~~135 basins are divided after removing the flat and irregular areas (Fig. 4),~~ referring to the result of the field investigation and the remote sensing image, 135 basins are divided after removing the flat and irregular areas (Fig. 4~~.~~), ~~In the 135 basins,~~ and 48 basins of them were investigated on field, accounting for 36%.

Fig.3 Field investigation photos. **a** Loose material; **b** Middle and Late Proterozoic dolomite; **c** colluvium deposit; **d** Slope fracture; **e** Channel erosion phenomenon

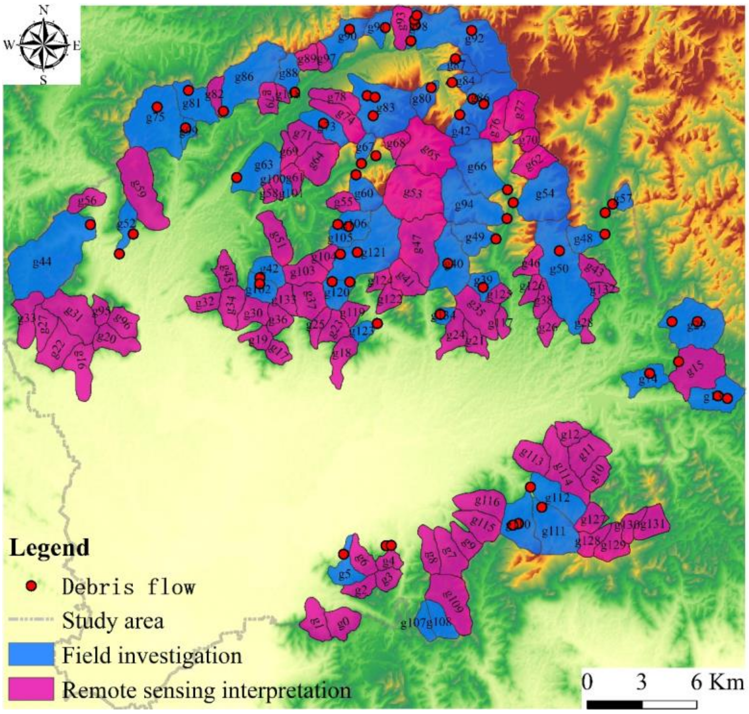

Fig. 4 Debris flow basin division and inventory.

Note: The data of debris flow points comes from Beijing Municipal Commission of Planning and Natural Resources websites (http://ghzrzyw.beijing.gov.cn/zhengwuxinxi/zxzt/dzzhfzzt/zzzhdcpg/202008/t20200807_1976436.html)

3.2 Debris flow controlling and triggering factors

The basic requirement for the assessment of debris flows is that some factors included are easily obtainable, ~~are~~ meaningful for susceptibility assessment, and can be used for evaluating the need for passive or active debris flow mitigation. According to previous studies, 19 factors are selected in this study. the factors are divided into two types (Table 1) because of their different characteristics. Watershed characteristic factors (Type A) can be directly quantified, once the basin is determined (Fig. 5). The influence of these parameters is bounded by the watershed; Geology and geomorphology factors (Type B) need to be further processed, even if the watershed is determined. The scope of these parameters is independent of the watershed boundary.

Table 1 Factors for susceptibility assessment

Factors and Description			Significance	obtaining ways
Watershed characteristic factors (Type A)	A_1	The planimetric (projected) area of the catchment	Geometric parameter; affecting the accumulative total volume of water and representing the potential magnitude(Zhang et al., 2011; Cao et al., 2016; Chang and Chien, 2007)	derived from DEM
	A_2	The curved surface area of the catchment	Real contact area between rainfall and basin	derived from DEM
	A_3	The surface roughness of the catchment	Dimensionless parameters, reflecting the fragmentation degrees of the surface and the ground surface micro-topography. Wu et al. (2019) believe the factor can further reflects the ability of the earth to resist wind erosion.	Calculated by $A_3 = A_2 / A_1$
	A_4	The perimeter of catchment	Geometric parameter, controlling the boundaries of a watershed	derived from DEM
	A_5	Form factor	Hydrologic parameter, related to the distribution of flow rate hydrograph(Chang and Chien, 2007)	Calculated by $A_5 = \frac{A_4}{2\sqrt{\pi A_1}}$
	A_6	The curve length of the main channel	Importance for the travel distance of materials and affecting the potential of erosive agents to dislodge and transport materials(Gómez and Kavzoglu, 2005)	derived from DEM
	A_7	The straight length of the main channel	Geometric parameter, representing the change of material source in space	derived from DEM
	A_8	Bending coefficient of the main channel	Affecting the discharge situation of debris flows(Li et al., 2020a; Zhang et al., 2013)	Calculated by $A_8=A_6/A_7$
	A_9	The gradient of the main channel	Hydraulic gradient parameter, affecting water transport capacity	Calculated by $A_9=A_{12}/A_6$
	A_{10}	Maximum elevation in the catchment	Affecting vegetation and bedrock exposure	derived from DEM
	A_{11}	Minimum elevation in the catchment	Affecting vegetation and bedrock exposure slightly	derived from DEM
	A_{12}	Maximum relative relief in the catchment	The higher the value of A_{12} is, the large relative relief provides favorable terrain conditions for the initiation of the debris flow source.	Calculated by $A_{12}=A_{10}-A_{11}$
	A_{13}	Basin volume: the volume above the level of the minimum elevation in the basin	Representing the maximum material source that can be produced in an ideal state, loose material volume	derived from DEM
	A_{14}	Drainage density	Representing the geological structure, lithology, and the degree of rock weathering comprehensively and affecting the	the ratio of the total length of river network lines to A_1

			range of lateral erosions and retrogressive(Cao et al., 2016; Zhang et al., 2011)	
Geology and geomorphology factors (Type B)	B_1	Lithology	Affecting the rock mass shear strength and permeability (Donati and Turrini, 2002)	derived from 1:50,000 geological maps
	B_2	Proximity to faults	correlated with slope failures by generally reducing the strength of the rock mass (Dramis and Sorriso-Valvo, 1994; Korup, 2004; Kellogg, 2001; Kritikos and Davies, 2015).	derived from 1:50,000 numerical geological maps
	B_3	Slope (degrees)	correlated with the probability of landslide occurrence (Dai and Lee, 2002; Lee and Choi, 2004; He and Beighley, 2008). The greater the slope, the greater the vertical component of gravity (Donati and Turrini, 2002), and the higher frequency of slope failures (Lee and Sambath, 2006; Lee and Talib, 2005)	derived from DEM
	B_4	Slope aspect	affecting slope instability directly or indirectly, as a result of drying winds, sunlight, rainfall and vegetation (Dai and Lee, 2002; Dai et al., 2001).	derived from DEM
	B_5	Curvature	Affecting slope stability. While Lee and Talib (2005) and Ohlmacher (2007) argue on how curvature affect slope stability.	derived from DEM

Note: The geological maps are provided by Beijing institute of geological and prospecting engineering and the digital elevation model-(DEM) of study area are from SRTM-DEM with a solution. of 30 m (http://gdex. cr. usgs. gov/gdex/).

