https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences Discussions

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

Yiwei Zhang[1], Jianping Chen[1,*], Qing Wing[1], Chun Tan[2,3], Yongchao Li[4,5,6], Xiaohui Sun[7], Yang Li[8]

1 College of Construction Engineering, Jilin University, Changchun 130026, China
2 China Water Northeastern Investigation, Design and Research Co., Ltd, Changchun, Jilin 130026, China
3 North China Power Engineering Co., Ltd. of China Power Engineering Consulting Group, Changchun, Jilin 130000, China
4 Key Laboratory of Shale Gas and Geoengineering, Institute of Geology and Geophysics, Chinese Academy of Sciences, China.
5 University of Chinese Academy of Sciences.
6 Innovation Academy for Earth Science, Chinese Academy of Sciences, China.
7 Department of Earth Sciences and Engineering, Taiyuan University of Technology, Taiyuan 030024, China
8 Beijing institute of geological and prospecting engineering, Beijing 100020, China
* Corresponding author. Tel.:+86 13843047952
* Email address: chenjp@jlu.edu.cn

Abstract

Debris flow is one of the main causes of life loss and infrastructure damage in mountainous areas, so these hazards must 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 method, data-driven and fuzzy logic methods. 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 some new factors are proposed. The results of the 17 models are verified by the results published by the authority, and validated by the other two indexes as well as Area Under Curve (AUC). Through the comparison and analysis of the results, the method to optimize is proposed, including reasonable application of field investigation and expert experience, simplification of factors and scientific classification. Finally, the final optimal susceptibility map with full discussion has the potential to 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.

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 (Hu et al. 2011; Hungr et al. 2005; Iverson 1997; 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). Besides, as the capital of China, Beijing has strong influence and radiation at home and abroad, where geological disasters are widely concerned (Li et al. 2020a; Xie et al. 2004). 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 establishing 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. 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 (Li et al. 2020b; Wu et al. 2019) have been proposed to evaluate debris flow susceptibility assessment based on different qualitative and quantitative approaches and geo-environmental information (Liu and Wang 1995).

The economy in mountainous areas is often backward, we cannot supervise and verify every basin due to the limited funds. Surely, they are also wasteful and unnecessary. 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, the susceptibility assessment of debris flows has been extensively and quantitatively studied(Li et al. 2020b). While due to the nonlinearity of debris flow system and the openness and complexity of geological environment, we realize that it is chaotic, with many factors affecting the system. 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 basis. However, the experience is often subjective and needs a lot of professional experience accumulation. Therefore, it is very important to express the experience of experts objectively and easily understandably to serve decision makers. The application of fuzzy set

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences Discussions
Open Access
EGU

theory in GIS environments is effective for similar problems(Luo and Dimitrakopoulos 2003; Porwal et al. 2006).

According to the summary above, the primary object of my present study is to explore a geographic information system(GIS)-based quantitative model based on expert experience and field investigation. And the model is consistent with the system characteristics of debris flow gully and can also indicate the characteristics of disaster chain and that the geomorphic evolution of basin rather than simple 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 terrain of Pinggu is high in the northeast and low in the southwest. It is surrounded by mountains, account 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) .With Pinggu District of Beijing taken as the research object, the following reasons are considered: First of all, 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. Next, the regional boundary is basically divided by ridge line and stream line, and the regional geological environment is relatively uniform; Last but not the least, the relationship between the precision of the base map and the size of the study area is also relatively reasonable.

