Evaluation of landslide susceptibility based on VW-AHP-IV model: a case of Pengyang County, Ningxia, China

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Abstract

Landslide is one of the most common and severe geological disasters, which significantly endangers people's lives and properties. Therefore, the evaluation of landslide susceptibility in a specific area is important for disaster control and mitigation. This paper selected Pengyang County as the study area. It divided the indicator state levels, and further assigned a score for each indicator according to the related information values (IV) based on the analysis of graded area ratio and landslide occurrence frequency distribution. Because the solo analytical hierarchy process (AHP) method always causes large errors during the weight determination, a variable-weight based weighted information value (VW-AHP-IV) model was applied in this paper for landslide susceptibility evaluation. The study area was classified into four grades by the natural breakpoint method: high susceptibility area (11.80%), medium susceptibility area (29.23%), low susceptibility area (42.45%) and very low susceptibility area (16.52%). In addition, this paper also discussed the influences of precipitation and human activities. According to the evaluation results and discussion, the study area was classified into three prevention and control areas: focus prevention and control area, sub-focus prevention and control area, and general prevention and control area. For each area, the corresponding prevention and control suggestions were proposed in order to reduce the occurrence of landslide disasters.

1 Introduction

Geological disasters are disastrous geological phenomena formed under various geological actions, which are affected by both natural environment and human activities (Wang et al. 2000). Landslides are one of the most common types of geological disasters that cause a large number of socio-economic, environmental and human casualties worldwide due to the characteristics of complex causes, wide damage, and strong continuity (Wang et al. 2019; Francisco et al. 2015; El Jazouli et al. 2019). In recent years, with urbanization and infrastructure have been promoted, China saw a significant increase in the number of geological disasters (Mao et al. 2021). It is estimated that there were 6,181 geological disasters (including 4,220 landslides, accounting for 68.27%) occurred in 2019, resulting over 300 deaths and injuries, causing serious damage and economic losses (Ministry of Natural Resources, P. R. China 2019). Therefore, scientific and accurate evaluation of landslide susceptibility is of great significance to disasters prevention and mitigation, people's lives and property protection, economic protection, and the achievement of in harmony with people and the environment.

Landslide susceptibility reflects the spatial probability of landslides in a certain area, which is to predict the spatial location of possible landslide under specific geological environment conditions (Li and Wang 2020). In recent years, scholars across the world have researched on evaluation methods of landslide susceptibility including qualitative methods and quantitative methods (Ferentinou et al. 2013; Zhou et al. 2016). Qualitative methods generally include data-based probability analysis method and experience-based qualitative reasoning method (Yan et al. 2019), commonly used analytic hierarchy process (AHP) (Wind and Saaty 1980) and weighted linear combination method (Jacek 2000; Ayalew et al. 2004) etc. Quantitative methods mainly include mathematical evaluation model based on data, deterministic model

based on physical mechanics and probability model based on reliability measure (Tang and Zhang 2011), commonly used information value (IV) model (Chen et al. 2014), neural network method (Lee et al. 2003), logistic regression model (Ohlmacher and Davis 2003), frequency ratio method (Lee and Pradhan 2007) and evidence weighted model (Chen et al. 2016; Hong et al. 2017; Wang et al. 2016) etc.

At present, there are many researches on geological disasters using quantitative or qualitative methods, among which IV model and AHP are the two most commonly used methods (Zhang et al. 2020; Lu et al. 2020; Wang et al. 2020). However, in the traditional IV model, the contribution rate of each evaluation indicator to the occurrence of geological disasters is equal, but in fact, the weights of various indicators that contribute on the occurrence of geological disasters are different (Chen et al. 2021). Although the weighted information value (AHP-IV) model can give different weights to each indicator (Niu 2014), it should be noted that the indicator weight given by the model is constant, which leads to a fact that when an indicator is better than other indicators to a certain extent, it may be "neutralized" by poor indicators, so that the evaluation results are inconsistent with the reality. In addition, when grading or scoring the state of evaluation indicators, the classification still relies on subjective experience or isometric division, resulting in excessive influence of subjective factors and lack of objective basis (Chen et al. 2021). Therefore, if these evaluation models and methods are not improved and optimized, it is difficult to objectively, accurately and quantitatively evaluate the susceptibility of regional landslides.

Landslide disasters in western China are serious, which caused significant loss of life and rapid land degradation (Huang 2009; Sun et al. 2018). Among them, as a typical landslide susceptibility area in western China, Pengyang County, Ningxia Hui Autonomous Region (Ningxia H. A. R) has been troubled and harmed by landslides for a long time. Since the 1980s, a total of 525 landslides have occurred in the study area, significantly endangering the safety of local people's lives and property, and hindering the development of local society and economy. In order to prevent and control geological disasters, many scholars have analyzed the effect of returning farmland to forest on reducing geological disasters such as landslides (Li et al. 2006; Qi 2017; Liu et al. 2018). Some scholars have also studied the formation mechanism of landslides in this area and explored the formation conditions of loess landslides (Shang et al. 2011; Long et al. 2021). In addition, Mao (2009) evaluated the risk of geological disasters in Pengyang County based on GIS and applied the IV model. Yu et al. (2012) conducted risk evaluation and prediction research on important geological disaster points in Pengyang County. However, these studies only used a single method for landslide susceptibility, and lacked in the model comparison and validation, which caused many concerns on the accuracy, stability and reliability. Moreover, the results did not provide further planning for local landslides prevention and control, so the practical significance of landslide susceptibility evaluation was lost in their studies.

At present, there are relatively few in-depth studies on landslide disasters in the Pengyang County, which makes significant challenges on the disaster prevention and mitigation. However, the IV model and the AHP-IV model cannot objectively, accurately and effectively evaluate the susceptibility of regional landslides. In addition, the method of grading the evaluation indicator state based on subjective experience or isometric division there is a problem of too much influence of subjective factors and lack of

objective basis. Therefore, it is of great significance to investigate historical landslides in Pengyang County, establish an applicable landslide susceptibility model, and compile zoning map of landslide susceptibility, so as to determine the high susceptibility area of landslide.

To solve the problem of unreasonable constant weight evaluation, this paper adopted a penalty-incentive variable weight (VW) theory to redistribute the constant weight, and then established a variable weight evaluation model. After comprehensively analyzed the graded area ratio of each indicator and the distribution state of landslide occurrence frequency curve, the indicator state was graded. The value of information in the indicator state level was then calculated. Finally, the grading score was carried out according to the information value, so as to solve the problems of excessive influence of subjective factors and lack of objective basis in grading. The weighted information value model based on variable weight (VW-AHP-IV) is used to improve and optimize the landslide susceptibility evaluation, which is expected to provide recommendations for the urban and rural development planning and disaster prevention and mitigation in Pengyang County.

2 Methodology

2.1 Technical route

The technical route of landslide susceptibility evaluation in this paper is shown in Fig. 1.

<Fig. 1 Flowchart of landslide susceptibility evaluation>

Firstly, data of the study area were collected, including landform map, geological map (1:50,000) and landslide geological disasters information provided by the Department of Natural Resources of Ningxia. Annual average precipitation data were obtained from China Meteorological Data Network (http://data.cma.cn/). Normalized Difference Vegetation Index (NDVI) and Digital Elevation Model (DEM) data were extracted from geospatial data cloud (http://www.gscloud.cn/), and land use types were from Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences (https://www.resdc.cn/).

Based on above data, the study area profile and landslide formation mechanism were analyzed, and landslide inventory maps were produced for progressive modeling treatment. It should be noted that each landslide in the landslide inventory diagram can be represented by a point on a regional scale. In this paper, we used the geostatistical analyst tool in GIS to select 80% (420) of the landslides in the original database as the training dataset and the remaining 20% (105) as the validation dataset. This split ratio of training and validation data sets is reasonable and is widely used in related fields (Yang et al. 2021). According to the formation mechanism of landslide and the actual geo-environmental conditions, lithology, landform, slope, distance to river, NDVI and aspect were selected as the evaluation indicators of landslide susceptibility. According to the graded area ratio of each indicator and the distribution state of landslide occurrence frequency curve, the indicator state level was divided.

The value of information of each evaluation indicator state level was calculated by the IV model. AHP and VW theory were used to calculate the constant weight and variable weight of each indicator. The study area is also divided into 5112 evaluation units. It should be noted that, due to the small area of the study area and the large indicator dispersion, the irregular polygon grid method is used to divide the evaluation unit. As a result, landslide susceptibility evaluation models were constructed.

The landslide susceptibility index (LSI) was calculated according to the comprehensive index method. The natural breakpoint method was used to classify the grades of landslide susceptibility and draw the zoning maps of landslide susceptibility in the study area and county town area. When analyzing and discussing the zoning map of landslide susceptibility, precipitation and human activities were selected as predisposing factors to participate in it. Finally, the landslide susceptibility zoning map and the human activity map were integrated to classify the landslide susceptibility prevention and control zones in the study area, and proposed prevention and control suggestions.

2.2 Methods

2.2.1 AHP-IV model

The IV model is a quantitative statistical analysis method derived from information theory to quantitatively describe information (Shannon 1948). It has been widely used in geological disaster susceptibility evaluation in recent years (Pourghasemi et al. 2018). When AHP method is introduced, the AHP-IV model provides the corresponding quantitative score to the calculated the state level information value of each indicator, while the AHP is utilized to determine the indicators' weights. Finally, LSI is calculated by the comprehensive index method. AHP is a MCDA (Multi-criteria decision analysis) method that aims to qualitatively, quantitatively, hierarchically and systematically combined different indicators and personal priority (Saaty 1980; Saaty and Vargas 1985; Saaty 2013). It can be combined with the actual situation of the research object to make the evaluation system and the evaluation object more integrated.