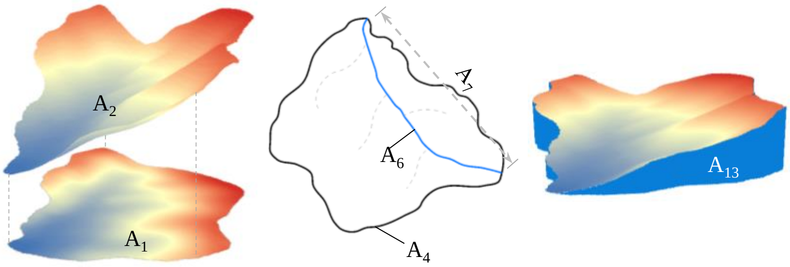

Fig. 5 Graphical illustration of some Type A factors. $\mathbf{A_1}$ is the planimetric (projected) area of the catchment; $\mathbf{A_2}$ is the curved surface area of the catchment; $\mathbf{A_4}$ is ~~the~~ the perimeter of catchment; $\mathbf{A_6}$ is the curve length of the main channel; $\mathbf{A_7}$ is the straight length of the main channel; $\mathbf{A_{13}}$ is basin volume

3.3 Fuzzy logic in susceptibility modelling

Fuzzy set theory is proposed by Zadeh (1965). It is an efficient way of expressing the concept of partial set membership degree. This concept differs from classical binary (0-1 value) logic. More words with a transitional fuzzy descriptions (such as low, medium, and high) are used (Kritikos and Davies, 2015). This fuzzy expression is particularly applicable to geological hazard classification. In the theory of fuzzy sets, elements have different degrees of membership in the interval [0,1]. 1 represents complete membership, and 0 represents non membership. Ross (1995) showed that fuzzy systems are useful in two general situations (Kritikos and Davies, 2015). The method is very consistent with the characteristics of debris flow system, whose predisposing factors are fuzzy in nature and mechanism is complex and not fully understood. Application of fuzzy logic method, the critical step is to find the suitable fuzzy membership of factors. And fuzzy membership degree is equivalent to the weight in expert scoring method, which is calculated by objective method rather than given subjectively.

3.4 Fuzzy memberships

3.4.1Grey Relational Analysis (GRA) in susceptibility modeling

GRA is proposed by Deng (1982) and it is an important part of grey system theory (Wang et al., 2014). Comparing with mathematical statistics methods which need lots of sample data, typical probability distribution and large calculation, GRA is applicable to small sample size ~~and~~ with ~~whether~~ the data ~~is~~ whether regular or not. There will be no inconsistency between qualitative analysis and quantitative analysis (Deng, 1988). Besides it is to excogitate the leading and potential factors that affect the development of the system, and quantitatively describe the development and change trend of the system by studying whether the relative change trend of the grey factor variables with complex relationship is consistent in the process of system development and evolution (Liu et al., 2004). Thus, grey correlation analysis is introduced to quantify the correlation between each factor and the evaluation results according to field investigation expert experience. First, the procedure of GRA is to translate the performance of every alternative into a comparability sequence (Lin and Lin, 2002; Kuo et al., 2008; Wei et al., 2017). Therefore, according to technical standard, “Specification of geological investigation for debris flow stabilization (DZ/T0220-2006)”, published by the China Ministry of Lands and Resources, the preliminary assessment results of debris flow susceptibility are obtained, which are used as the reference sequence of grey relation method (Table 2). Second, the grey correlation coefficient of all A factors is calculated by Eq. (1). Finally, the average grey relational coefficient (the correlation degree) is calculated by Eq. (2) as the fuzzy memberships (Table 3).

$$\xi_i(k) = \frac{\min_i \min_k |x_0(k)-x_i(k)| + 0.5 \max_i \max_k |x_0(k)-x_i(k)|}{|x_0(k)-x_i(k)| + 0.5 \min_i \min_k |x_0(k)-x_i(k)|} \quad (1)$$

Where $\xi_i(k)$ is the grey relational coefficient, i=1, 2, …, n are the number i type A factors, k=1, 2, …, n are the number of basins, $x_0(k)$ is the reference sequence (ideal target sequence), $x_i(k)$ is the number i type A factor sequence

$$r_i = \frac{1}{N}\sum_{i=1}^{n} \xi_i(k) \quad (2)$$

Where r_i is the correlation degree in the range (0,1). N is the total number of basins in Table 2

Table 2 Quantitative evaluation grade standard table for Debris flow susceptibility

name	g5	g13	g14	g29	g39	g40	g42	g44	g48	g49	g50	g52	g54
score	59	54	50	63	61	66	55	65	78	69	85	46	70
name	g57	g60	g63	g66	g67	g72	g73	g75	g80	g81	g83	g84	g85
score	56	63	58	73	62	84	62	67	84	69	80	75	86
name	g86	g87	g88	g90	g91	g92	g94	g98	g99	g101	g102	g105	g106
score	73	84	60	70	80	84	71	78	61	65	67	65	70
name	g107	g108	g110	g111	g112	g120	g121	g123	g134	-	-	-	-
score	45	45	69	69	74	62	63	73	56	-	-	-	-

Note: （130⩾score ⩾116, VH），（115⩾score ⩾87, M），（86⩾score ⩾44, L），（43⩾score ⩾15, N）
VH=very high susceptibility, M=moderate susceptibility, L=low susceptibility, N= Non-debris flow

Table 3 The fuzzy memberships of type A factors

Factor	A_1	A_2	A_3	A_4	A_5	A_6	A_7
Fuzzy membership	0.77	0.77	0.63	0.6	0.54	0.55	0.67
Factor	A_8	A_9	A_{10}	A_{11}	A_{12}	A_{13}	A_{14}
Fuzzy membership	0.71	0.55	0.55	0.59	0.61	0.79	0.54

3.4.2 Data-driven method in susceptibility modeling

landslide is one of the main fixed sources of debris flow in mountainous area. Shallow landslides are one of the most common categories of landslides. They frequently involve large areas and different soils in various climatic zones (Benda and Dunne, 1987; Selby, 1982; Borrelli et al., 2014). Great debris flows may result from numerous, small slope failures that subsequently coalesce (Fairchild, 1987; Roeloffs, 1996), from flow enlargement due to incorporation of bed and bank debris (Pierson et al., 1990; Bovis and Dagg, 1992), or from large, individual landslides that mobilize partially or almost totally (Vallance and Scott, 1997; Iverson et al., 1997). Debris flows may also scour steep channels to bedrock and accelerate sediment delivery to downstream, lower-gradient channels. The spatial and temporal distribution of shallow landslides are important controls on landscape evolution and a major component of both natural and management-related disturbance regimes in mountain drainage basins (Tsukamoto et al., 1982; Dietrich et al., 1986; Benda, 1987; Crozier et al., 1990). Therefore, the landslide susceptibility assessment methods can be used for reference to debris flow susceptibility assessment.

For type B factors which cannot be characterized by a specific number, the frequency ratio (FR) method and the cosine amplitude method can be used to derive their fuzzy memberships. The FR ratio defined as Eq. (3). Considering the fuzzy membership must be in the interval [0,1], the FR values of the different categories are normalized by the largest FR value (Lee, 2006; Pradhan, 2010, 2011a, b) within the same type factor (Table 4) in order to derive the function.

$$FR = \frac{N_{(Di)}/N_{(Ci)}}{N_{(D)}/N_{(A)}} \tag{3}$$

where $N_{(Di)}$ is the number of debris flow pixels in the category i, $N(ci)$ is the total number of pixels in the category i, $N_{(D)}$ is total number of debris flow pixels in the study area, and $N_{(A)}$ is the total number of pixels in the study area.

The cosine amplitude method (Ross, 1995) is also widely used (Ercanoglu and Gokceoglu, 2004; Kanungo et al., 2006; Kanungo et al., 2009; Ercanoglu and Temiz, 2011) to establish relationships among elements of two or more datasets (Kritikos and Davies, 2015). Assuming that n is the number of data samples (categories of a factor used in the analysis) represented as an array $X = \{x_1, x_2, \ldots, x_n\}$ and that each of its elements, x_i, is a vector of length m (i.e. the size of the raster image) and can be expressed as $X = \{x_{i1}, x_{i2}, \ldots, x_{im}\}$, then each element of a relation r_{ij} results from a pairwise comparison of a factor category x_i with a category of the debris flow distribution layer x_j (debris flow or non-debris flow). The memberships can be calculated by Eq. (4):

$$r_{ij} = \frac{\left|\sum_{k=1}^{m} x_{ik}x_{jk}\right|}{\sqrt{\left(\sum_{k=1}^{m} x_{ik}^2\right)\left(\sum_{k=1}^{m} x_{jk}^2\right)}} \tag{4}$$

Analogy with the study of Kanungo et al. (2006), we defined the r_{ij} value for any given factor category as the ratio of the total number of debris flow pixels in the category to the square root of the product of the total number of pixels in that category and the total number of debris flow pixels in the area. Values of r_{ij} close to 1 indicate similarity whereas values close to 0 indicate dissimilarity between the two datasets (Kritikos and Davies, 2015). What's more, every thematic layer must use the same pixel size to use the method properly.