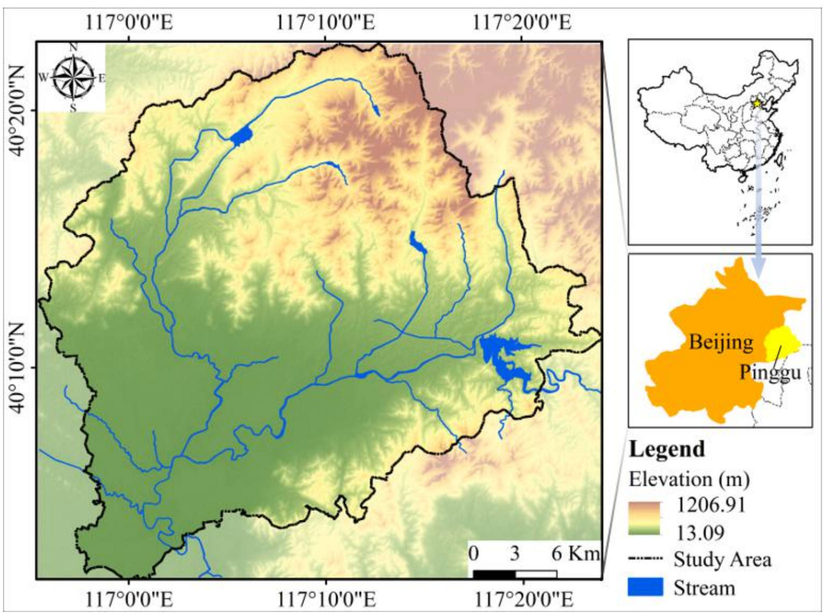


Fig. 1 Study area

1. Data and Methodology

In this study, the susceptibility assessment of debris flow hazard was based on the drainage basins unit. In a debris flow susceptibility assessment 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).

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

Therefore drainage networks were extracted from the ASTER-DEM by using the ArcGIS ArcHydro Toolbox and regions without obvious watershed characteristics are 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 are used to calculate the fuzzy membership for different type factors. Because the field survey data are based on the watershed, it is scientific to make full use of qualitative understanding to determine the weight of the parameters of watershed characteristics factors; 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. Throughout the modeling process, our primary assumption here are as follows: First, while local properties surely affect the timing, size, and behavior of a mass movement, the dominant control on where they occur is the local surface topography, as it in turn defines local slope and shallow subsurface flow convergence; Second, all the evaluated basins have the possibility of debris flow; Thirdly, each evaluation factors should be available for all basins, otherwise, it should be excluded; Finally, the model should also need to integrate the system characteristics of debris flow disaster, the future development trend of climate change, and the social demand under the theoretical background of the new era to carry out reasonable modeling.

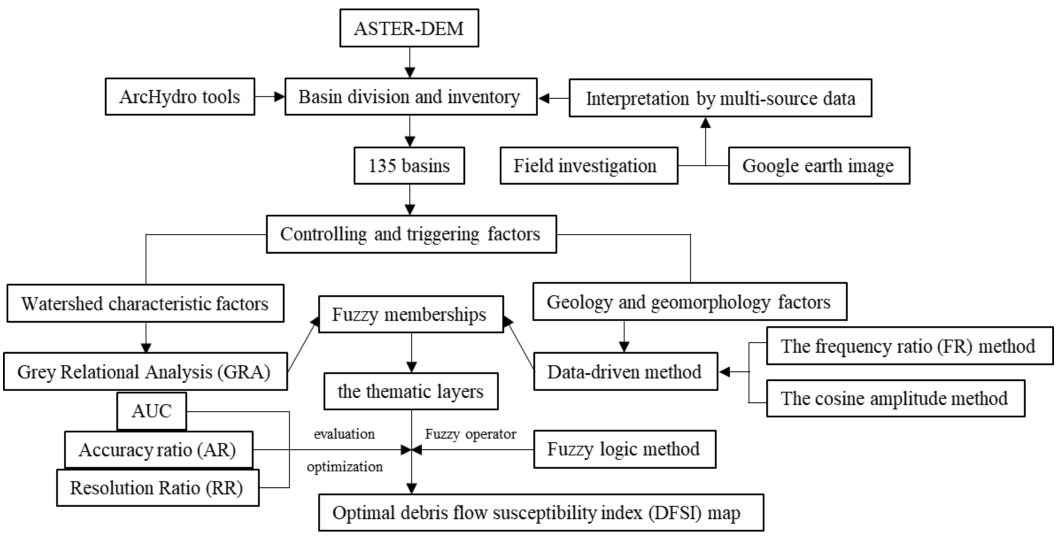


Fig.2 Workflow of debris flow susceptibility assessment

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 team. 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,

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

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. In the 135 basins, 48 basins 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