The equation for calculating IV of state level of each evaluation indicator is as follows:

$$\mathrm{I}\left(\mathrm{x_i}\right) = \ln\frac{\mathrm{N_i}/\mathrm{N}}{\mathrm{S_i}/\mathrm{S}}$$

1

Where: $\mathrm{x_i}$ represents the state i corresponding to the evaluation indicator x; $\mathrm{I}\left(\mathrm{x_i}\right)$ is the information value of geological disasters in the state i corresponding to the evaluation indicator x; $\mathrm{N_i}$ is the number of geological disasters in the state i corresponding to the evaluation indicator x; N is the total number of geological disasters in the study area; $\mathrm{S_i}$ is the area in the state i corresponding to the evaluation indicator x; S is the total area of the study area.

The equation for calculating the LSI is as follows:

$$LSI = \sum_{k=1}^{n} (R_k \times W_k)$$

2

Where: LSI is the landslide susceptibility index; R_k is the scoring value to evaluation indicator k; W_k is the weight value to evaluation indicator k; n is the number of evaluation indicators.

2.2.2 Variable weight theory

Wang (1985) proposed the idea of variable weight, and Li (1995; 1996) proposed a comprehensive decision-making model based on variable weight. This model effectively solved the issue of one-sidedness for actual decision-making. This is, when the indicator score changes, its weight is always a certain value.

State variable weight vector is defined. Set $X = (x_1, ..., x_m)$ is the state vector of indicator j, $S(X) = \left(S_1\left(X\right), ..., S_m(X)\right)$ is the state variable weight vector. The research of variable weight theory shows that the variable weight vector is the Hadmard normalized product of constant weight vector and state variable weight vector (Li 1995) (Eq. 3).

$$W(X) = W\frac{S(X)}{\sum_{j=1}^{m}(W_j \bullet S_j(X))}$$

3

Where: $W(X)$ is the variable weight vector; W is the constant weight vector; $S(X)$ is the state variable weight vector; W_j is the constant weight vector of indicator j; $S_j(X)$ is the state variable weight vector of indicator j.

On this basis, Duan (2003) proposed the penalty-incentive segmented coordination theorem, which has been successfully applied to various decision-making problems (Eq. 4) (Fig. 2).

$$S_j(X) = \begin{cases} \frac{a-b}{\alpha-\lambda}\lambda ln\frac{\lambda}{x_j} + ax_j \in (0, \lambda] \\ \frac{b-a}{\alpha-\beta}x_j + \frac{a\alpha-b\lambda}{\alpha-\lambda}x_j \in (\lambda, \alpha] \\ \frac{a-b}{2(\alpha-\lambda)(\beta-\alpha)}\left(\beta-x_j\right)^2 + cx_j \in (\alpha, \beta] \\ cx_j \in (\beta, \mu] \\ k(1-\mu)ln\frac{1-\mu}{1-x_j} + cx_j \in (\mu, 1) \end{cases}$$

4

Where: x_j is the scoring; a, b, and c are the appraisal strategy; and k is the adjustment coefficient; and the parameters meet the following conditions:0 < λ < α < β < μ < 1, 0 < c < b < a < 1, and (b-c)/(β-α) =(a-b)/2(α-λ).

<Fig. 2 Penalty and incentive variable weight function (Duan, 2003)>

3 Study Area

The study area-Pengyang County is located in the southeast edge of Ningxia H. A. R, China, on the east side of Liupan Mountain. The geographical coordinates are between 106°15'-107°12'E and 35°42'-36°18'N, with a total area of about 2555km^2(Fig. 3a). The topography of the study area is generally high in the northwest and low in the southeast, showing a wavy slope. According to the topography, it can be divided into loess hills, rock hills and river valley terraces (Liu et al. 2018) (Fig. 3b). The study area is a typical semi-arid continental monsoon climate, characterized by drought and little rain, strong wind and sand, and large diurnal temperature difference. The annual average temperature is 1.46℃, and annual average precipitation is 617.5mm. In terms of time, the amount of precipitation varies greatly throughout the year, and the distribution is uneven; in terms of space, the amount of precipitation shows a decreasing trend from south to north.

< Fig. 3 Location, landform, geology, land use of the study area:

(a) location; (b) landform; (c) geology; (d) land use>

The rock hills landform in the southwest of the study area are mainly Cretaceous and Paleogene sandstones and conglomerates. The river valley terraces in the south are covered by heavily weathered Quaternary sediment sandy soils, and Ordovician dolomites are exposed in some areas. Cretaceous and Neogene sandstones and conglomerates, while the northern loess hills are covered by Quaternary deposit

loess, and a small part of the area is exposed to Cambrian limestone and Jurassic mudstone. The study area has two faults: Lane-Aselang fault and Niushou-Luoshan-Kongtong Mountain fault, both of which are approximately north-south strike (Fig. 3c).

As the geological environment of the study area is increasingly affected by human activities, landslide disasters occur frequently. The survey showed that by the end of 2017, a total of 544 geological disasters (including landslides and ground collapses) had occurred in the study area, of which 525 were landslides, accounting for 96 percent of the total geological disasters. The land use in the study area can be divided into five categories: grassland, construction land, bare land, cropland and forestland (Fig. 3d). However, due to overgrazing, deforestation, excessive reclamation and irrational use of water resources, the degradation of large areas of pasture and the degradation of grassland vegetation in sandy areas in the study area have led to an increase in the trend of local land sanding and soil erosion (Zhang et al. 2010).In addition, infrastructure construction, such as building houses on slopes, building kilns, pipeline engineering, building roads and railways, is also an important reason for the frequent occurrence of landslides in the study area (Mao et al. 2011).

4 Evaluation Processes

4.1 Mechanism of landslide formation

The basic conditions for the occurrence of landslides are divided into internal conditions and external conditions. The internal conditions are mainly composed of landform, lithology, slope, aspect, fault density, epicentral distance, NDVI, distance to river and distance to fault (Chen and Zhang 2021; Wang et al. 2020). The external conditions are mainly predisposing factors such as rainfall, human activities and earthquakes (Zhou 2018; Ji 2016; Yu 2018). The precondition for a landslide is that there is a sliding space in the front and both sides of the slope. The mechanism is that the shear stress on the sliding surface exceeds the shear strength of the sliding surface, that is, the sliding force exceeds the anti-sliding force, and the sliding body is under its own gravity sliding forward under the action (Dong & Yang 2017).

4.2 Grading and scoring of indicators

According to the actual geo-environmental conditions and the occurrence mechanism of landslides in the study area, this paper selected lithology, landform, slope, distance to river, NDVI and aspect as evaluation indicators of landslide susceptibility. According to the graded area ratio and the distribution state of landslides occurrence frequency curve, the number, density and susceptibility of landslides in different intervals of each evaluation indicator were analyzed, so as to grade different states of the indicator (Fig. 4).

(1) Lithology

The type of lithology is the material basis for the occurrence and development of landslide disasters. The weathering resistance, strength, stress distribution and other parameters of lithology depend on the type

and softness of the lithology (Sun 2013). The lithology types in the study area are divided into hard and thick dolomite, limestone rock group (C), hard sandstone, conglomerate rock group (B1), soft sandstone, conglomerate rock group (B2), sandy soil (A2) and loess (A1). Among them, loess has the characteristics of loose structure, low strength, easy to soften in contact with water, and development of joints and fissures, which determine that loess has a very important influence in the evaluation of landslide susceptibility (Mao et al. 2010).

(2) Landform

The type of landform is one of the important indicators affecting the development and distribution of landslide disasters (Zhou et al. 2020). The landform of the study area can be divided into loess hills, rock hills and river valley terraces. Loess hills and river valley terraces are extremely susceptible to erosion, denudation, and erosion by precipitation and surface runoff, which can lead to slope instability. In contrast, rock hills are more stable and not prone to landslide disasters.

(3) Slope

Slope is an important evaluation indicator of landslide disaster, and the size of slope affects the stress distribution and the thickness of slope deposits (Chen et al. 2019). The DEM data of the study area were applied to the GIS surface analysis aspect tool to obtain the terrain slope indicator. According to the graded area ratio and the distribution state of landslides occurrence frequency curve, the slope was divided into five grades: 0 ~ 5.19°, 5.19 ~ 9.40°, 9.40 ~ 13.47°, 13.47 ~ 18.24° and > 18.24°. Generally, the steeper the slope, the worse the stability of the slope and the higher the susceptibility of landslide.

(4) Distance to river

The bank slopes of the slope are subjected to the lateral erosion and downcutting of the river to form steep ridges, which are prone to landslide disasters accumulating over time (Wang 2017; Li and Wang 2019). According to the graded area ratio and the distribution state of landslides occurrence frequency curve, this paper divided the distance from the study area to the river into five grades: 0 ~ 0.5km, 0.5 ~ 1km, 1 ~ 1.5km, 1.5 ~ 2km and > 2km. The closer the distance, the more severe the erosion and the higher the susceptibility of landslides.

(5) NDVI

There is a strong correlation between the occurrence of geological disasters and vegetation coverage (Feng 2020). NDVI is the normalized vegetation indicator, which can be used to reflect the vegetation growth state and spatial distribution density, that is, to characterize the vegetation coverage (Hu 2020). According to the graded area ratio and the distribution state of landslides occurrence frequency curve, NDVI was divided into five grades according to -0.0837 ~ 0.2379, 0.2379 ~ 0.3899, 0.3899 ~ 0.5032, 0.5032 ~ 0.6347 and 0.6347 ~ 0.9886. The larger the value, the greater the vegetation indicator and the lower the landslide susceptibility.

(6) Aspect

Aspect refers to the direction in which the slope normal of the hillside is projected on the horizontal plane (Lu et al. 2020). Because different aspects are affected differently by natural conditions such as solar radiation intensity and precipitation, aspect is also one of the important indicators affecting the distribution of geological disasters. The DEM data of the study area were applied to the GIS surface analysis aspect tool to extract the aspect indicator, and according to the graded area ratio and the distribution state of landslides occurrence frequency curve, it was divided into four grades according to northeast, southeast, southwest and northwest.