Table 4 Factor categories and their fuzzy membership degrees

Factor	**Factor class**	**Number of pixels**	**Number of pixels %**	**Number of pixels classified as debris flows**	**Number of pixels classified as debris flow %**	**Frequency ratio (FR)**	**Normalized frequency ratio**	**r_{ij}**	**Comprehensive ratio (FRR)**
Lithology	Quanternary sediments-unconsolidatede clastic sediments	7562017	0.320	48190	0.017	0.026	0.021	0.091	0.002
	Coarse-grained sediments	1148321	0.049	21741	0.008	0.076	0.063	0.061	0.004
	Medium-grained sediments	259619	0.011	12013	0.004	0.186	0.154	0.045	0.007
	Fine-grained sediments	754655	0.032	76380	0.027	0.407	0.337	0.114	0.038
	High-grade metamorphics	986435	0.042	154332	0.055	0.629	0.522	0.162	0.085
	Granitoids	725651	0.031	140936	0.050	0.781	0.648	0.155	0.100
	Mafic extrusive	75495	0.003	16398	0.006	0.873	0.724	0.053	0.038
	Terrigenous clastic rock	3289458	0.139	986495	0.352	1.205	1.000	0.41	0.410
	Limestones	8804379	0.373	1343754	0.480	0.614	0.509	0.478	0.243
proximity to faults	<100	1057209	0.045	231016	0.083	0.878	1.000	0.198	0.198
	100-500	3778095	0.160	774566	0.277	0.824	0.938	0.363	0.341
	500-1000	3894600	0.165	716963	0.256	0.740	0.842	0.349	0.294
	1000-2000	5707265	0.241	760699	0.272	0.536	0.610	0.36	0.220
	2000-3000	2749240	0.116	246925	0.088	0.361	0.411	0.205	0.084
	>3000	6421103	0.272	69382	0.025	0.043	0.049	0.109	0.005
slope (degrees)	0-5	9674508	0.410	153889	0.055	0.064	0.056	0.162	0.009
	5-10	2815606	0.119	383198	0.137	0.547	0.480	0.255	0.123
	10-15	2955913	0.125	521040	0.186	0.709	0.622	0.298	0.185
	15-20	2879704	0.122	570515	0.204	0.797	0.699	0.312	0.218
	20-25	2432724	0.103	498303	0.178	0.824	0.723	0.291	0.210
	25-30	1620325	0.069	350686	0.125	0.870	0.764	0.244	0.187
	30-35	837185	0.035	209574	0.075	1.007	0.883	0.189	0.167
	35-40	294141	0.012	82000	0.029	1.121	0.983	0.118	0.116
	40-45	77038	0.003	21133	0.008	1.103	0.968	0.06	0.058
	>45	30091	0.001	8529	0.003	1.140	1.000	0.038	0.038
Slope aspect	Flat	380875	0.016	463	0.000	0.005	0.005	0.009	0.000
	North	2370048	0.100	296900	0.106	1.006	1.000	0.318	0.111
	Northeast	2193998	0.093	279917	0.100	0.513	0.510	0.218	0.092
	East	2873308	0.122	295555	0.106	0.414	0.411	0.224	0.111

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	Southeast	3122267	0.132	353489	0.126	0.455	0.453	0.245	0.108
	South	3219111	0.136	354420	0.127	0.443	0.440	0.246	0.133
	Southwest	3144353	0.133	400064	0.143	0.512	0.509	0.261	0.135
	West	3525895	0.149	436381	0.156	0.498	0.495	0.273	0.140
	Northwest	2787380	0.118	381679	0.136	0.551	0.547	0.255	0.318
Curvature	Concave	490900	0.021	109157	0.039	0.893	1.000	0.136	0.136
	Less concave	2037602	0.269	394583	0.141	0.778	0.871	0.259	0.226
	Flat	18364429	15.992	1769210	0.631	0.387	0.433	0.549	0.238
	Less convex	2202019	8.482	416142	0.149	0.759	0.850	0.266	0.226
	Convex	522285	0.692	112740	0.040	0.867	0.971	0.139	0.135

3.5 DFSI map

To derive the debris flow susceptibility index (DFSI) map by overlaying the factor thematic layers using fuzzy logic method, the "fuzzified" factors represented by information layers in raster format with values ranging from 0 to 1 need to be combined. Compared with other four fuzzy operators, Fuzzy Gamma (Eq.5) is more suitable for the research (Kritikos and Davies, 2015). To determine the appropriate γ value, the results of different gamma values were compared by the greatest distance (Kritikos and Davies, 2015) between the average DFSI curves of the debris flows locations and non-debris flows locations (For example, flat pixels)(Fig. 6). Finally, 0.9 is determined for the γ value, because there is the greatest difference between debris flow and non-debris flows locations areas. In order to illustrate the superiority of our model through comparison, ~~seventeen~~ 17 results are calculated in ArcGIS.

$$\mu_{(x)} = \left(1 - \prod_{i=1}^{n}(1-\mu_i)\right)^{\gamma} * \left(\prod_{i=1}^{n}\mu_i\right)^{1-\gamma} \tag{5}$$

where $\mu_{(x)}$ is the combined membership value, μ_i is the fuzzy membership function for the ith map, i=1,2, …, n are the numbers of thematic layers to be combined, and γ is a parameter in the range (0,1).

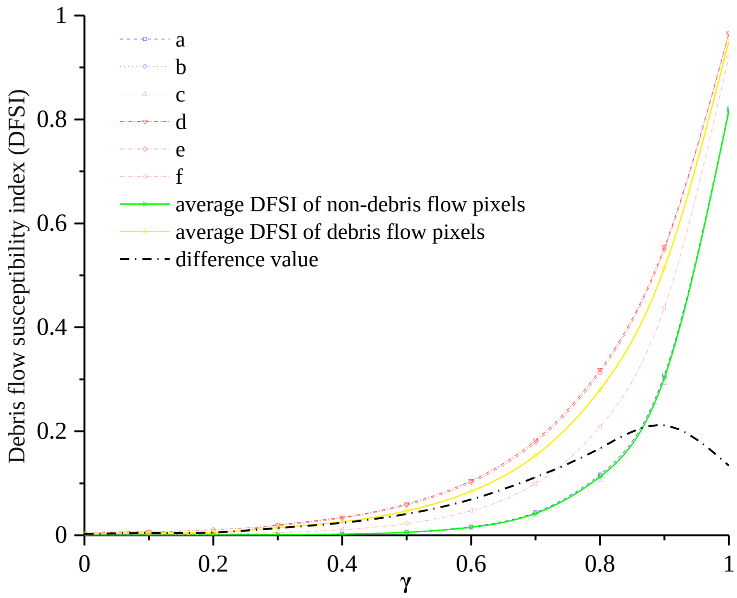

Fig. 6 Effect of γ value on Debris flow susceptibility index (DFSI). Curves d, e and f correspond to debris flow pixels, and curves a, b and c correspond to non-debris flow area where a Debris flow is unlikely. According to curve i, the maximum difference between the average DFSI values is observed for γ≈0.9

To find the optimal model, ~~seventeen~~ 17 results were compared (Table 5). According to the distribution map of potential geological hazard points and susceptibility map in Pinggu District published by Beijing Municipal Commission of Planning and Natural Resources(Bmcp&Nr, 2020), three indexes are used to verify the validity and accuracy of the model.

The results of the model are independent of the model itself, so the predictive performance of the final map is not just "the goodness of fit" of the data (Chung et al., 1995; Remondo et al., 2003). A relatively reliable technique for quantitatively assessing how well a model is the construction of validation or success rate curves (Chung and Fabbri, 1999; Westen et al., 2003; Remondo et al., 2003; Frattini et al., 2010) based on a comparison between the spatial distribution of debris flows and modelled debris flow susceptibility. The curves illustrate the debris flow recorded in the area with respect to susceptibility values also expressed as cumulative percentages of the total area. The area under the curve (AUC) defines the success rate (Marjanović et al., 2011). Generally, AUC values above 0.7 indicate model performance can be acceptable, while below 0.7, the performance is considered poor (Kritikos and Davies, 2015).