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Open Access
Discussions

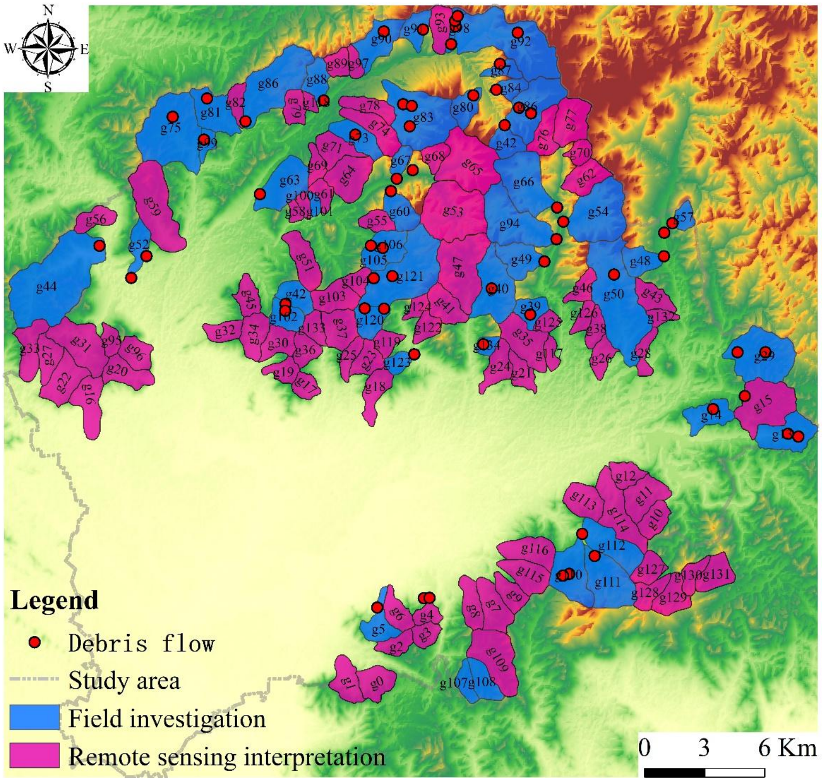


Fig. 4 Debris flow basin division and inventory.

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 at least some facros 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 paper 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) factors need to be further processed, even if the watershed is determined. The scope of these parameters is independent of the watershed boundary. 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 in my 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.

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Open Access
Discussions
EGU

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(Cao et al. 2016; Chang and Chien 2007; Zhang et al. 2011)	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. 2020b; 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 range of lateral erosions and retrogressive(Cao et al. 2016; Zhang et al. 2011)	the ratio of the total length of river network lines to A_1
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 numerical geological maps
	B_2	Proximity to faults	correlated with slope failures by generally reducing the strength of the rock mass	derived from 1:50,000

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

			(Dramis and Sorriso-Valvo 1994; Kellogg 2001; Korup 2004; Kritikos and Davies 2015).	numerical geological maps
	B_3	Slope (degrees)	correlated with the probability of landslide occurrence (Dai and Lee 2002; He and Beighley 2008; Lee and Choi 2004). 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/).

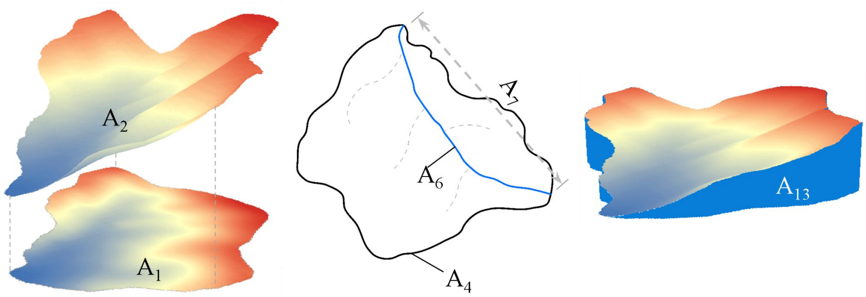


Fig. 5 Graphical illustration of some Type A factors. $\mathbf{A_1}$ is the planimetric (projected) area of the catchment; $\mathbf{A_2}$ is the curved surface area of the catchment; $\mathbf{A_4}$ is the the perimeter of catchment; $\mathbf{A_6}$ is the curve length of the main channel; $\mathbf{A_7}$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

3.3 Fuzzy logic in susceptibility modelling

Fuzzy set theory proposed by Zadeh (1965) is a effective method to express the concept of partial set membership degree. This concept is different from the classical binary (two-valued) logic by using fuzzy descriptions such as low, moderate, high, steep, favourable and close to (Kritikos and Davies 2015). 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 most critical step is to find the suitable fuzzy membership of the factor. And fuzzy membership degree is equivalent to the weight in expert scoring method, which is calculated by objective method rather than given subjectively.

