Geologic hazard susceptibility and disaster risk mapping based on information value model for the MianChi county, China

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Geologic hazard susceptibility and disaster risk mapping based on information value model for the MianChi county, China

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Abstract. Geologic hazard mainly contain collapse, landslide, debris flow, ground fissure, surface collapse and subsidence. which had been influencing peopole’s life and production greatly. The space distribution of geologic hazards of MianChi county were investigated by field survey. This paper both obtained the geologic hazard susceptibility and disaster risk partitions map based on information value model. The article considered a total of 6 potential factors: slope gradient, slope altitude, slope style, structure of rock and soil, vegetation index and rainfall. The results conform to the actual outcomes and can be used for guiding practices.

1. Introduction
The main type of geologic hazard includes collapse, landslide, debris flow, ground fissure, surface collapse and subsidence. In the world, many geologic hazards occur to bring greater damage about human life and property in every year. Direct financial loss had reached 845.2billions yuan (RMB) and 69,227 dead and 374,644 wounded and 17,923 missing in the 5ꞏ12 WenChuan earthquake. In recent decades, geologic risk evaluation has became one of the hottest topics at the filed. Some scholars had been performed some works in geologic risk evaluation at Switzerland and France so on[1-4]. In China, some relevent researches also had been studied. For example, the index system and model was established [5]. The system of geologic hazard risk assessment had studied and developed based on Geographic Information System (GIS) and test ran in Chinese [6]. The evaluation of dangerousness and risking of collapses and landslides and debris flows were carried out for the Upper Yellow River [7-8]. The geologic hazard warning and risk assessment research had performed at landslide filed [9]. The risk matrix evaluation was established and practiced at Baota district in Yanan city [10]. Chinese scholars also obtained the classification of geologic hazard casualty rates and the method of risking assessment combined qualitative with quantify [11-12].Accroding to report in literature, several different methods of susceptibility mapping have been proposed and applied, such as the logistic regression model [13-16], the frequency ratio (FR) model [17-18], the certainty factor (CF) model [19-20], the weights of evidence method [21], the index of entropy (IOE) model [22], the artificial neural network model [23-24], the support vector machine (SVM) [25-26] and the decisiontree methods [27-28]. All these models provide solutions for integrating information levels and mapping the outputs. The main objective of this paper was to draw a geologic hazard susceptibility and disaster risk map of the MianChi county, China using the information value model. To identify the accuracy of quantitative evaluation by the model, we investigated the geologic disasters of the study area for three-month and compared the results of investigation and quantitative evaluation.

2. Description of the study area
MianChi county located in the east of Sanmenxia city and the western of Henan province, China. The area is approximately 1379km² (112°02′E-111°32′and 34°35′N-35°05′N). The topographic feature is consists of structural middle mountain and denudation low mountain and denudation hill and valley terrace with altitudes ranging from 500 to 1,000 m, besides, the altitude only is 200m on the valley of the midstream of the Yellow River in the northernmost county. The county belongs to continental climate with an average annual precipitation of 662.4 mm. The multi-year average amount of precipitation gradually increases from northwest to southeast (Fig.2). There are four rivers in the study area. The length of flow path of the Yellow River is 58.5 km and the drainage area is 562.86 km². the drainage area of Jianhe river is 592 km² and perennial stream flow is 1.010m³/s. The average annual discharge of Jiankou river and Hongyang river is 0.71m³/s and 0.59m³/s respectively. There are 262 geologic hazard spots (142 landslides and 90 collapses and 19 debris flows and 11 surface collapses ) were detected by interpreting aerial photographs (1:50,000) and 246 spots (131 landslides and 88 collapses and 16 debris flows and 11 surface collapses ) verified by field surveys.

3. Methodology

The adopted methodology for evaluating and mapping the geologic hazard susceptibility and disaster risk in MianChi county main is the information value (IV) method. The formation of geological hazard is affected by many factors (such as topography, valley incision condition, valley density and development stage, slope gradient, slope aspect, altitude, material composition and physical and mechanical property of slope and hydrogeological condition and so on). The evaluation of geologic hazard susceptibility and disaster risk selected eight factors (disaster density, slope gradient, slope altitude, slope style, rock and soil structure, vegetation index, rainfall index, and human engineering activity). The weight of each factor is given in Table 1. The information value which calculated influence factors for deformation and fracture of slope through the information analytical model acts quantitative index. It is simple, easy, practical and popular. The calculation principle and process as follows:

(1) The information value \( I(x_i/A) \) is calculated by single factor (index) :

\[
I(x_i, A) = \log \frac{P(x_i/A)}{P(x_i)}
\]

Where \( P(x_i/A) \) is the probability of appearing \( x_i \) under the deformation and fracture of a slope. \( P(x_i) \) is the probability of appearing index \( x_i \) in the study area. The totality probability is calculated by sample frequency at concreteness operation.

\[
I(x_i, A) = \log \frac{N_i/N}{S_i/S}
\]

Where \( S \) is element number of samples. \( N \) is element number of deformation and fracture in them. \( S_i \) means that there are \( x_i \) elements. \( N_i \) means that there are \( x_i \) deformation and fracture elements.
(2) The element information value $I_i$ of a slope deformation and fracture is calculated under the combination of $P$ factors.

$$I_i = I(x_1, A) = \sum_{i=1}^{P} \lg \frac{N_i}{S_i}$$

(3) According to H value, the stability class of element is determined. When $I_i < 0$ the deformation and fracture possibility of an element less than average. $I_i = 0$ means them both be equal. $I_i > 0$ the deformation and fracture possibility of an element greater than average. This mean that the grater element information value, the more advantageous a slope deformation and fracture.

(4) The region is divided into different classes through statistic analysis to find out the threshold value of mutational site.

| Index | Disaster density | Slope gradient | Slope altitude | Slope style | Rock and soil structure | Vegetation | Rainfall | Human engineering activity |
|-------|------------------|----------------|----------------|-------------|------------------------|------------|----------|---------------------------|
| Weight| 0.15             | 0.14           | 0.07           | 0.12        | 0.13                   | 0.10       | 0.09     | 0.20                      |

4. Results and discussion

4.1 Evaluation index quantification

Evaluation index contain quantitative (such as slope gradient, slope altitude and rainfall) and qualitative (such as structure of rock and soil and slope style). Quantitative index obtained from appropriate changed observed value. Qualitative index came from relatively contribution value of each single index for different classes. The classification standard of evaluation index need to be established.

4.2 Slope gradient index

In the study area, the slope susceptibility is defined as 1 with the gradient exceeding 40°, because appearance of landslide and collapse is altocfrequency in the slope. However, the slope susceptibility is defined as 0 with gradient less than 10° for occurring landslide and collapse being low-frequency. The linear uniformization (0 to 1) was performed of the slope susceptibility with gradient 10° to 40° accroding to the frequency of landslide and collapse among different gradients. Fig.3 is the gradient uniformization map of the study area.

4.3 Slope altitude index

In the nature, landslide and collapse usually occure the altitude between 50 to 100m, therfore, the susceptibility is defined as 1 with greater than 80m. The susceptibility of slope altitude between 0 to 80m was uniformed from 0 to 1. The gradient index uniformization map shows in the Fig.4.
4.4 Slope style index

The description and quantification of slope style use the surficial curvature. The straight and convex slope curvature (SC) is equal or greater than 0 (SC $\geq 0$). However, the concave and stagewise slope curvature is less than 0 (SC $< 0$). Landslide and collapse main appears on the straight and convex slope. So when SC $\geq 0$, the susceptibility is greater and SC $< 0$ is lowest. Fig.5 is the slope style index uniformization map according to curvature from digital elevation model (DEM) data.

4.5 Structure of rock and soil index

In the study area, the structure of rock and soil contains the middle thickness stiffness infrequent cracked quartz sandstone and limestone formation, the middle thickness stiffness extrusive rock formation, the thin to middle mudding softer sandstone formation, sandy gravel and middle fine sand double-deck soil mass and silty clay. The silty clay has the characteristics of greater thickness and developmental joint so that collapse in the southern hilly area. However, the covering layer of silty clay is thinner thickness and subterranean and is apt to landslide in the northern hilly area. The overlying quaternary silty clay is thinner and subterranean. The bedrock valleyand was cut deeper and weathered intense, so that landslide is easy to occur. The structure of rock and soil index uniformization (0 to 1) was performed according to investigation for the susceptibility of landslide and collapse (Fig.6).
4.6 Vegetation index
The normalized difference vegetation index (NDVI) is calculated using the computational formula: NDVI=(NIR-R)/(NIR+R). Where NIR is the reflected value of the red band and R is the near-infrared band in the MODIS remote sensing data. NDVI is kept between -1 to 1. When NDVI<0, it shows that the surface ground is covered with clouds, water, and snow, and so forth, which reflects visible light strongly. When NDVI=0 (NIR is approximately equal to R), it shows that the surface ground is exposed rock and soil. When NDVI>0, it shows that the surface ground is covered by vegetation and the value increases with the thickness of covering (Fig. 7).