Although AUC is an effective evaluation method, the results are not comprehensive as mathematical features for selecting the best measurement model because of insufficiency data for validation. In order to ensure the objectivity of the results, we can only effectively use the recorded debris flow gully as positive, while the others as negative. Thus, a two-category test is proposed to verify the model in this paper. First, the DFSI map of each model are divided into two categories by Natural Breaks (Jenks) method (Fig. 7). Then the accuracy ratio (AR) is defined as the frequency of the number of debris flow both classified by model and simultaneously recorded in site to the number of debris flow recorded in site. The Resolution Ratio (RR) is defined as the number of debris flow classified by model and simultaneously recorded in site to the total number debris flow classified by the model (in red color). Take R_4 for example, there are total 135 basins in the research area, but only 46 records of debris flows (Fig.3). And in the results of two categories by Natural Breaks (Jenks) method, 20 basins are divided in to debris flow, while there are only 14 debris flows among them. Then AR is calculated by dividing 14 into 46 and RR was calculated by dividing 14 into 20.

The higher the two values, the better the susceptibility map. Finally, the performance of models (P value) can be obtained by the Eq. (6). AUC values less than 0.6 are directly eliminated. Comparing the results of rest models, the result of R_{16} is optimal, and the results of DFSI map are in good agreement with those of field investigation (Fig. 8).

$$P = AUC + \sqrt{(AR * RR)} \quad (6)$$

Table 5 Predictive performance of different models

Result and Description			**AUC**	**Two-category test**		**Performance index (centesimal ~~grade~~grade)**
				Accuracy Ratio (AR)	**Resolution Ratio (RR)**	
A factors only or B factors only	R_1	B factors with r_{ij}	0.460	/	/	/
	R_2	B factors with FR	0.687	/	/	/
	R_3	B factors with FRR	0.602	/	/	/
	R_4	All A factors	0.786	0.304	0.700	83
	R_5	Selected A factors	0.760	0.391	0.750	94
All factors as a single thematic layer	R_6	All A factors and B factors with r_{ij}	0.776	0.261	0.667	74
	R_7	All A factors and B factors with FR	0.779	0.283	0.684	78
	R_8	All A factors and B factors with FRR	0.753	0.326	0.600	76
	R_9	Selected A factors and B	0.746	0.348	0.727	86

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		factors with r_{ij}				
	R_{10}	Selected A factors B factors with FR	0.761	0.348	0.727	87
	R_{11}	Selected A factors B factors with FRR	0.740	0.348	0.727	85
A factors combined into one thematic layers, B factor combined into another thematic layers	R_{12}	All A factors and B factors with r_{ij}	0.708	0.5	0.511	82
	R_{13}	All A factors and B factors with FR	0.753	0.848	0.394	99
	R_{14}	All A factors and B factors with FRR	0.711	0.870	0.404	96
	R_{15}	Selected A factors and B factors with r_{ij}	0.726	0.348	0.667	80
	R_{16}	Selected A factors and B factors with FR	0.768	0.739	0.442	100
	R_{17}	Selected A factors B factors with FRR	0.740	0.457	0.600	88

Note: Selected A factors with fuzzy membership more than 0.6; FRR represents the product of FR and r_{ij}; Performance index is normalized by the largest FR value

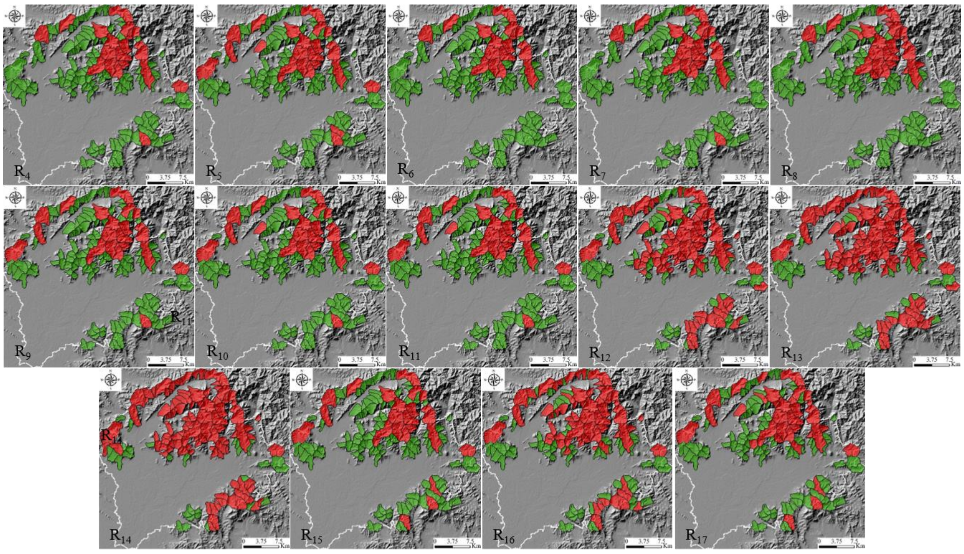

Fig.7 Results of two categories by Natural Breaks (Jenks) method

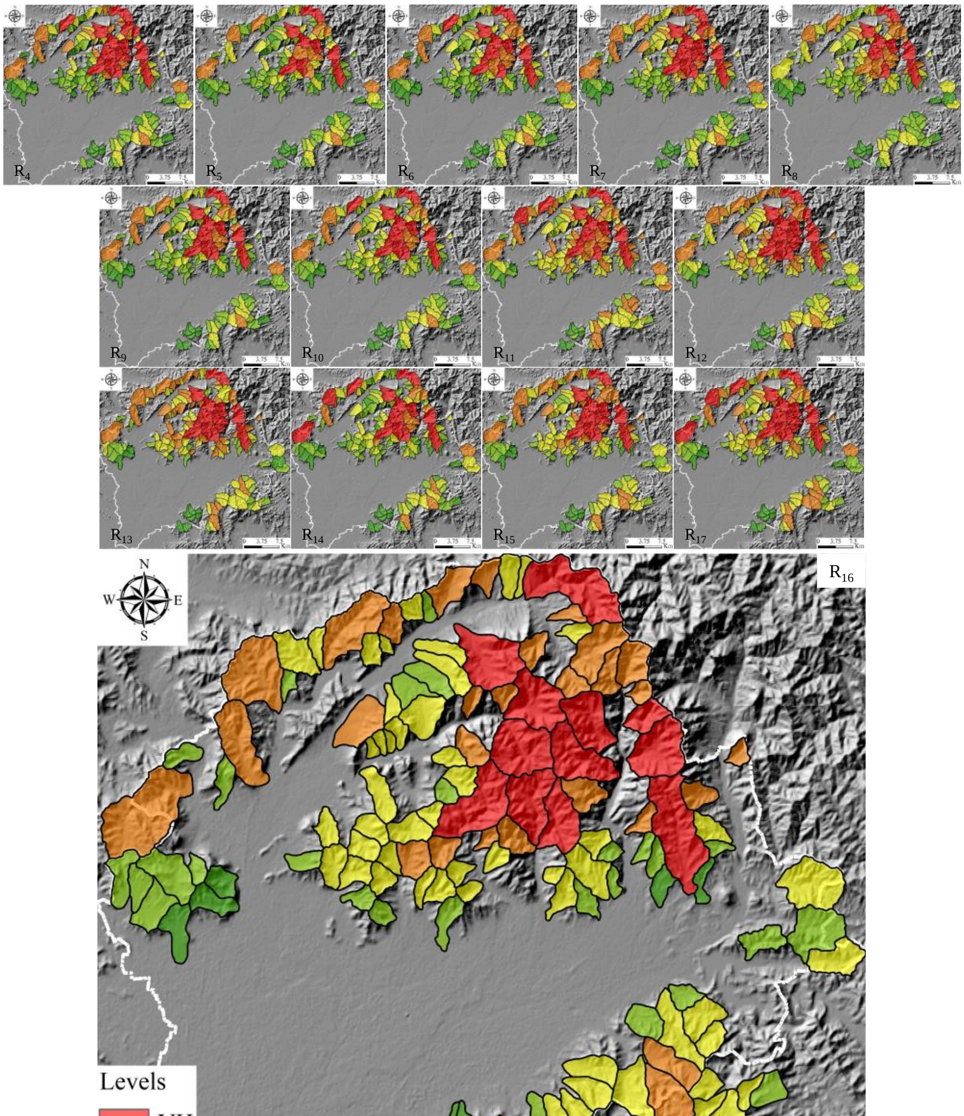

Fig. 8 Debris flow susceptibility maps. Note: AUC results of R_1-R_4 below 0.7 were not shown.