<Fig. 4 Statistical chart for grading the state of indicators in the study area>

In this paper, 80% (420) of the landslide training data were randomly selected to apply Eq. 1 to calculate the value of information for each evaluation indicator state level. The corresponding indicator state level scoring by the value of information of each indicator state level. Among them, the more information value of the indicator state level is, the worse the indicator level is, the lower the indicator level score is, and the more likely to produce landslides (Table 1 and Fig. 5).

Table 1
Information values of evaluation indicator state level in the study area

Indicators	State level	Landslide	Area/km^2	IV	Scoring
Landform	Loess hills	244	1768.06	-0.1746	0.5
	Rock hills	12	223.32	-1.1179	0.9
	River valley terraces	164	564.21	0.5702	0.1
Lithology	Loess (A1)	193	1283.31	-0.0887	0.5
	Soft sandstone, conglomerate (B2)	100	483.56	0.2297	0.3
	Hard sandstone, conglomerate (B1)	66	599.07	-0.3999	0.7
	Hard and thick dolomite, limestone (C)	7	82.67	-0.6631	0.9
	sandy soil (A2)	54	106.98	1.1221	0.1
Aspect	Northeast	116	798.55	-0.1234	0.9
	Southeast	101	569.26	0.0765	0.1
	Southwest	97	583.94	0.0106	0.5
	Northwest	106	603.84	0.0659	0.3
Slope /°	< 5.19	65	463.30	-0.1582	0.9
	5.19 ~ 9.40	114	707.11	-0.0192	0.7
	9.40 ~ 13.47	114	693.17	0.0007	0.5
	13.47 ~ 18.24	85	492.02	0.0499	0.3
	> 18.24	42	199.99	0.2451	0.1
NDVI	-0.0837 ~ 0.2379	42	283.00	-0.1019	0.7
	0.2379 ~ 0.3899	90	461.75	0.1705	0.1
	0.3899 ~ 0.5032	140	817.80	0.0408	0.3
	0.5032 ~ 0.6347	118	747.79	-0.0406	0.5
	0.6347 ~ 0.9886	30	245.25	-0.2953	0.9
Distance to river /km	< 0.5	83	399.05	0.2355	0.1
	0.5 ~ 1	78	389.41	0.1978	0.3
	1 ~ 1.5	66	363.81	0.0988	0.5

Indicators	State level	Landslide	Area/km^2	IV	Scoring
	1.5 ~ 2	57	328.51	0.0542	0.7
	> 2	136	1074.81	-0.2614	0.9

<Table 1 Information values of evaluation indicator state level in the study area>

<Fig. 5 Single-indicator partition map for susceptibility evaluation in the study area>

4.3 Determination of indicator weights

4.3.1 Constant weight determination

In this paper, AHP was used to calculate the constant weights of indicators, including constructing the judgment matrix, calculating the weight vector and checking the consistency of the judgment matrix. The importance of the evaluation indicators was compared with each other through expert scoring, and the corresponding judgment matrix was constructed and the weight vector was calculated (Table 2).

Table 2
Comparative judgment matrix and weighs of indicators

	Lithology	Landform	Slope	Distance to river	NDVI	Aspect	Weight
Lithology	1	2	3	4	5	6	0.3825
Landform		1	2	3	4	5	0.2504
Slope			1	2	3	4	0.1596
Distance to river				1	2	3	0.1006
NDVI					1	2	0.0641
Aspect						1	0.0428
$n = 6; \lambda_{max} = 6.1225; RI = 1.24; CI = \frac{\lambda_{max} - n}{n-1} = 0.0245; CR = \frac{CI}{RI} = 0.0194 < 0.1$							

<Table 2 Comparative judgment matrix and weighs of indicators>

4.3.2 Variable weight determination

In this paper, 5112 evaluation units could be obtained by spatial superposition of all evaluation indicators. The key to the calculation of the variable weight vector lies in the determination of the state variable weight vector, and the state variable weight vector can be constructed directly using the mean value of the state vector, or it can be obtained by constructing an equalization function (Li 1995). According to the grade division of the evaluation indicator and the final susceptibility grade division requirements, the equilibrium function is used to determine each parameter in the state variable weight

vector. Take λ = 0.2, α = 0.4, β = 0.6, μ = 0.8, adjustment coefficient k = 1.5, a = 0.5, b = 0.3, c = 0.2, and get the state variable weight vector (Table 3).

Table 3
The state vector takes the value

Scoringx_j	0.1	0.3	0.5	0.7	0.9
State variable weight vector $S(X)$	0.64	0.40	0.23	0.20	0.41

<Table 3 The state vector takes the value>

According to $S(X)$ and constant weight, the variable weight theory was used to calculate the variable weight of each indicator in the evaluation unit. The output results are shown in Table 4. In constant weight evaluation, each indicator has only one weight, while in variable weight evaluation, the weight varies with the different evaluation units of the indicator.

Table 4
Variable weighting

Evaluation Unit	Lithology	Landform	Slope	Distance to river	NDVI	Aspect
1	0.2154	0.3923	0.1602	0.1576	0.0313	0.0429
2	0.2103	0.3831	0.1564	0.1539	0.0306	0.0654
3	0.2195	0.3999	0.1632	0.1606	0.0319	0.0245
4	0.2156	0.3927	0.1603	0.1578	0.0314	0.0419
…	…	…	…	…	…	…
5107	0.5006	0.1177	0.2088	0.0843	0.0524	0.0358
5108	0.5086	0.1196	0.2122	0.0857	0.0532	0.0204
5109	0.5120	0.1204	0.2136	0.0862	0.0308	0.0367
5110	0.5017	0.1180	0.2093	0.0845	0.0302	0.0561
5111	0.5204	0.1224	0.2171	0.0876	0.0313	0.0209
5112	0.5125	0.1205	0.2138	0.0863	0.0308	0.0358

<Table 4 Variable weighting>

5 Results

The landslide susceptibility comprehensive index $LSI_{(AHP-IV)}$ = 0.1 to 0.8235 and $LSI_{(VW-AHP-IV)}$ = 0.1 to 0.8535 were calculated according to Eq. 2, respectively. Natural breakpoint method (Lai and Chen 2019) was used to classify the landslide susceptibility into four grades (Table 5): high susceptibility area,

medium susceptibility area, low susceptibility area and very low susceptibility area, and the landslide susceptibility zoning maps of the study area and county town area were prepared (Fig. 6).

Table 5
Grading of landslide susceptibility comprehensive index

Grading	High susceptibility area	Medium susceptibility area	Low susceptibility area	Very low susceptibility area
AHP-IV model	<0.3365	0.3365 ~ 0.4683	0.4683 ~ 0.5987	>0.5987
VW-AHP-IV model	<0.2967	0.2967 ~ 0.4406	0.4406 ~ 0.6031	>0.6031

<Table 5 Grading of landslide susceptibility comprehensive index>

<Fig. 6 Landslide susceptibility zoning map: (a) AHP-IV model of study area; (b) VW-AHP-IV model of study area; (c) AHP-IV model of county town area; (d) VW-AHP-IV model of county town area>

6 Discussion

6.1 Rationality and importance of indicators

From the perspective of landform types, the information value of the river valley terraces (I = 0.5702) is greater than 0, while the information value of the loess hills (I=-0.1746) and rock hills (I=-1.1179) is less than 0. It indicates that river valley terraces promote the occurrence of landslides, and loess hills and rock hills inhibit the occurrence of landslides. In fact, landform indirectly control the distribution of landslides by influencing the intensity of human activities. Generally speaking, the ups and downs of landform and poor living conditions mean that the intensity of human activities is reduced. Most of the engineering construction and agricultural activities in the study area are distributed in the river valley terrace areas, which leads to a large number of landslide disasters. Therefore, in the future, while controlling the intensity of human activities in this area, we will increase the control of these newly formed landslides.

For lithology, the information value of hard and thick dolomite, limestone rock group, hard sandstone, conglomerate rock group, loess, soft sandstone, conglomerate rock group and sandy soil are − 0.6631, -0.3999, -0.0887, 0.2297 and 1.1221. Generally speaking, the lithology group with loose soil and low hardness is more prone to landslides. However, the information value corresponding to loess is not the highest. The reason may be that the loess area in the study area is widely distributed and the occurrence of landslide disasters is not concentrated enough. On the contrary, although the distribution of sandy soil areas is small, most of them are located in urban areas, and landslide disaster births are relatively concentrated.

Regarding the slope, we can clearly see that the value of information is positively correlated with the size of the slope. Among them, the information value of 0 ~ 5.19°(I=-0.1582) and 5.19 ~ 9.40°(I=-0.0192) is less than 0, which means that the gentle terrain can prevent the occurrence of landslides. The information value of 9.40 ~ 13.47°, 13.47 ~ 18.24° and > 18.24° levels is greater than 0, which are 0.0007, 0.0499 and 0.2451 respectively. The analysis of the information value results shows that within a certain range, as the slope increases, the probability of landslides occurrence increases.

In general, the information value decreases as the distance to the river increases. The information value of the level greater than 2km (I=-0.2614) from the river is the only negative value, which has a negative impact on the occurrence of landslides. Other levels have a positive impact on the occurrence of landslides. Theoretically, the smaller the distance to the river, the greater the erosion effect of river water, and the easier it is for landslides to occur. Therefore, the results of this study are in strong agreement with the theory.

For NDVI, a value of 0.5032 can be used as a threshold, and areas with NDVI < 0.5032 may be prone to landslides. Continued agricultural activities may be the reason why the NDVI value is between 0.2379 ~ 0.3899 and the maximum information value is 0.1705. Compared with cropland, forest can effectively alleviate the occurrence of shallow landslides. In addition, the area with NDVI of -0.0837 ~ 0.2379 (I=-0.1019) will have an information value that is less than 0. It may be caused by partly covering the woodland by cloudy weather when the image was taken.