4.7 Rainfall index
According to rainfall characteristics, the quantification factor of rainfall adopts the non-uniform rainfall coefficient (RNC). The RNC is defined as the average rainfall of the flood season (from July to September) divided by the perennial average rainfall. The RNC objectives reflect the non-uniformity of rainfall that degree of concentration and relative rainfall intensity. The greater RNC (rainfall is more concentrated) results in the greater relative rainfall intensity (Fig. 8).

4.8 Human engineering activity index
It is always a difficult research problem how to quantify the human engineering activity to influence geological disasters (landslide, collapse, and ground subsidence) for the complexity of disaster-causing mechanisms. According to the characteristic of covering or crossing whole areas, roads, and mines obviously affect the disaster and have the representation. The range of road and mine activity is treated as the datum line and performed buffer analysis to normalize the human engineering activity quantification index. The results were shown in Fig. 9.

4.9 The subdivision of computing element
The subdivision of computing element was performed from DEM to obtain topography information (Fig. 10). 4803 elements were obtained with valley topographic characteristics. The size and form greatly impact on the susceptibility and disaster compartment. The grid and satellite photo (SPOT-5) were overlaid in order to verify the reasonability of element subdivision and the result shown that evaluation is satisfactory.
5. Conclusion

5.1 Evaluation of geological hazards susceptibility

There are three zones (high, middle and low) of geological hazards susceptibility in the study area. The high susceptibility zone (I) area is about 381.98km², which has two subregions as follows: Guo-Tianchi subregion (I₁) area is about 76.51km². Potou-Chencun-Zhangcun along S247 line subregion (I₂) area is about 305.47km². The middle susceptibility zone (II) is wide distribution in the study area (845.36km²). There are 84 geological hazard spots and three subregions as follows: Nancun-Duancun-Potou subregion (II₁) area is approximately 255.74km². Nancun-Duancun-Rencun-Hongyang subregion (II₂) area is approximately 291.26 km². Yangshao-Chengguan-Yinghao-Chencun-Guoyuan-Tianchi subregion (II₃) area is approximately 298.36km². The low susceptibility zone (III) area is 193.66km². There are three subregions as follows:
Yinghao-Zhangcun-Chencun-Chengguan subregion (Ⅲ₁) area is 77.43km². Nancun-Duancun subregion (Ⅲ₂) area is approximately 75.49km². Guoyuan-Tianchi subregion (Ⅲ₃) area is approximately 40.74km².

Fig.11 The geological hazard susceptibility map  Fig.12 The geological disaster risk map

5.2 Evaluation of geological disaster risk

Similarly above, there are 3 geological disaster risk zones which is greater and medium and less risk zone respectively in the Fig.12. The greater risk zone (Ⅰ) mainly distributes in western and southern mining area and northern (along the S237 provincial highway) of MianChi county. The area of greater risk zone (Ⅰ) is about 253.20km². There are two subregions in the zone, which is Yinghao-Chencun-Zhangcun-Potou-Yangshao-Rencun-Hongyang along the S247 provincial highway subregion (Ⅰ₁) (177.07km²) and Guoyuan-Tianchi subregion (Ⅰ₂) (76.13km²). The medium risk zone(Ⅱ) disperse in every villages and towns (935.30km²). There are five subregions in the zone, as follows: Zhangcun-Chencun-Potou-Duancun subregion (Ⅱ₁) (375.68km²) main distribute in low-relief terrain of the western of MianChi county and the coastwise of Yellow River. The eastern of Duancun subregion (Ⅱ₂) (about 74.31km²) main distribute in low-relief terrain of the eastern of Duancun countryside. Rencun-Hongyang subregion (Ⅱ₃-Ⅱ₄) (about 161.05km²) main distribute in Rencun and Hongyan town. Chencun-Yangshao-Chengguan-Guoyuan-Tianchi subregion (Ⅱ₅) (324.26km²) main distribute in hilly area of the southern of MianChi county. The less risk zone (Ⅲ) is distributed aside from the above two zones (Ⅰ and Ⅱ). The area is about 232.50km². There are four subregions, Yinghao-Zhangcun-Chencun (Ⅲ₁) and Duancun-Rencun (Ⅲ₂) and Nancun and (Ⅲ₃) and Guoyuan-Tianchi (Ⅲ₄) in the zone. The area is about 76.50km², 23.01km², 96.69km² and 36.30km² respectively.

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