4 Results and Discussion

Through the modelling process, relatively satisfactory results are obtained in this paper. The predictive performance of the output debris flow susceptibility maps, obtained from ~~seventeen~~ 17 different models, is verified by comparing with maps published by authority. By comparing the results, the following results are discussed:

Firstly, comparing R_1, R_2, R_3, R_4 and R_5, it can be concluded that the model based on field investigation and expert experience is more effective than data- driven directly, when the information is insufficient. This is mainly because when the basin area reaches a certain size, it is no longer controlled by one or several factors, but becomes a complex system. It is not only the factors that affect the system, but also the system will react on each factor. Geomorphic evolution is basically the result of ~~the~~ interaction of the endogenic and exogenic geological processes. A geological period can be regarded as the beginning of an endogenic geological processes to the next one. In the early stage of geological period, endogenic geological processes play a major role, and in the later relatively stable period, exogenic geological processes will take on more important parts~~exogenic geological processes will play a more and more important role~~. In this large cycle, the basin continuously occurs a small cycle of energy accumulating and releasing~~accumulating and releasing energy~~, which leads to extremely complex system changes. In addition, there is a contradiction between the scale of geological evolution and the scale of engineering activities. So limited information can be obtained under these conditions that leads to the unreliability of data-driven evaluation. Therefore, in the current period, field investigation and expert experience are fundamental.

Secondly, by comparing R_4 and R_5, R_6 and R_9, R_7 and R_{10}, R_8 and R_{11}, R_{12} and R_{15}, R_{13} and R_{16}, R_{14} and R_{17}, it can be concluded that the accuracy and resolution of the model can be improved by simplifying the factors, which will eliminate the ones with weak correlation and independence.~~eliminate the weak correlation and independence factors.~~ In practical application, even if the susceptibility map is obtained, the classification of the susceptibility degree is still a very difficult problem. Because everyone's subjective definition of "susceptibility degree" is different. By simplifying the factors, the main ~~factors~~ ones can be selected, which magnifies the differences between basins, so the boundaries between different susceptibility degrees are more obvious.

Thirdly, by comparing R_6 and R_{12}, R_7 and R_{13}, R_8 and R_{14}, R_9 and R_{15}, R_{10} and R_{16}, R_{11} and R_{17}, it can be concluded that the model in which factors are classified into two types is better than the ~~method~~ one in which all factors as a single thematic layer without classification. Because the factors categorized separately are more closely linked and has consistent influence on the system in mechanism. We can also infer that the non-linear combination characteristics between different types are stronger and scientific classification can improve the performance of the model.

Fourthly, comparing R_{12} and R_{13}, R_{15} and R_{16}, it can be concluded that the frequency ratio method is better than the cosine amplitude method in the study. Different from the study of (Kritikos and Davies, 2015), the watershed unit rather than the grid unit is used, which indicates that the former has a wide range of application, while the latter has a disadvantage of strict conditions.

Based on the results of the above four analyses, the most optimal model should have the features of being based on expert experience, using selected factors, classifying factors before using them, and using frequency ratio method. Then the model R_{16} is selected according to the features, which is well in accordance with theoretical method performance score, and gets fine mutual verification.

There is also much to discuss, the selection of factors is still a very complex dilemma. Although 19 factors selected cannot fully evaluate the character of a basin, it is necessary to consider that they are easily and relatively accurately obtainable for each basin. This will facilitate a wide range of applications. Besides, rainfall and total amount of loose material source are also very important influencing factors. But according to the Beijing hydrological manual, the rainfall change in the study area is not obvious, so it is ~~not considered~~excluded in model. And the total amount of loose material source cannot be obtained for the watershed without on-site investigation, so calculations are impossible. In fact, we indirectly consider the influence of natural loose material source by evaluating geological conditions, but cannot consider the impact of human activities. As for the factors describing debris flow magnitude, usually, several channels have the recorded data.

The scientific and systematic principle of model building is another challenge. To correctly classify the factors, it is necessary to grasp the characteristics of the formation, movement and accumulation of debris flow. Therefore, the classification should comprehensively consider the development background (geology, geomorphology, climate, hydrology, soil, vegetation, human activities and other factors). The practical principle refers to that the study should not only fully obtain scientific and accurate results, but also make the professional results understood by decision makers. Although the susceptibility grade and susceptibility value of each watershed is obtained, the results are relatively effective in this study area. In addition, with the development of technology and theory, we should replace some traditional factors which are not easy to quantify with more precise quantitative factors to improve the efficiency and accuracy of evaluation, such as surface roughness instead of drainage density.

For the results derived from Table 3, we would like to further discuss. It can be seen from the results that the occurrence of debris flow is highly correlated with basin volume, basin area and main gully bending coefficient with fuzzy membership above 0.7 in Beijing area. Rainfall in the study area is abundant to induce the debris flow. Loose source and sinks the total volume of catchment become more important. The watershed area determines the total volume of catchment. For the same rainfall, generally, the larger the area, the larger the catchment ~~is~~. The bending coefficient reflects the replenishment sources along the channel. The greater the coefficient, the slower the flow ~~is~~. Then loose source along the channel has more time to replenish. Basin volume characterizes the maximum amount of loose material that can be supplied. These three features reflect the development characteristics of debris flow in the study area. It also provides ideas for disaster prevention and mitigation.

Finally, we should consider decision making under uncertainty, because the debris flow phenomenon is extremely complex. The classification of geologists (high, moderate and low) is ambiguous for decision makers. It is more beneficial for them to use mathematically rigorous definitions. Considering that geological conditions tend to vary greatly from region to region, it is not appropriate to define a fixed limit. the Jenks method (chosen in this paper) can be used to classify sensitivity maps according to the characteristics of the data itself. We can also further process the data according to the needs of decision makers, such as identifying 10% of the watersheds in the entire region as high risk. However, the applicability of the model to extreme rainfall and seismic conditions is not considered.

5 Conclusion

In ~~the present~~this study, a new combination model for debris-flow susceptibility based on GIS was developed in Pinggu. The objective and motivation of this study is to demonstrate a simple, extensible, and convenient analytical model for the debris flow prediction. Three methods are selected in the model with their own advantages. GRA has great advantages in the case of less samples, data-driven method is mainly used to reduce subjectivity and fuzzy logic is fitted to solve nonlinear problems with fuzzy classification. The output optimal debris flow susceptibility maps ~~obtained from the optimal models~~ demonstrated satisfactory performance ~~predicting approximately 50 % of the debris flow gully~~ with the relative higher susceptibility values corresponding to AUC~~≥~~=0.768. ~~Considering that the data used for verification is only the recorded debris flow points rather than all debris flow records in the area, its accuracy should be higher.~~ The predictive performance of the susceptibility maps and the spatial correlation of debris flow gully with H and VH susceptibility with recorded debris flows illustrate that the assessment at regional scale using the proposed method is feasible. Compared with the previous results(Li et al., 2020b) based on grid units~~ in this area~~, the evaluation results are basically the same, but the model are more targeted for debris flow disasters for decision makers. Besides, considering that the meaning of the used factors is clear and the data is easy to obtain, these conditions mentioned enable the model to be widely applied.

In addition, a new factor (Basin) is proposed in our study, which contributes higher weight up to 0.79. From our 17 results by comparing the control variables, we suggest that other scholars should pay more attention to the classification and streamlining of factors, which has indicated the potential value to improve model accuracy. It was also found that the watershed characteristic parameters can better reflect the advantages of watershed unit, but further development is needed.