In the case of aspect, aspect with an inclination direction of northeast (I=-0.1234) are not prone to landslides, while aspects are southeast (I = 0.0765), southwest (I = 0.0106) and northwest (I = 0.0659) have a higher probability to cause a landslide. On the whole, the probability of occurrence of shady slope landslides in the study area is relatively high. Related studies have also reported this phenomenon. The reason may be that the soil around the shady slope is relatively moist and the vegetation is sparse (Chen and Li 2020; Chen et al. 2020).

In summary, the state level of the indicators in this paper is rationally graded, which makes the above-mentioned indicators correlate with the occurrence of landslides in the study area. However, more attention needs to be paid to levels with indicator state information values greater than 0. They tend to have a higher probability of landslides (Fig. 7).

<Fig. 7 Information value of each evaluation indicator>

The constant weights of landform, distance to river, lithology, NDVI, slope and aspect are 0.2504, 0.1006, 0.3825, 0.0641, 0.1596 and 0.0428, respectively. The variable weights of the indicators are shown in Fig. 8. It can be clearly seen that in the landform, distance to river, NDVI and aspect indicators, the average value of the variable weight is higher than the theoretical value of the constant weight. Among them, the phenomenon of landform and aspect is more significant. The average value of variable weight of other indicators is slightly lower than the theoretical value of constant weight. Lithology, landform,

slope and distance to river have obvious influences on the landslide susceptibility in the study area, while the influence of NDVI and aspect is small.

<Fig. 8 Single-parameter importance analysis of each evaluation indicator>

6.2 Comparison and validation of models

In this paper, four susceptibility zoning maps of the study area and the county town area were created, based on AHP-IV model and VW-AHP-IV model. It can be clearly seen that the susceptibility zoning map created by the VW-AHP-IV model is in the study area and the county town area of the high and medium susceptible area significantly increase, while the area in the low susceptible area is reduced. The number of landslides falling in it is also the same law (Fig. 9 and Table 6). It should be kept in mind that the aim of susceptibility mapping should be to include the maximum number of landslides in the highest susceptibility classes whilst trying to achieve the minimum spatial area for these classes. Therefore, it can be concluded that after the VW-AHP-IV model redistributes the constant weight of each evaluation indicator, the variable weight model established has a greater improvement in stability and accuracy. In addition, the susceptibility zoning map created by the VW-AHP-IV model has a higher accuracy and is more in line with the actual situation of the study area.

Table 6
The number and proportion of landslides in each susceptibility subzone

Regional statistics		**Number and proportion (%)**			
Landslide susceptibility		High	Medium	Low	Very low
AHP-IV model	In study area	98(18.67)	188(35.81)	215(40.95)	24(4.57)
	In county town area	5(55.56)	2(22.22)	2(22.22)	0(0)
VW-AHP-IV model	In study area	145(27.62)	196(37.33)	162(30.86)	22(4.19)
	In county town area	7(77.78)	2(22.22)	0(0)	0(0)

<Table 6 The number and proportion of landslides in each susceptibility subzone>

<Fig. 9 The area and proportion of landslide susceptibility zoning map: (a) AHP-IV model of study area; (b) VW-AHP-IV model of study area; (c) AHP-IV model of county town area; (d) VW-AHP-IV model of county town area>

ROC curve with the corresponding AUC value is a commonly used method to validate the accuracy of landslide susceptibility zonation mapping (Pourghasemi et al. 2012). In this paper, this method was used to evaluate the performance of the AHP-IV and VW-AHP-IV models, respectively. AUC represents the area under the ROC curve, and its value ranges from 0 to 1. The closer to 1, the better the model performance. Generally, when AUC > 0.5, the evaluation results are considered to have application value. ROC curves and AUC values of the two models under randomly selected 20% (105) landslide validation data are shown in Fig. 10. In the training set, the AUCs of the AHP-IV model and VW-AHP-IV model are 0.727 and

0.816, respectively, and in the test set, they are 0.719 and 0.802, respectively. It can be seen that the reliability, stability and accuracy of the VW-AHP-IV model are higher, and the created landslide susceptibility zoning results are more ideal, and it is more suitable for the evaluation of landslide susceptibility in the study area.

In fact, the AUC value of the VW-AHP-IV model is not very good, but compared with some existing studies, it is definitely sufficient. For example, Zhao et al. (2019) used the LR method to evaluate the susceptibility of landslides in Yueqing City, China, and they believed that results with an AUC value between 0.7 and 0.8 can be regarded as acceptable results. Conoscenti et al. (2016) also believe that a model with an AUC value > 0.7 can produce an acceptable zoning map of landslide susceptibility. In addition, based on other related studies (Capecchi et al. 2015; Youssef 2015), it is reasonable to determine that the performance of the landslide susceptibility model is better with the AUC value > 0.7 as the threshold, and it has been widely recognized by many scholars. From a long-term perspective, the VW-AHP-IV model breaks the traditional information model's inherent thinking that the "contribution" of each indicator to the occurrence of geological disasters is not fully considered. On the basis of determining the constant weight of the indicator based on the AHP, using variable weights to assign different weights to evaluation units with different indicators can obtain a zoning map of landslide susceptibility that is more in line with actual geo-environmental conditions. Therefore, the VW-AHP-IV model has more development potential. At the same time, the promotion of the VW-AHP-IV model requires more extensive and in-depth research in different regions and scales.

< Fig. 10 ROC curves of the model: (a) training; (b) validation>

6.3 Susceptibility zoning characteristics

According to the zoning map of landslide susceptibility prepared by VW-AHP-IV model (Fig. 6b and Fig. 6d), it can be seen that the landslide susceptibility in the study area is spatially distributed in strips along the river valley, and the regional aggregation is dispersed with the town as the center. In addition, the density of landslide disasters in the study area is concentrated in the south and scattered in the north, showing the characteristics of high in the south and low in the north. The county town area is the main place for human habitation, and human activities are very frequent, so the area and proportion of high and medium landslide susceptibility areas account for the majority of the total area of the county town area. This is basically consistent with the conclusions of Mao (2009) and Yu et al. (2012) on the evaluation of landslide susceptibility in the study area.

(1) High susceptibility area

The high susceptibility area in the study area is mainly located around Panyang county, Baiyang town, Gucheng town, Honghe town, Xinji town and Chengyang town, with a total area of 301.44km^2, accounting for 11.80% of the study area. There are 145 landslides in this area, accounting for 27.62% of the total number of landslides in the study area. The high susceptibility area of the county town area is 8.87km^2, accounting for 70.29% of the total area. The high susceptibility area in the study area is mainly located in

the river valley terrace where steep slopes and gullies are developed. In addition, the undulating slope, the sandy soil and the vegetation cover, mainly grassland and cultivated land, are also the main factors for landslide generation.

(2) Medium susceptibility area

The medium susceptibility area in the study area is mainly located around Luowu town and Mengyuan town, with a total area of 747.12km^2, accounting for 29.23% of the study area. There are 196 landslides in this area, accounting for 37.33% of the total number of landslides in the study area. The high susceptibility area of the county town area is 3.55km^2, accounting for 28.13% of the total area. The medium susceptibility area in the study area is mainly located in the loess hilly area. There are many rivers and large slopes in this area, which increase the probability of landslides. In addition, the aspect is mainly southeast, which leads to longer exposure to irradiation and weathering also has a greater impact on landslide generation.

(3) Low susceptibility area

The low susceptibility area in the study area is mainly distributed around Jiaocha town, Fengzhuang town and Xiaocha town, with a wide distribution area of 1084.88km^2, accounting for 42.45% of the study area. There are 162 landslides in this area, accounting for 30.86% of the total number of landslides in the study area. The low susceptibility area of the county town area is 0.2km^2, accounting for 1.58% of the total area, and no landslide occurs in the area. The low susceptibility area of the study area is mainly located in the loess hilly area, and a few parts are located in rock hilly area. The rocks in the area are relatively ruptured, and dominated by hard sandstone and conglomerate. There are fewer rivers, which are less subject to hydrodynamic erosion and downcutting. The vegetation cover is mainly forest land and construction land, which has a strong stabilizing effect on the slope and reduces the probability of landslides.

(4) Very low susceptibility area

The very low susceptibility area in the study area is mainly located in the southwest, around Wangwa town and Caomiao town, with a total area of 422.15km^2, accounting for 16.52% of the study area. There are 22 landslides in the area, accounting for 4.19% of the total number of landslides in the study area. Due to frequent human activities, there is no very low susceptibility area in the county town area. The very low susceptibility area in the study area is mainly located in the rock hilly area, and a few parts are located in the loess hilly area. The rocks are relatively intact, and dominated by hard dolomite and conglomerate, so the surface lithology is relatively stable. The vegetation cover of the area is mainly forestland and grassland, which has a strong stabilizing effect on the slope and reduces the instability of the slope.

6.4 Predisposing factors analysis

6.4.1 Precipitation

Precipitation is one of the most important factors that predispose to landslide disasters (Dikshit et al. 2020). Precipitation will scour the slope foot, and infiltration along the fissure will increase the dead weight of rock mass, increase the hydrostatic pressure of slope rock mass, soften rock mass to a certain extent, and increase the probability of landslide (Hu 2020). However, because the study area is located inland, the annual average precipitation is small, and the spatial change is not significant, so the impact of precipitation on the landslide should not be overemphasized here.

6.4.2 Human activity

With the increasing range of human activities, the disturbance to nature is becoming stronger and stronger, and the spatial structure of regional land use changes, resulting in frequent landslides. Among the controlling and influencing factors of landslides, geo-environmental conditions change slowly, and human activities are one of the most active factors (Hu et al. 2012). Human activities in the study area mainly include:

(1) The implementation of human activities such as building roads, excavating slopes and cutting slopes severely damaged the stability angle of the original slope and exceeded the critical height of the slope, resulting in unstable slopes (Qin 1999). In addition, the slope of some areas is too steep, and there is little slope protection, which is easy to form landslide disaster, threatening the safety of passing vehicles and pedestrians.