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Discussions

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 whether the data is 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 (Kuo et al. 2008; Lin and Lin 2002; 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 numbers of basin, $x_0(k)$ 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

gully	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
gully	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
gully	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
gully	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

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences Discussions

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. In the case of sufficient rainfall, the basin directly determines the total amount of catchment, and the bending coefficient reflects the replenishment of the source along the river. The basin volume is closely related to the number of supplementary sources. Therefore, it is necessary to do well in rainfall monitoring and early warning in large watersheds, check for loose matter accumulation in river basins before rainy season, and pay attention to slope protection of basin with large volume potential energy for the purpose of disaster prevention and reduction.

3.4.2 Data-driven method in susceptibility modeling

Without regard to the influence of human activities, 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; Borrelli et al. 2014; Selby 1982). 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 (Bovis and Dagg 1992; Pierson et al. 1990), or from large, individual landslides that mobilize partially or almost totally (Iverson et al. 1997; Vallance and Scott 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 (Benda 1987; Crozier et al. 1990; Dietrich et al. 1986; Tsukamoto et al. 1982). 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 derived 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; Pradhan 2011a; Pradhan 2011b) within the same type factor (Table 4) in order to derive the function.

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

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 widely used (Ercanoglu and Gokceoglu 2004; Ercanoglu and Temiz 2011; Kanungo et al. 2009; Kanungo et al. 2006) 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):

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences Discussions

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

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). In order to use properly, every thematic layer must have the same pixel size.

Table 4 Factor categories and their fuzzy membership degrees

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

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

	East	2873308	295555	0.414	0.411	0.224	0.111
	Southeast	3122267	353489	0.455	0.453	0.245	0.108
	South	3219111	354420	0.443	0.440	0.246	0.133
	Southwest	3144353	400064	0.512	0.509	0.261	0.135
	West	3525895	436381	0.498	0.495	0.273	0.140
	Northwest	2787380	381679	0.551	0.547	0.255	0.318
Curvature	Concave	490900	109157	0.893	1.000	0.136	0.136
	Lessconcave	2037602	394583	0.778	0.871	0.259	0.226
	Flat	18364429	1769210	0.387	0.433	0.549	0.238
	Less convex	2202019	416142	0.759	0.850	0.266	0.226
	Convex	522285	112740	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 operator, Fuzzy Gamma (Eq.6) 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 results are calculated in ArcGIS (Fig. 7).

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

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).

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

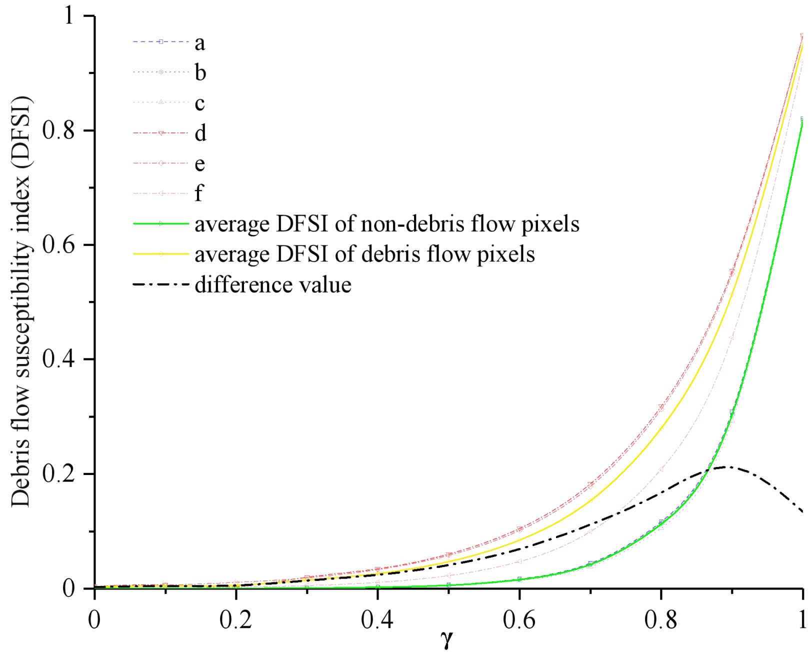


Fig. 6 Effect of γ value on Debris flow susceptibility index (DFSI). Curves d, e and f correspond to debris flow pixels, and curves a, b and c correspond to non-debris flow area where a Debris flow is unlikely. According to curve i, the maximum difference between the average DFSI values is observed for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

In order to find the optimal model, seventeen results were compared (Table 6). 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; Frattini et al. 2010; Remondo et al. 2003; Westen et al. 2003) 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 is 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

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Open Access
EGU
Discussions

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 basin 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).