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~~Preliminary research indicates that: first of all, the evaluation results are obtained by combining the landslide susceptibility analysis method with the debris flow. It reveals a systematic idea and disaster chain phenomenon. Further more, we should pay more attention to the relative susceptibility value rather than absolute values in different models, unless we need further study such as risk assessment. It is realized that the performance of the model is determined by the effect of its classification. What's more, comprehensive consideration of endogenic and exogenic geological processes in susceptibility assessment has better expected results. Last but not least, under the engineering geological environment with acceptable difference, it has advantages of practical significance to regard the administrative region as a research area for policy making. because different regions have different status constraints in population quality and economy.~~

In short, an effort has been made to develop a cost- and time-efficient debris flow susceptibility assessment model. The model has an acceptable degree of accuracy for regional-scale planning and contributes to make susceptibility and risk maps more accessible to individuals and local authorities. The GIS-based methods and modern data availability especially through online databases are significantly beneficial to this aim. However, a challenge remains in producing results with ~~meaningful~~ practical accuracy for the scale of planning, using available resources. Previous studies~~, as well as the present work,~~ highlight that the effectiveness of the final map depends on the quality of input data. ~~Comparison with a very high-resolution LIDAR-derived DEM indicated that the spatial accuracy of the DEM varies between different landforms (lakes, river channels, riverbeds, floodplains etc.) and the areas of greatest errors are predominantly confined to valley floors .However, with overall RMS error of 8.15 m, the DEM meets the internationally accepted accuracy standards as set out by US Geological Survey (USGS 1997) and is of sufficient quality for regional-scale studies such as the present one.~~ Updating and improving existing debris flow catalogues and inventories are crucial for the development of reliable susceptibility and risk assessment methods.

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Reference

Akbar, T. A. and Ha, S. R.: Landslide hazard zoning along Himalayan Kaghan Valley of Pakistan—by integration of GPS, GIS, and remote sensing technology, Landslides, 8, 527-540, 10.1007/s10346-011-0260-1, 2011.

Benda, L. E.: Sediment routing by debris flow, 1987.

Benda, L. E. and Dunne, T.: Sediment routing by debris flow, in: Erosion and sedimentation in the Pacific Rim, edited by: Beschta, R. L., Blinn, T., Grant, G. E., Swanson, F. J., and Ice, G. G., IAHS Publ, 213-223, doi:10.1111/j.1753-4887.1977.tb06503.x, 1987.

The distribution map of potential geological hazard points and susceptibility map in pinggu district: http://ghzrzyw.beijing.gov.cn/zhengwuxinxi/zxzt/dzzhfzzt/zzzhdcpg/202008/t20200807_1976436.html, last

Borrelli, L., Cofone, G., Coscarelli, R., and Gullà, G.: Shallow landslides triggered by consecutive rainfall events at Catanzaro strait (Calabria–Southern Italy), Journal of Maps, 11, 730-744, 10.1080/17445647.2014.943814, 2014.

Bovis, M. and Dagg, B.: Debris flow triggering by impulsive loading - mechanical modeling and case-studies, Canadian Geotechnical Journal, 29, 345-352, 10.1139/t92-040, 1992.

Cao, C., Xu, P., Chen, J., Zheng, L., and Niu, C.: Hazard assessment of debris-flow along the baicha river in heshigten banner, inner mongolia, china, Int J Environ Res Public Health, 14, 1-19, 10.3390/ijerph14010030, 2016.

Chang, T. C. and Chien, Y. H.: The application of genetic algorithm in debris flows prediction, Environmental Geology, 53, 339-347, 10.1007/s00254-007-0649-2, 2007.

Chiou, I. J., Chen, C. H., Liu, W. L., Huang, S. M., and Chang, Y. M.: Methodology of disaster risk assessment for debris flows in a river basin, Stoch Env Res Risk A, 29, 775-792, 10.1007/s00477-014-0932-1, 2015.

Chung, C.-J. F. and Fabbri, A. G.: Probabilistic prediction models for landslide hazard mapping, Photogrammetric Engineering And Remote Sensing, 65, 1389-1399, 10.1016/S0924-2716(99)00030-1, 1999.

Chung, C. J. F., Fabbri, A., and Westen, C. J. v.: Multivariate regression analysis for landslide hazard zonation, Geographical Information Systems in Assessing Natural Hazards, 5, 107-133, 1995.

Conoscenti, C., Ciaccio, M., Caraballo-Arias, N. A., Gómez-Gutiérrez, Á., Rotigliano, E., and Agnesi, V.: Assessment of susceptibility to earth-flow landslide using logistic regression and multivariate adaptive regression splines: A case of the Belice River basin (western Sicily, Italy), Geomorphology, 242, 49-64, 10.1016/j.geomorph.2014.09.020, 2015.

Crozier, M. J., Vaughan, E. E., and Tippett, J. M.: Relative instability of colluvium-filled bedrock depressions, Earth Surface Processes and Landforms, 15, 329-339, 10.1002/esp.3290150404, 1990.

Dai, F. C. and Lee, C. F.: Landslide characteristics and slope instability modeling using GIS, Lantau Island, Hong Kong, Geomorphology, 42, 213-228, 10.1016/S0169-555X(01)00087-3, 2002.

Dai, F. C., Lee, C. F., Li, H.-Z., and Xu, C.: Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong, Environmental Geology, 40, 381-391, 10.1007/s002540000163, 2001.

Deng, J. L.: Control problems of grey systems, Systems and Control Letters, 1, 288-294, 10.1016/S0167-6911(82)80025-X, 1982.

Deng, J. L.: Grey prediction and decision, Huazhong University of Science and Technology Press, Wuhan1988.

Di, B., Zhang, H., Liu, Y., Li, J., Chen, N., Stamatopoulos, C. A., Luo, Y., and Zhan, Y.: Assessing susceptibility of debris flow in southwest china using gradient boosting machine, Sci Rep, 9, 12532, 10.1038/s41598-019-48986-5, 2019.

Di Napoli, M., Carotenuto, F., Cevasco, A., Confuorto, P., Di Martire, D., Firpo, M., Pepe, G., Raso, E., and Calcaterra, D.: Machine learning ensemble modelling as a tool to improve landslide susceptibility mapping reliability, Landslides, 17, 1897-1914, 10.1007/s10346-020-01392-9, 2020.

Dietrich, W. E., Wilson, C. J., and Reneau, S. L.: Hollows, colluvium, and landslides in soil-mantled landscapes, in: Hillslope Processes, edited by: Abrahams., A. D., Allen & Unwin, Boston, 1986.

Donati, L. and Turrini, M. C.: An objective method to rank the importance of the factors predisposing to landslides with the GIS methodology: application to an area of the Apennines (Valnerina; Perugia, Italy), Engineering Geology, 63, 277-289, 10.1016/S0013-7952(01)00087-4, 2002.

Dong, J.-J., Lee, C.-T., Tung, Y.-H., Liu, C.-N., Lin, K.-P., and Lee, J.-F.: The role of the sediment budget in understanding debris flow susceptibility, Earth Surface Processes and Landforms, 34, 1612-1624, 10.1002/esp.1850, 2009.

Dramis, F. and Sorriso-Valvo, M.: Deep-seated gravitational slope deformations, relatedlandslides and tectonics, Engineering Geology, 38, 231-243, 10.1016/0013-7952(94)90040-X, 1994.

Ercanoglu, M. and Gokceoglu, C.: Use of fuzzy relations to produce landslide susceptibility map of a landslide prone area (West Black Sea Region, Turkey), Engineering Geology, 75, 229-250, 10.1016/j.enggeo.2004.06.001, 2004.

Ercanoglu, M. and Temiz, F. A.: Application of logistic regression and fuzzy operators to landslide susceptibility assessment in Azdavay (Kastamonu, Turkey), Environmental Earth Sciences, 64, 949-964, 10.1007/s12665-011-0912-4, 2011.

Fairchild, L. H.: The importance of lahar initiation processes, Reviews in Engineering Geology, 7, 51-62, 10.1130/REG7-p51, 1987.

Fang, Z., Wang, Y., Peng, L., and Hong, H.: A comparative study of heterogeneous ensemble-learning techniques for landslide susceptibility mapping, International Journal of Geographical Information Science, 35, 321-347, 10.1080/13658816.2020.1808897, 2020.