(2) Human activities that change the stress conditions of slopes, such as building houses and kilns by splitting slopes. For example, villagers in loess hilly-gully region mostly build houses or kilns by splitting slopes. Because the loess cut slope is usually of large slope and the slope height generally exceeds its safety critical height, the stability of the slope is damaged and the corresponding support measures are not given. This human factor is the most prominent and easy to be ignored, thus it is easy to cause landslide disasters (Zhao et al. 2015).

(3) Human activities, such as overgrazing, over-reclamation, irrational use of water resources and indiscriminate felling, which change the state of geological environment, degrade large areas of grassland and grassland vegetation in sandy areas, aggravate local land desertification and soil erosion, and increase the probability of landslide.

For the above reasons, this paper selected the study area with land use of construction land and dense cropland (expansion area) as the area with high intensity of human activities; the area with land use of grassland and sparse cropland as the area with moderate intensity of human activities; and the area with land use of woodland and bare land as the area with low intensity of human activities .

6.5 Zoning of landslide prevention and control

The main purpose of landslide susceptibility evaluation is to provide suggestions for landslide prevention and control. According to the landslide susceptibility and the intensity of human activities, the study area is divided into three categories: focused prevention and control areas, sub-focused prevention and control areas and general prevention and control area, and corresponding prevention and control suggestions were made according to the characteristics of each division (Table 7).

Table 7
Prevention and control suggestions for each subzone in the study area

Prevention and control	Landslide susceptibility	Human activities	Causes	Suggestions
Focused prevention and control area	High	High	1 River erosion of slope banks; 2 Lithology: sandstone, quaternary sediments; 3 Steep slope gradient; 4 Human activities: excessive reclamation, excessive grazing and unreasonable use of water resources.	1 Strengthen the inspection and monitoring of the landslide potential sites near rivers; 2 Treatment the potential sites according to the principle of priority: using anti-slip piles, anchor ropes and other measures to stabilize the slopes; 3 Treatment the potential sites according to the principle of priority: using retaining walls, slope protection and other engineering measures to stabilize slopes; 4 Strict control of human activities; 5 Active measures: returning farmland to forest and grass etc.
	Medium	High	1 River erosion of slope banks; 2 Lithology: loess; 3 Low vegetation cover index; 4 Human activities: excessive grazing.	1 Strengthen the inspection and monitoring of the landslide potential sites near rivers; 2 Strictly control human activities and limit the reclamation of agricultural land in areas that have not yet been destroyed; 3 Maintain water and soil; 4 Strengthen the popularization of science and raise residents' awareness of prevention.
Sub-focused prevention and control area	Low or very low	High	1 Lithology: loess; 2 Highly undulating gradients; 3 Human activities: excessive reclamation and unreasonable use of water resources.	1 Strengthen the inspection and monitoring of slopes with high gradient; 2 Establish a group of special monitoring network system; 3 Strictly control of human activities.

Prevention and control	Landslide susceptibility	Human activities	Causes	Suggestions
	High or medium or low or very low	Moderate	1 River erosion of slope banks; 2 Lithology: hard sandstone and conglomerate; 3 Large difference in gradient.	1 Strengthen the attention to the weather forecast; 2 Focused inspection and monitoring of loess slopes during periods of heavy rainfall; 3 Strict control of human activities.
	High or medium	Low	1 Lithology: loess; 2 Heavy rainfall; 3 Vertical joint development.	1 Strengthen the attention to the weather forecast 2 Focused inspection and monitoring of loess slopes during periods of heavy rainfall.
General prevention and control area	Low	Low	1 Lithology: limestone; 2 High vegetation cover index; 3 Human activities are slight; 4 Slope stability.	1 Protecting the local geological environment; 2 Strengthen scientific propaganda, popularize disaster prevention knowledge; 3 Improve residents' awareness of prevention and self-rescue level.
	Very low	Low	1 High vegetation cover index; 2 Human activities are slight; 3 Slope stability.	1 Strengthen the inspection and monitoring of landslide disaster sites; 2 Strengthen the popularization of science, popularize disaster prevention knowledge.

<Table 7 Prevention and control suggestions for each subzone in the study area>

7 Conclusions

In this paper, the VW-AHP-IV model was used to evaluate the landslide susceptibility by taking Pengyang County, Ningxia, China as a case study. The basic geological environment conditions and landslide formation mechanism of the study area were analyzed. The effects of precipitation and human activities as predisposing factors on landslides were discussed. The following conclusions were obtained:

(1) The high and medium susceptibility areas are mainly distributed in the southern steep slope and valley cutting zone, accounting for 11.80% (301.44km^2) and 29.23% (747.12km^2) of the total area of the study area, respectively. The low susceptibility area is mainly distributed in the gentle loess area in the north, and the very low susceptibility area is mainly distributed in the mountainous area with lush

vegetation in the southwest, accounting for 42.45% (1084.88km^2) and 16.52% (422.15 km^2) of the total study area, respectively.

(2) According to the analysis of the rationality and importance of the evaluation indicators, it can be seen that the lithology, landform, slope and distance to river have a large influence on the landslide susceptibility, while the NDVI and aspect have a small influence. Among them, the indicator grading state of river valley terrace landform, sandy soil, slope greater than 18.24°, distance to river less than 0.5km, NDVI of 0.2379 ~ 0.3899 and aspect of southeast has the strongest correlation with landslide occurrence and should be paid attention to.

(3) It can be seen that the number and density of landslides in susceptible areas prepared by the VW-AHP-IV model significantly increase in both high and medium susceptible areas, while in low susceptible areas is decreases. Therefore, it proves that the VW-AHP-IV model can effectively solve the unreasonable situation caused by the internal differences of indicators and make the evaluation results more consistent with the actual situation. In addition, based on the remaining 20% (105) of the original database as the training dataset, the ROC curves were applied to validate the 2 models separately, and it was concluded that the VW-AHP-IV model is more reliable, stable and accurate, and more suitable for landslide susceptibility evaluation in the study area.

(4) Finally, according to the combination of landslide susceptibility zoning map and human activity intensity map. The study area was classified into focus prevention and control area, sub-focus prevention and control area, and general prevention and control area. And the appropriate prevention and control suggestions were made for different subzones.

We must acknowledge that the landslide susceptibility zoning map prepared in this paper is time-sensitive, as certain regional condition indicators may change significantly in the future. Therefore, we should continue to pay attention to the development of landslides in Pengyang County, and the VW-AHP-IV model constructed by updating the dynamic condition indicator real-time data can be revised in time for landslide susceptibility zoning map.