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

Table 5 Predictive performance of different models

Result and Description			AUC	Two-category test		Performance index (centesimal 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 factors with r_{ij}	0.746	0.348	0.727	86
	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

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Discussions
Open Access

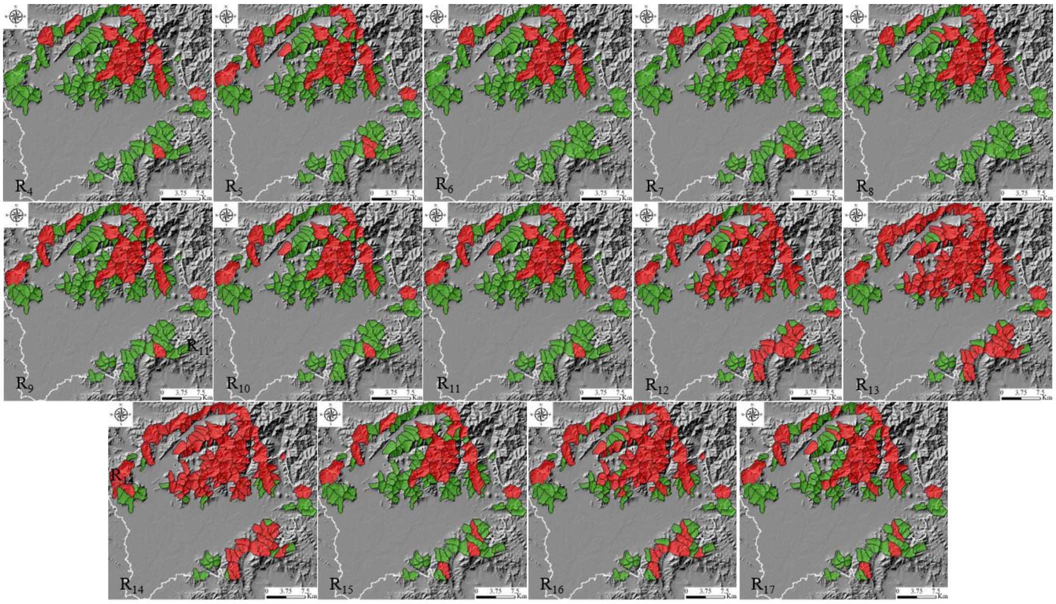
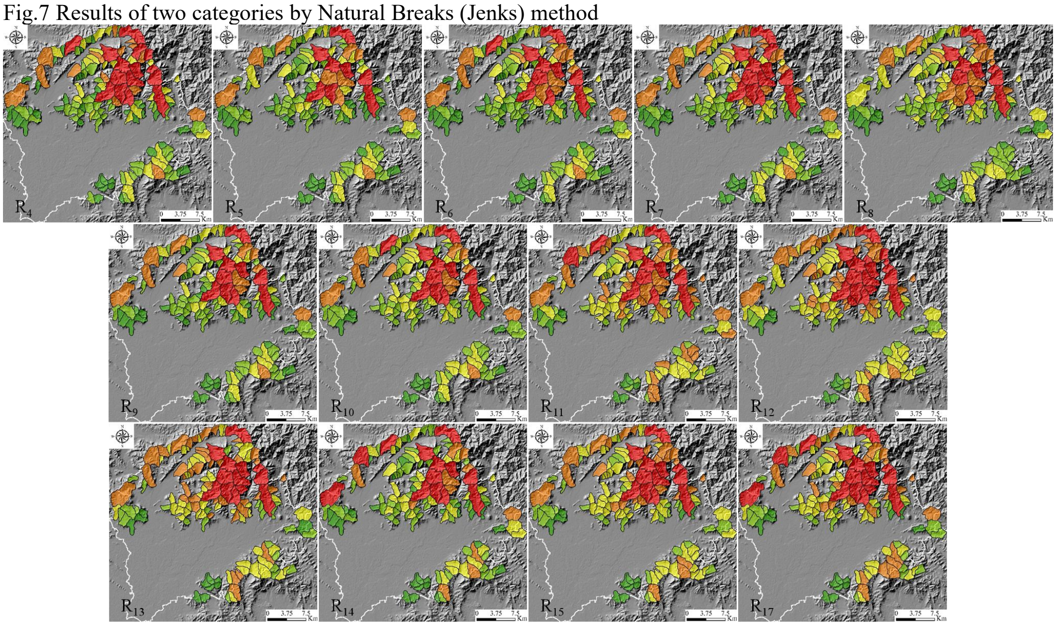