Frattini, P., Crosta, G., and Carrara, A.: Techniques for evaluating the performance of landslide susceptibility models, Engineering Geology, 111, 62-72, 10.1016/j.enggeo.2009.12.004, 2010.

Gómez, H. and Kavzoglu, T.: Assessment of shallow landslide susceptibility using artificial neural networks in Jabonosa River Basin, Venezuela, Engineering Geology, 78, 11-27, 10.1016/j.enggeo.2004.10.004, 2005.

Guzzetti, F., Carrara, A., Cardinali, M., and Reichenbach, P.: Landslide hazard evaluation: a review of current techniques and their application in a multi-scale study, Central Italy, Geomorphology, 31, 181-216, 10.1016/s0169-555x(99)00078-1, 1999.

He, Y. and Beighley, R. E.: GIS-based regional landslide susceptibility mapping: a case study in southern California, Earth Surface Processes and Landforms, 33, 380-393, 10.1002/esp.1562, 2008.

Hu, K., Wei, F., and Li, Y.: Real-time measurement and preliminary analysis of debris-flow impact force at Jiangjia Ravine, China, Earth Surface Processes and Landforms, 36, 1268-1278, 10.1002/esp.2155, 2011.

Hungr, O., McDougall, S., and Bovis, M.: Entrainment of material by debris flows, in: Debris-flow Hazards and Related Phenomena., edited by: Jakob, M., and Hungr, O., Praxis.Springer Berlin Heidelberg, 135-158, 2005.

Iverson, R. M.: The physics of debris flows, Reviews of Geophysics, 35, 245-296., 10.1029/97RG00426, 1997.

Iverson, R. M., Reid, M. E., and LaHusen, R. G.: Debris-flow mobilization from landslides, Annual Review of Earth and Planetary Sciences, 25, 85-138, 10.1146/annurev.earth.25.1.85, 1997.

Kanungo, D. P., Arora, M., Sarkar, S., and Gupta, R.: A fuzzy set based approach for integration of thematic maps for landslide susceptibility zonation, Georisk, 3, 10.1080/17499510802541417, 2009.

Kanungo, D. P., Arora, M. K., Sarkar, S., and Gupta, R. P.: A comparative study of conventional, ANN black box, fuzzy and combined neural and fuzzy weighting procedures for landslide susceptibility zonation in Darjeeling Himalayas, Engineering Geology, 85, 347-366, 10.1016/j.enggeo.2006.03.004, 2006.

Kellogg, K. S.: Tectonic controls on a large landslide complex: Williams Fork Mountains near Dillon, Colorado, Geomorphology, 41, 355-368, 10.1016/S0169-555X(01)00067-8, 2001.

Khan, U., Tuteja, N. K., and Sharma, A.: Delineating hydrologic response units in large upland catchments and its evaluation using soil moisture simulations, Environmental Modelling & Software, 46, 142-154, 10.1016/j.envsoft.2013.03.005, 2013.

Khan, U., Tuteja, N. K., Sharma, A., Lucas, S., Murphy, B., and Jenkins, B.: Applicability of Hydrologic Response Units in low topographic relief catchments and evaluation using high resolution aerial photograph analysis, Environmental Modelling & Software, 81, 56-71, 10.1016/j.envsoft.2016.03.010, 2016.

Korup, O.: Geomorphic implications of fault zone weakening Slope instability along the Alpine Fault South Westland to Fiordland, New Zealand Journal of Geology and Geophysics, 47, 257-267, 10.1080/00288306.2004.9515052, 2004.

Kritikos, T. and Davies, T.: Assessment of rainfall-generated shallow landslide/debris-flow susceptibility and runout using a GIS-based approach: application to western Southern Alps of New Zealand, Landslides, 12, 1051-1075, 10.1007/s10346-014-0533-6, 2015.

Kuo, Y., Yang, T., and Huang, G.-W.: The use of grey relational analysis in solving multiple attribute decision-making problems, Computers & Industrial Engineering, 55, 80-93, 10.1016/j.cie.2007.12.002, 2008.

Lee, S.: Application and verification of fuzzy algebraic operators to landslide susceptibility mapping, Environmental Geology, 52, 615-623, 10.1007/s00254-006-0491-y, 2006.

Lee, S. and Choi, J.: Landslide susceptibility mapping using GIS and the weight-of-evidence model, International Journal of Geographical Information Science, 18, 789-814, 10.1080/13658810410001702003, 2004.

Lee, S. and Sambath, T.: Landslide susceptibility mapping in the Damrei Romel area, Cambodia using frequency ratio and logistic regression models, Environmental Geology, 50, 847-855, 10.1007/s00254-006-0256-7, 2006.

Lee, S. and Talib, J. A.: Probabilistic landslide susceptibility and factor effect analysis, Environmental Geology, 47, 982-990, 10.1007/s00254-005-1228-z, 2005.

Lee, S., Ryu, J.-H., Min, K., and Won, J.-S.: Landslide susceptibility analysis using GIS and artificial neural network, Earth Surface Processes and Landforms, 28, 1361-1376, 10.1002/esp.593, 2003.

Li, Y., Chen, J., Zhang, Y., Song, S., Han, X., and Ammar, M.: Debris flow susceptibility assessment and runout prediction: A case study in shiyang gully, beijing, china, International Journal of Environmental Research, 14, 365-383, 10.1007/s41742-020-00263-4, 2020a.

Li, Y., Chen, J., Li, Z., Han, X., Zhai, S., Li, Y., and Zhang, Y.: A case study of debris flow risk assessment and hazard range prediction based on a neural network algorithm and finite volume shallow water flow model, Environmental Earth Sciences, 80, 10.1007/s12665-021-09580-z, 2021a.

Li, Y., Chen, J., Tan, C., Li, Y., Gu, F., Zhang, Y., and Mehmood, Q.: Application of the borderline-SMOTE method in susceptibility assessments of debris flows in Pinggu District, Beijing, China, Natural Hazards, 105, 2499-2522, 10.1007/s11069-020-04409-7, 2020b.

Li, Z., Chen, J., Tan, C., Zhou, X., Li, Y., and Han, M.: Debris flow susceptibility assessment based on topo-hydrological factors at different unit scales: a case study of Mentougou district, Beijing, Environmental Earth Sciences, 80, 10.1007/s12665-021-09665-9, 2021b.

Liang, W.-j., Zhuang, D.-f., Jiang, D., Pan, J.-j., and Ren, H.-y.: Assessment of debris flow hazards using a Bayesian Network, Geomorphology, 171-172, 94-100, 10.1016/j.geomorph.2012.05.008, 2012.

Lin, C. L. and Lin, C. L.: The use of the orthogonal array with grey relational analysis to optimize the electrical discharge machining process with multiple performance characteristics, International Journal of Machine Tools and Manufacture, 42, 237-244, 10.1016/S0890-6955(01)00107-9, 2002.

Liu, L. and Wang, S.: Fuzzy comprehensive evaluation on landslide and debris flow risk degree in Zaotong, Yunnan, Mountain Research, 13, 261-266, 1995.

Liu, S., Dang, Y., and Fang, Z.: Grey system theory and its applications, Science Press, Beijing2004.

Liu, Y., Guo, H. C., Zou, R., and Wang, L. J.: Neural network modeling for regional hazard assessment of debris flow in Lake Qionghai Watershed, China, Environmental Geology, 49, 968-976, 10.1007/s00254-005-0135-7, 2005.

Lü, J., Wang, C., Liu, H., and Zhang, X.: Division of beijing geological environment system, Urban geology, 12, 19-25, 10.3969/j.issn.1007-1903.2017.03.004, 2017.

Luo, X. and Dimitrakopoulos, R.: Data-driven fuzzy analysis in quantitative mineral resource assessment, Computers & Geosciences, 29, 3-13, 10.1016/s0098-3004(02)00078-x, 2003.

Marjanović, M., Kovačević, M., Bajat, B., and Voženílek, V.: Landslide susceptibility assessment using SVM machine learning algorithm, Engineering Geology, 123, 225-234, 10.1016/j.enggeo.2011.09.006, 2011.