Declarations

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Figures

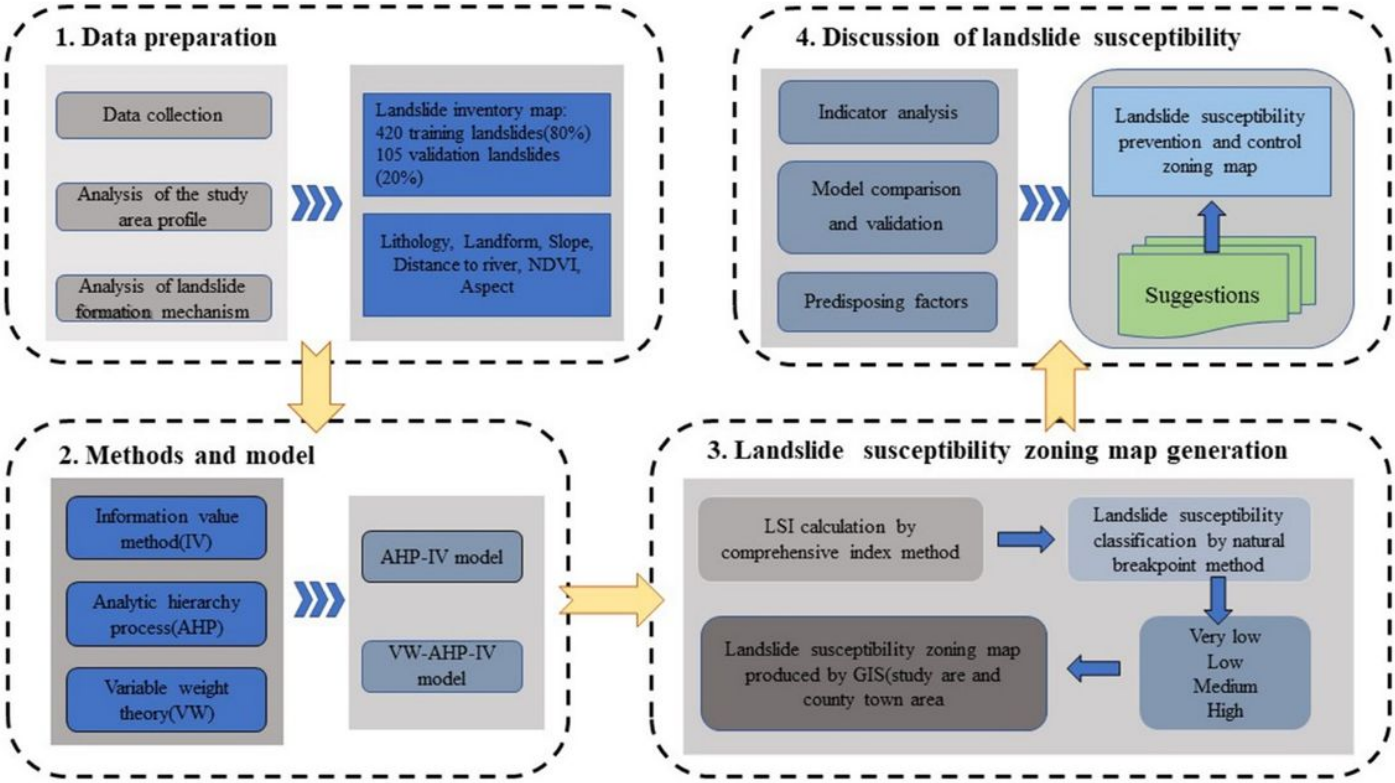

Figure 1

Flowchart of landslide susceptibility evaluation

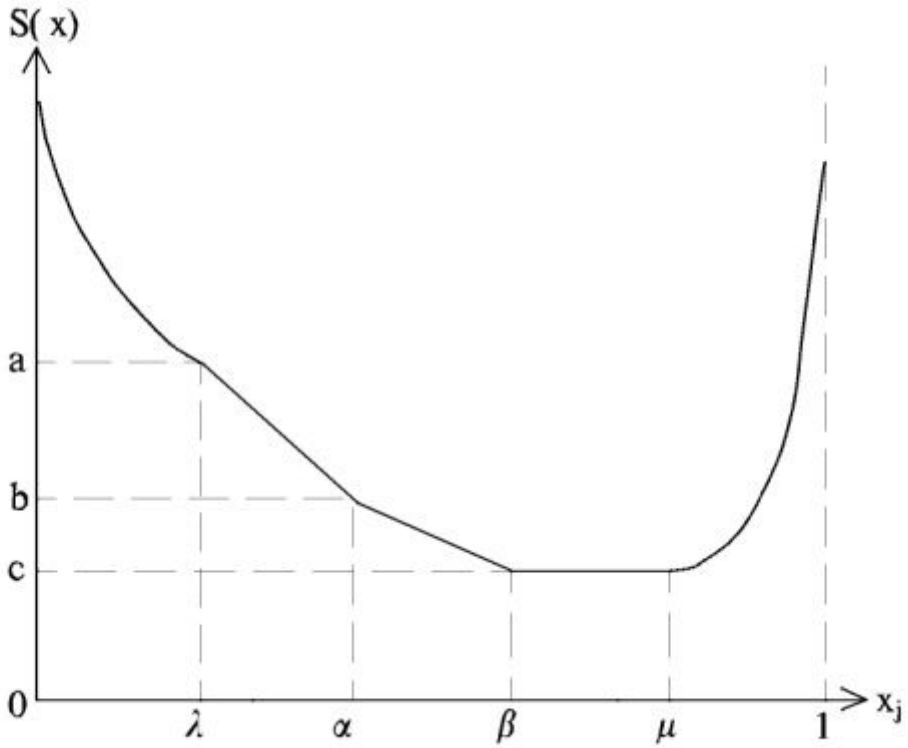

Figure 2

Penalty and incentive variable weight function (Duan, 2003)

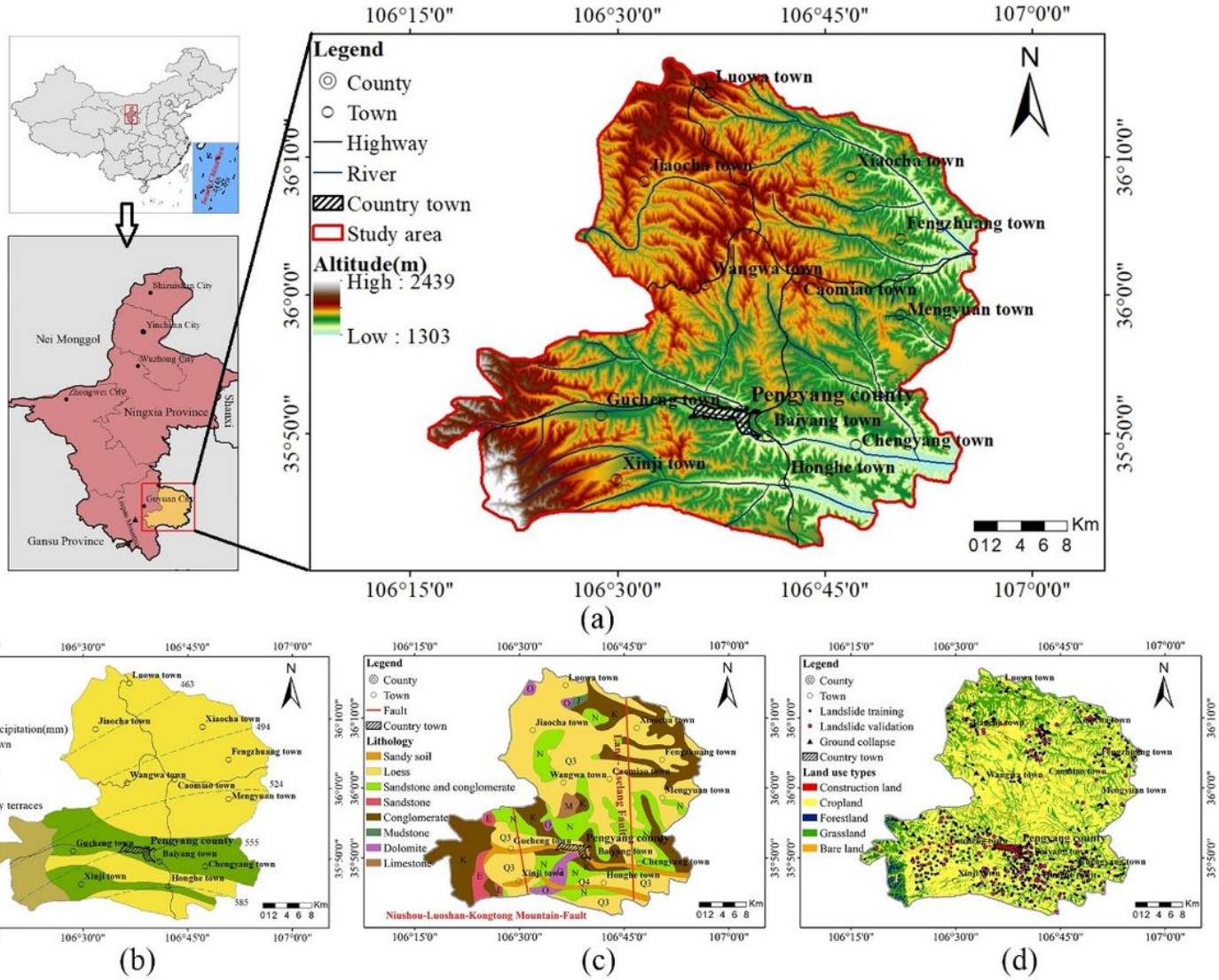

Figure 3

Location, landform, geology, land use of the study area:

(a) location; (b) landform; (c) geology; (d) land use

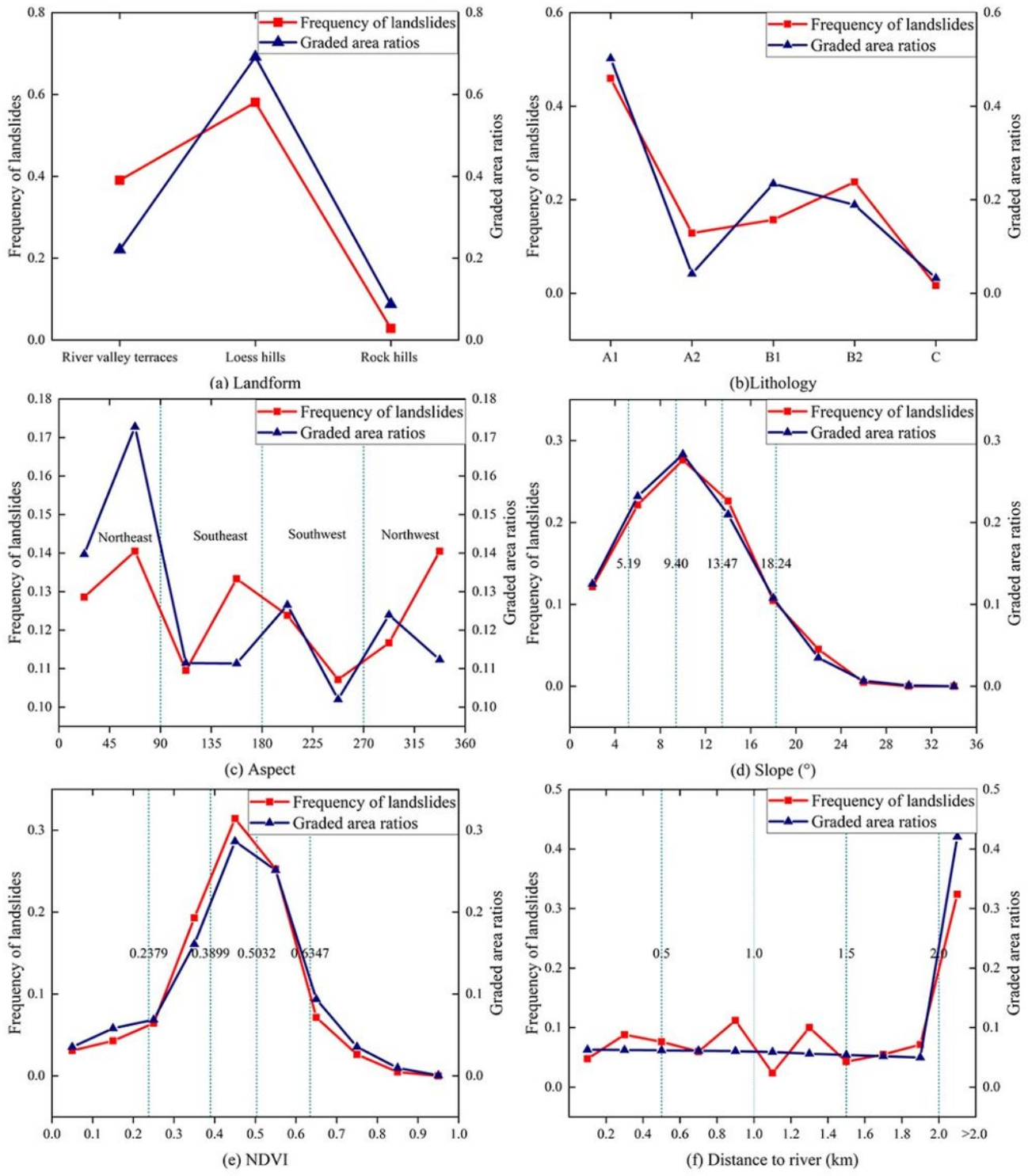

Figure 4

Statistical chart for grading the state of indicators in the study area

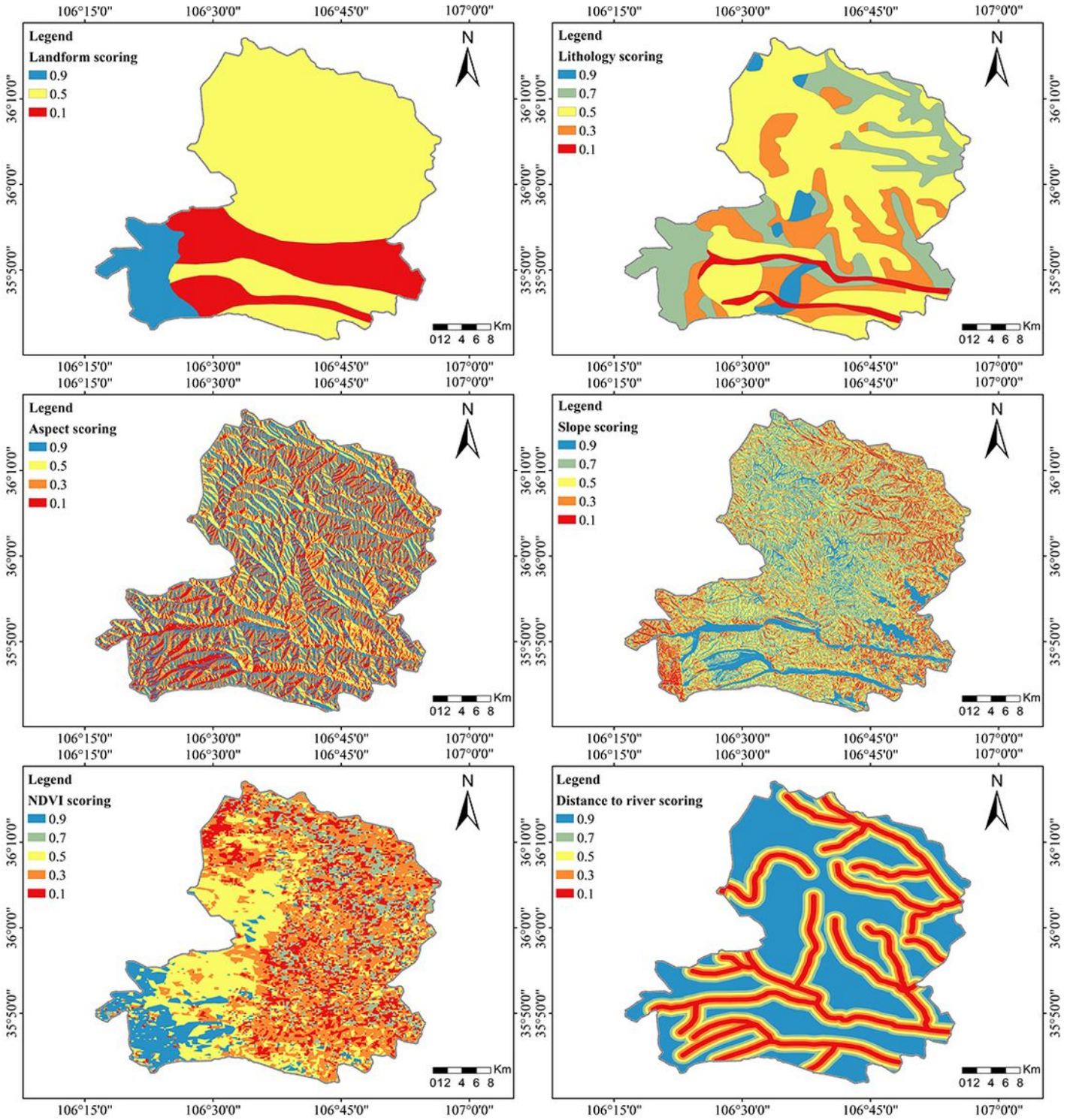

Figure 5

Single-indicator partition map for susceptibility evaluation in the study area

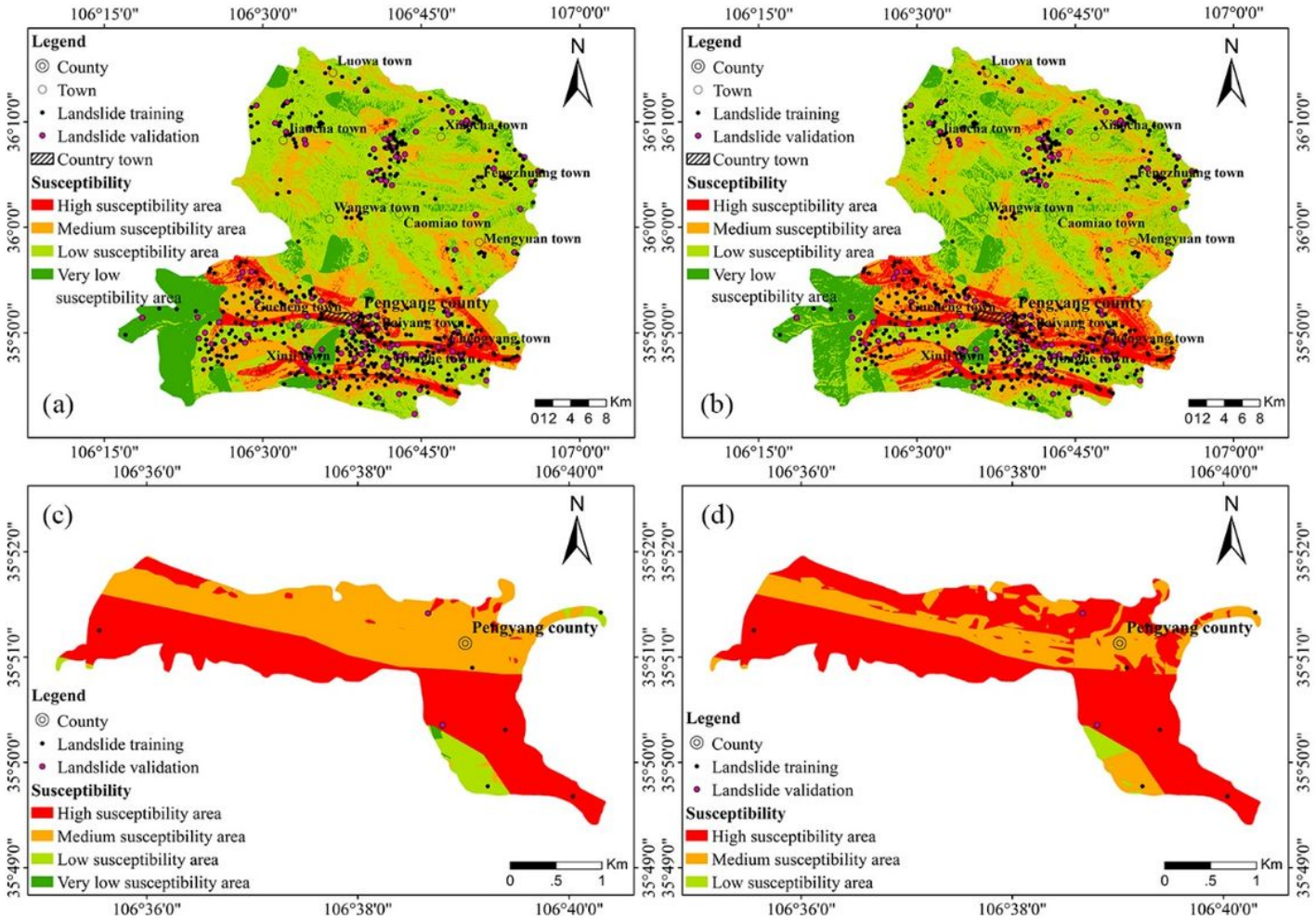

Figure 6

Landslide susceptibility zoning map: (a) AHP-IV model of study area; (b) VW-AHP-IV model of study area; (c) AHP-IV model of county town area; (d) VW-AHP-IV model of county town area