Fig.7 Results of two categories by Natural Breaks (Jenks) method



https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

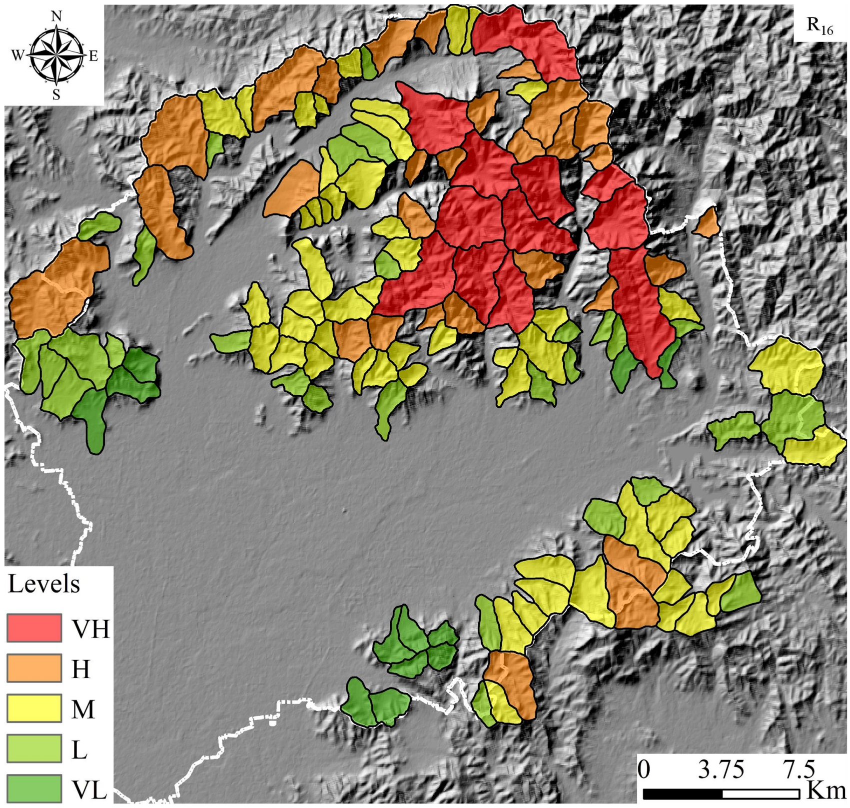


Fig 8 Debris flow susceptibility maps

4 Results and Discussion

According to the previous researches, 19 factors are selected. Although these factors cannot fully evaluate the character of a basin, it is necessary to consider that they are easily obtainable for each basin and can be obtained relatively accurately, ensuring that the model can be widely applied. Vegetation and rainfall factors are also very important, but there is little difference in vegetation and rainfall across the study area. Considering the background of global climate change, high temperature and extreme rainfall events will be increasing, which also makes them uncertain factor compared with factors compared. As for the factors describing debris flow magnitude, usually, several channels have the recorded data. Other factors that also influence the susceptibility of debris flow are usually difficult to obtain, including soil drainage, induration, thickness, conductivity, and strength properties; subsurface flow orientation; bedrock fracture flow; and root strength.

The predictive performance of the output debris flow susceptibility maps, obtained from seventeen different models, is verified by comparing with maps published by authority. By comparing the results, the following results are discussed:

First, 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 sufficient information cannot be obtained. 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 play a more and more important role. In this large cycle, the basin continuously occurs a small cycle of 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.

Second, 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 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 can be selected, which magnifies the differences between basins, so the boundaries between different susceptibility degrees are more obvious.

Third, 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 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.

Fourth, 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 et al. (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.