Melo, R., Vieira, G., Caselli, A., and Ramos, M.: Susceptibility modelling of hummocky terrain distribution using the information value method (Deception Island, Antarctic Peninsula), Geomorphology, 155-156, 88-95, 10.1016/j.geomorph.2011.12.027, 2012.

Meyer, N. K., Schwanghart, W., Korup, O., Romstad, B., and Etzelmüller, B.: Estimating the topographic predictability of debris flows, Geomorphology, 207, 114-125, 10.1016/j.geomorph.2013.10.030, 2014.

Ohlmacher, G. C.: Plan curvature and landslide probability in regions dominated by earth flows and earth slides, Engineering Geology, 91, 117-134, 10.1016/j.enggeo.2007.01.005, 2007.

Pierson, T. C., Janda, R. J., Thouret, J.-C., and Borrero, C. A.: Perturbation and melting of snow and ice by the 13 November 1985 eruption of Nevado del Ruiz, Colombia, and consequent mobilization, flow and deposition of lahars, Journal of Volcanology and Geothermal Research, 41, 17-66, 10.1016/0377-0273(90)90082-q, 1990.

Porwal, A., Carranza, E. J. M., and Hale, M.: A Hybrid Fuzzy Weights-of-Evidence Model for Mineral Potential Mapping, Natural Resources Research, 15, 1-14, 10.1007/s11053-006-9012-7, 2006.

Pourghasemi, H. R., Yousefi, S., Kornejady, A., and Cerda, A.: Performance assessment of individual and ensemble data-mining techniques for gully erosion modeling, Sci Total Environ, 609, 764-775, 10.1016/j.scitotenv.2017.07.198, 2017.

Pradhan, B.: Landslide susceptibility mapping of a catchment area using frequency ratio, fuzzy logic and multivariate logistic regression approaches, Journal of the Indian Society of Remote Sensing, 38, 301-320, 10.1007/s12524-010-0020-z, 2010.

Pradhan, B.: Manifestation of an advanced fuzzy logic model coupled with Geo-information techniques to landslide susceptibility mapping and their comparison with logistic regression modelling, Environmental and Ecological Statistics, 18, 471-493, 10.1007/s10651-010-0147-7, 2011a.

Pradhan, B.: Use of GIS-based fuzzy logic relations and its cross application to produce landslide susceptibility maps in three test areas in Malaysia, Environmental Earth Sciences, 63, 329-349, 10.1007/s12665-010-0705-1, 2011b.

Regmi, N. R., Giardino, J. R., McDonald, E. V., and Vitek, J. D.: A comparison of logistic regression-based models of susceptibility to landslides in western Colorado, USA, Landslides, 11, 247-262, 10.1007/s10346-012-0380-2, 2013.

Remondo, J., González, A., Terán, J. R. D. D., Cendrero, A., Fabbri, A., and Chung, C.-J. F.: Validation of landslide susceptibility maps; examples and applications from a case study in northern spain, Natural Hazards, 30, 437-449, 10.1023/B:NHAZ.0000007201.80743.fc, 2003.

Roeloffs, E.: Poroelastic techniques in the study of earthquake-related hydrologic phenomena, 38, 135-195, 10.1016/S0065-2687(08)60270-8, 1996.

Ross, T. J.: Fuzzy logic with engineering applications, McGraw-Hill, New York1995.

Selby, M. J.: Hillslope materials and processes, Oxford University Press, Oxford1982.

Sun, X., Chen, J., Bao, Y., Han, X., Zhan, J., and Peng, W.: Landslide Susceptibility Mapping Using Logistic Regression Analysis along the Jinsha River and Its Tributaries Close to Derong and Deqin County, Southwestern China, ISPRS International Journal of Geo-Information, 7, 10.3390/ijgi7110438, 2018.

Takahashi, T.: Debris flow mechanics,prediction and countermeasures, second, Taylor & Francis/Balkema, The Netherlands2014.

Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., and Dick, O. B.: Landslide susceptibility assessment in the Hoa Binh province of Vietnam: A comparison of the Levenberg–Marquardt and Bayesian regularized neural networks, Geomorphology, 171-172, 12-29, 10.1016/j.geomorph.2012.04.023, 2012.

Tsangaratos, P. and Ilia, I.: Landslide susceptibility mapping using a modified decision tree classifier in the Xanthi Perfection, Greece, Landslides, 13, 305-320, 10.1007/s10346-015-0565-6, 2015.

Tsukamoto, Y., Ohta, T., and Noguchi, H.: Hydrological and geomorphological studies of debris slides on forested hillslopes in japan, Journal des Sciences Hydrologiques, 27, 234, 1982.

Vallance, J. W. and Scott, K. M.: The Osceola mudflow from mount rainier: Sedimentology and hazard implications of a huge clay-rich debris flow, Geological Society of America Bulletin, 109, 143-163, 10.1130/0016-7606(1997)109<0143:TOMFMR>2.3.CO;2, 1997.

Wang, J., Yu, Y., Yang, S., Lu, G.-h., and Ou, G.-q.: A modified certainty coefficient method (M-CF) for debris flow susceptibility assessment: A case study for the Wenchuan earthquake meizoseismal areas, Journal of Mountain Science, 11, 1286-1297, 10.1007/s11629-013-2781-7, 2014.

Wei, Z., Shang, Y., Zhao, Y., Pan, P., and Jiang, Y.: Rainfall threshold for initiation of channelized debris flows in a small catchment based on in-site measurement, Engineering Geology, 217, 23-34, 10.1016/j.enggeo.2016.12.003, 2017.

Westen, C. J. v., Rengers, N., and Soeters, R.: Use of geomorphological information in indirect landslide susceptibility assessment, Natural Hazards, 30, 399-419, 10.1023/B:NHAZ.0000007097.42735.9e, 2003.

Wu, S., Chen, J., Zhou, W., Iqbal, J., and Yao, L.: A modified Logit model for assessment and validation of debris-flow susceptibility, Bulletin of Engineering Geology and the Environment, 78, 4421-4438, 10.1007/s10064-018-1412-5, 2019.

Wu, Y., Li, W., Liu, P., Bai, H., Wang, Q., He, J., Liu, Y., and Sun, S.: Application of analytic hierarchy process model for landslide susceptibility mapping in the Gangu County, Gansu Province, China, Environmental Earth Sciences, 75, 10.1007/s12665-015-5194-9, 2016.

Xie, H., Zhong, D., Wei, F., and Wang, S.: Classification of debris flow in the mountains of beijing, Journal of mountain science, 22, 212-219, 10.16089/j.cnki.1008-2786.2004.02.013, 2004.

Zadeh, L. A.: Fuzzy sets, Information & Control, 8, 338-353, 10.1016/S0019-9958(65)90241-X, 1965.

Zhang, W., Li, H. Z., Chen, J. p., Zhang, C., Xu, L. m., and Sang, W. f.: Comprehensive hazard assessment and protection of debris flows along Jinsha River close to the Wudongde dam site in China, Natural Hazards, 58, 459-477, 10.1007/s11069-010-9680-9, 2011.

Zhang, W., Chen, J.-p., Wang, Q., An, Y., Qian, X., Xiang, L., and He, L.: Susceptibility analysis of large-scale debris flows based on combination weighting and extension methods, Natural Hazards, 66, 1073-1100, 10.1007/s11069-012-0539-0, 2013.

Zhang, Y., Chen, J., Tan, C., Bao, Y., Han, X., Yan, J., and Mehmood, Q.: A novel approach to simulating debris flow runout via a three-dimensional CFD code: a case study of Xiaojia Gully, Bulletin of Engineering Geology and the Environment, 80, 5293-5313, 10.1007/s10064-021-02270-x, 2021.

Zhong, D., Xie, H., Wang, S., Wei, F., and Jin, H.: Debris flow in Beijing mountain, Commercial Press, Beijing2004.

Zou, Q., Cui, P., He, J., Lei, Y., and Li, S.: Regional risk assessment of debris flows in China—An HRU-based approach, Geomorphology, 340, 84-102, 10.1016/j.geomorph.2019.04.027, 2019.