In summary, the debris flow susceptibility assessment in this study follows the principles of scientific and practicality. First, classification of influencing factors follows the principles of scientific, which require the classification to be accurate and systematic. Then the same susceptibility degree can be classified into the same type reasonably. In order 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,

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

Natural Hazards and Earth System Sciences
Discussions

but also make the professional results understood by decision makers. The relative simplicity of the model with data easy to obtain is attractive, which can also provide necessary information for debris flow mitigation and land utilization. Although the susceptibility grade and susceptibility value of each watershed is obtained, the results are relatively effective in this study area. The purpose is to distinguish the difference of each channel for decision-making to work out pertinence measure. Once separated from this study area, the comparison with other regions in value will lose its practical significance. 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. Last, nonlinear methods is consistent with the nonlinear characteristics of debris flow system.

5 Conclusion

In the present study, a new combination model for debris-flow susceptibility based on GIS was developed in Pinggu, the eastern of Beijing. 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 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≥0.7. 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 flow illustrate that the assessment at regional scale using the proposed method is feasible. Compared with the previous results based on grid units in this area, the evaluation results are basically the same, but they are more targeted for debris flow disasters for decision makers{Li, 2020 #278}.Besides, considering that the meaning of the used factors is clear and the data easy to obtain, these conditions mentioned enable the model to be widely applied.

Preliminary research indicates that: First of all, the relatively ideal 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, to a great extent, 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 with an acceptable degree of accuracy for regional-scale planning and contribute to making hazard, susceptibility and risk maps more accessible to individuals and local authorities. The evolution of GIS-based methods and modern data availability especially through online databases significantly contribute towards this aim. However, a challenge remains in producing results with meaningful 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.

Acknowledgements

This research was financially supported by the Key Project of NSFC-Yunnan Joint Fund (Grant no. U1702241) and the National Key Research and Development Plan (Grant No. 2018YFC1505301). The authors would like to thank Yuchao Li, Zhihai Li, Jiejie Shen, Feifan Gu et al. for their contributions to the collection of field data, and the editor and anonymous reviewers for their comments and suggestions which helped a lot in making this paper better.

Reference

Benda LE (1987) Sediment routing by debris flow

Benda LE, Dunne T (1987) Sediment routing by debris flow. In: Beschta RL, Blinn T, Grant GE, Swanson FJ, Ice GG (eds) Erosion and sedimentation in the Pacific Rim, vol 165. IAHS Publ, pp 213-223. doi:doi:10.1111/j.1753-4887.1977.tb06503.x

BMCP&NR (2020) 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.

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

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

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

Chang TC, Chien YH (2007) The application of genetic algorithm in debris flows prediction Environmental Geology 53:339-347 doi:10.1007/s00254-007-0649-2

Chiou IJ, Chen CH, Liu WL, Huang SM, Chang YM (2015) Methodology of disaster risk assessment for debris flows in a river basin Stoch Env Res Risk A 29:775-792 doi:10.1007/s00477-014-0932-1

Chung C-JF, Fabbri AG (1999) Probabilistic prediction models for landslide hazard mapping Photogrammetric Engineering And Remote Sensing 65:1389-1399 doi:10.1016/S0924-2716(99)00030-1

Chung CJF, Fabbri A, Westen CJv (1995) Multivariate regression analysis for landslide hazard zonation Geographical Information Systems in Assessing Natural Hazards 5:107-133

Crozier MJ, Vaughan EE, Tippett JM (1990) Relative instability of colluvium-filled bedrock depressions Earth Surface Processes and Landforms 15:329-339 doi:10.1002/esp.3290150404

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

Dai FC, Lee CF, Li H-Z, Xu C (2001) Assessment of landslide susceptibility on the natural terrain of Lantau Island, Hong Kong Environmental Geology 40:381-391 doi:10.1007/s002540000163

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

Deng JL (1988) Grey prediction and decision. Huazhong University of Science and Technology Press, Wuhan

Di B et al. (2019) Assessing susceptibility of debris flow in southwest china using gradient boosting machine Sci Rep 9:12532 doi:10.1038/s41598-019-48986-5

Dietrich WE, Wilson CJ, Reneau SL (1986) Hollows, colluvium, and landslides in soil-mantled landscapes. In: Abrahams. AD (ed) Hillslope Processes. Allen & Unwin, Boston,

Donati L, Turrini MC (2002) 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 doi:10.1016/S0013-7952(01)00087-4

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

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

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

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

Fairchild LH (1987) The importance of lahar initiation processes Reviews in Engineering Geology 7:51-62 doi:10.1130/REG7-p51

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

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

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

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

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

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

Iverson RM (1997) The physics of debris flows Reviews of Geophysics 35:245-296. doi:10.1029/97RG00426

Iverson RM, Reid ME, LaHusen RG (1997) Debris-flow mobilization from landslides Annual Review of Earth and Planetary Sciences 25:85-138 doi:10.1146/annurev.earth.25.1.85

Kanungo DP, Arora M, Sarkar S, Gupta R (2009) A fuzzy set based approach for integration of thematic maps for landslide susceptibility zonation Georisk 3 doi:10.1080/17499510802541417

Kanungo DP, Arora MK, Sarkar S, Gupta RP (2006) 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 doi:10.1016/j.enggeo.2006.03.004

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

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

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

Korup O (2004) 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 doi:10.1080/00288306.2004.9515052

Kritikos T, Davies T (2015) 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 doi:10.1007/s10346-014-0533-6

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

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

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

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

Lee S, Talib JA (2005) Probabilistic landslide susceptibility and factor effect analysis Environmental Geology 47:982-990 doi:10.1007/s00254-005-1228-z

Li Y, Chen J, Li Z, Han X, Zhai S, Li Y, Zhang Y (2021a) 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 doi:10.1007/s12665-021-09580-z

Li Y, Chen J, Tan C, Li Y, Gu F, Zhang Y, Mehmood Q (2020a) Application of the borderline-SMOTE method in susceptibility

https://doi.org/10.5194/nhess-2021-254
Preprint. Discussion started: 20 September 2021

assessments of debris flows in Pinggu District, Beijing, China Natural Hazards 105:2499-2522 doi:10.1007/s11069-020-04409-7

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

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

Lin CL, Lin CL (2002) 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 doi:10.1016/S0890-6955(01)00107-9

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

Liu S, Dang Y, Fang Z (2004) Grey system theory and its applications. Science Press, Beijing

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

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

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

Ohlmacher GC (2007) Plan curvature and landslide probability in regions dominated by earth flows and earth slides Engineering Geology 91:117-134 doi:10.1016/j.enggeo.2007.01.005

Pierson TC, Janda RJ, Thouret J-C, Borrero CA (1990) 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 doi:10.1016/0377-0273(90)90082-q

Porwal A, Carranza EJM, Hale M (2006) A Hybrid Fuzzy Weights-of-Evidence Model for Mineral Potential Mapping Natural Resources Research 15:1-14 doi:10.1007/s11053-006-9012-7

Pradhan B (2010) 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 doi:10.1007/s12524-010-0020-z

Pradhan B (2011a) 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 doi:10.1007/s10651-010-0147-7

Pradhan B (2011b) 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 doi:10.1007/s12665-010-0705-1

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

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

Ross TJ (1995) Fuzzy logic with engineering applications. McGraw-Hill, New York

Selby MJ (1982) Hillslope materials and processes. Oxford University Press, Oxford

Takahashi T (2014) Debris flow mechanics,prediction and countermeasures. second edn. Taylor & Francis/Balkema, The Netherlands

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

Vallance JW, Scott KM (1997) 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 doi:10.1130/0016-7606(1997)109<0143:TOMFMR>2.3.CO;2

Wang J, Yu Y, Yang S, Lu G-h, Ou G-q (2014) 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 doi:10.1007/s11629-013-2781-7

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

Westen CJv, Rengers N, Soeters R (2003) Use of geomorphological information in indirect landslide susceptibility assessment Natural Hazards 30:399-419 doi:10.1023/B:NHAZ.0000007097.42735.9e

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

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

Zadeh LA (1965) Fuzzy sets Information & Control 8:338-353 doi:10.1016/S0019-9958(65)90241-X

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

Zhang W, Li HZ, Chen Jp, Zhang C, Xu Lm, Sang Wf (2011) Comprehensive hazard assessment and protection of debris flows along Jinsha River close to the Wudongde dam site in China Natural Hazards 58:459-477 doi:10.1007/s11069-010-9680-9

Zhang Y, Chen J, Tan C, Bao Y, Han X, Yan J, Mehmood Q (2021) 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 doi:10.1007/s10064-021-02270-x

Zhong D, Xie H, Wang S, Wei F, Jin H (2004) Debris flow in Beijing mountain. Commercial Press, Beijing

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