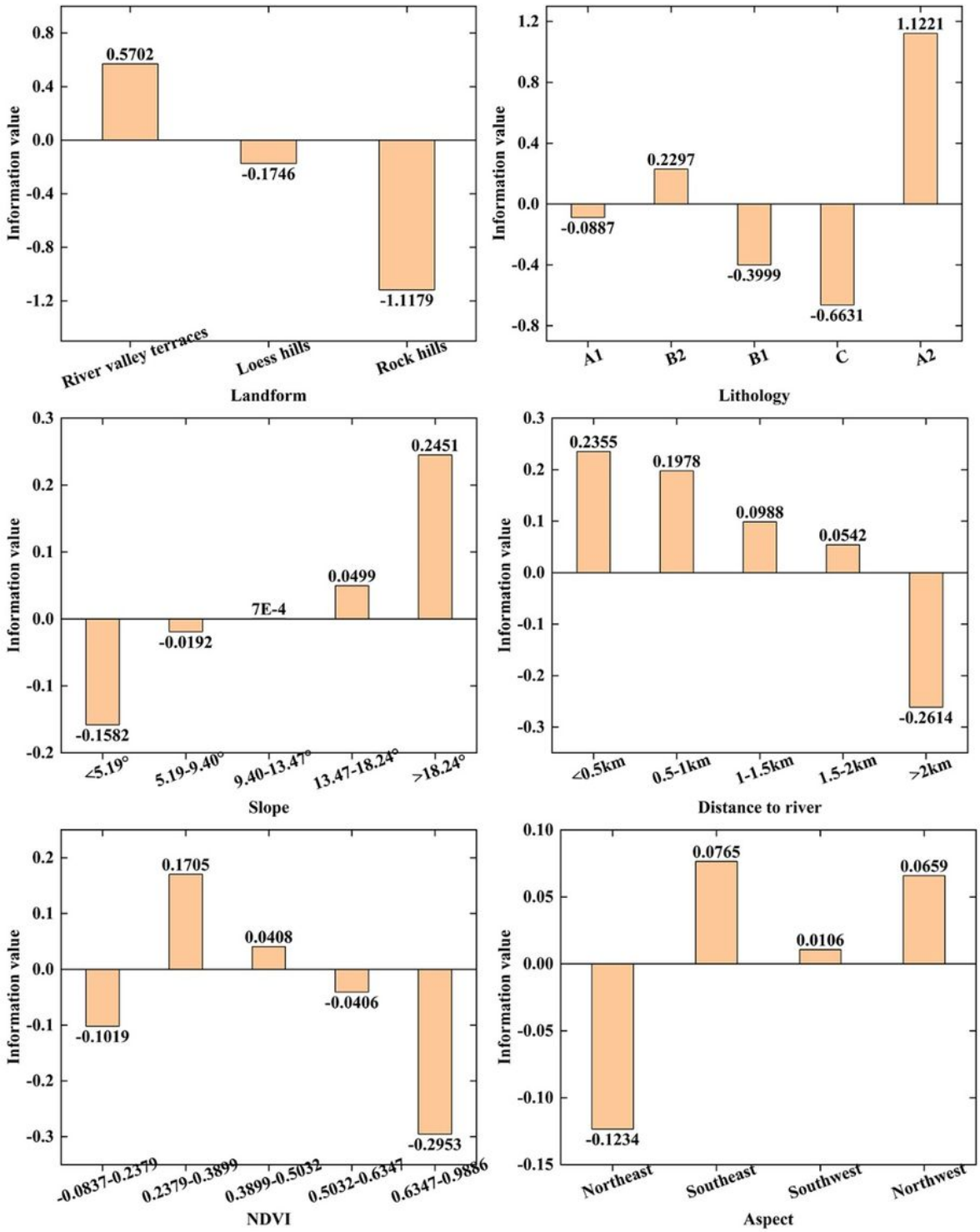

Figure 7

Information value of each evaluation indicator

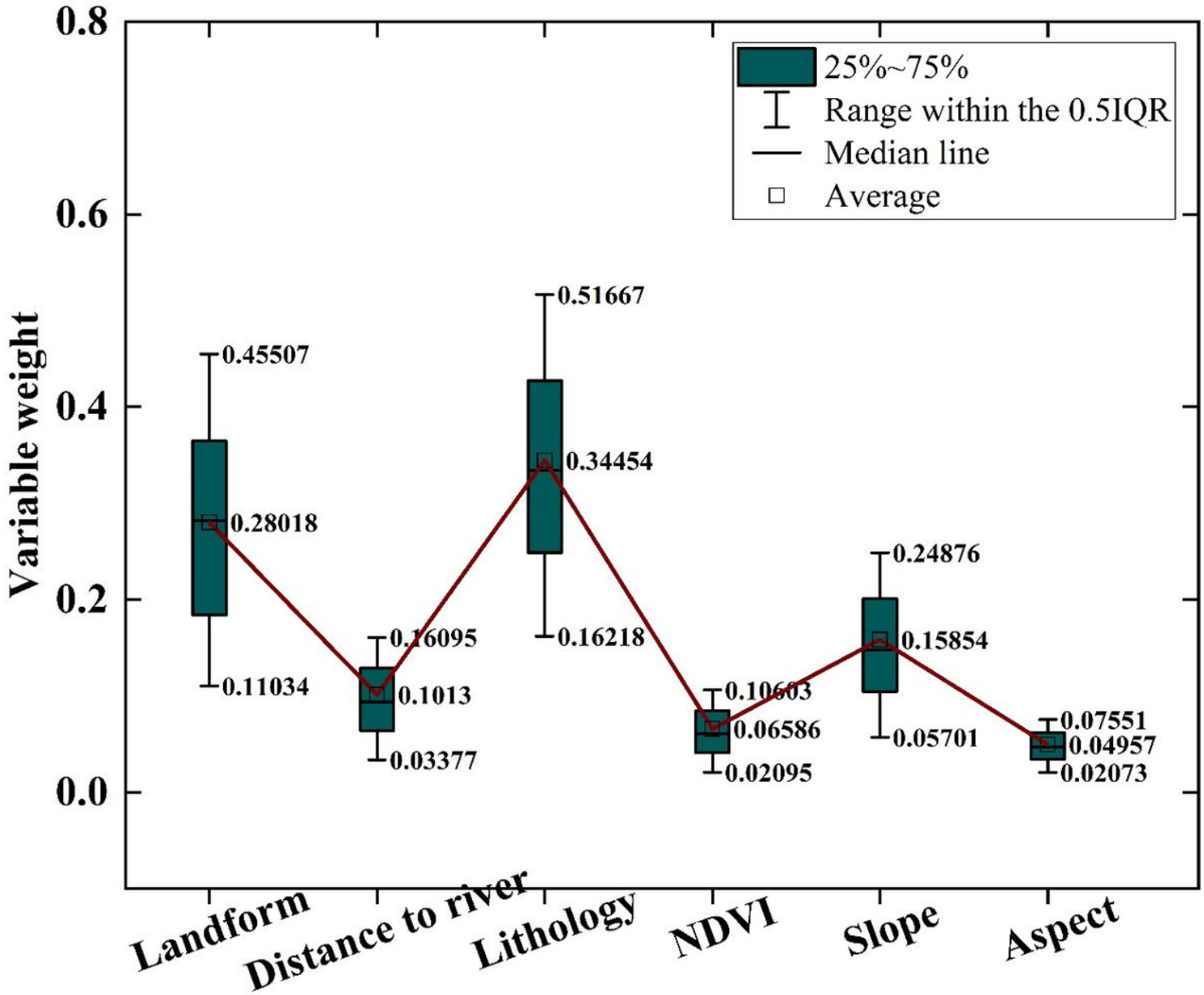

Figure 8

Single-parameter importance analysis of each evaluation indicator

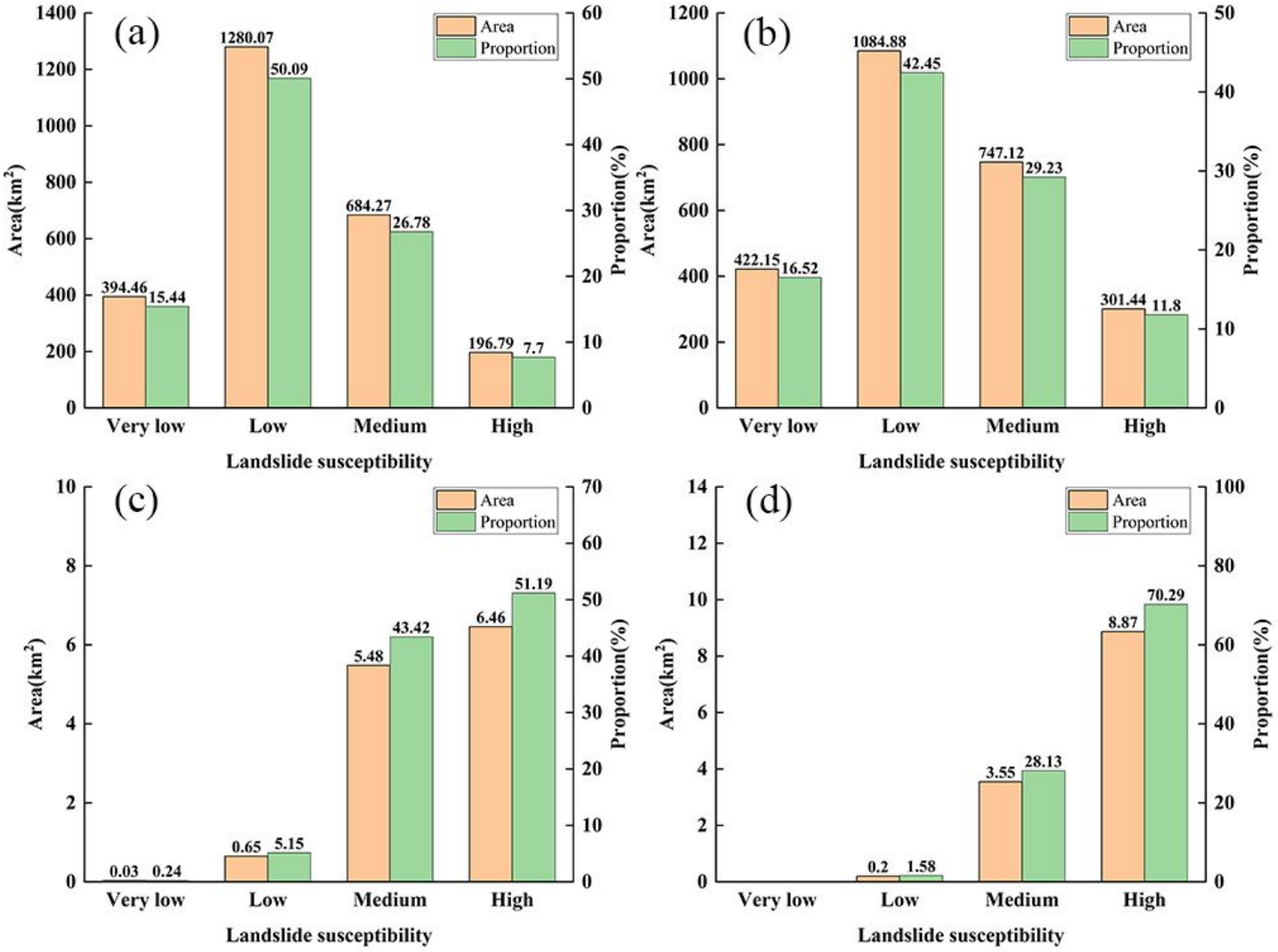

Figure 9

The area and proportion of landslide susceptibility zoning map: (a) AHP-IV model of study area; (b) VW-AHP-IV model of study area; (c) AHP-IV model of county town area; (d) VW-AHP-IV model of county town area

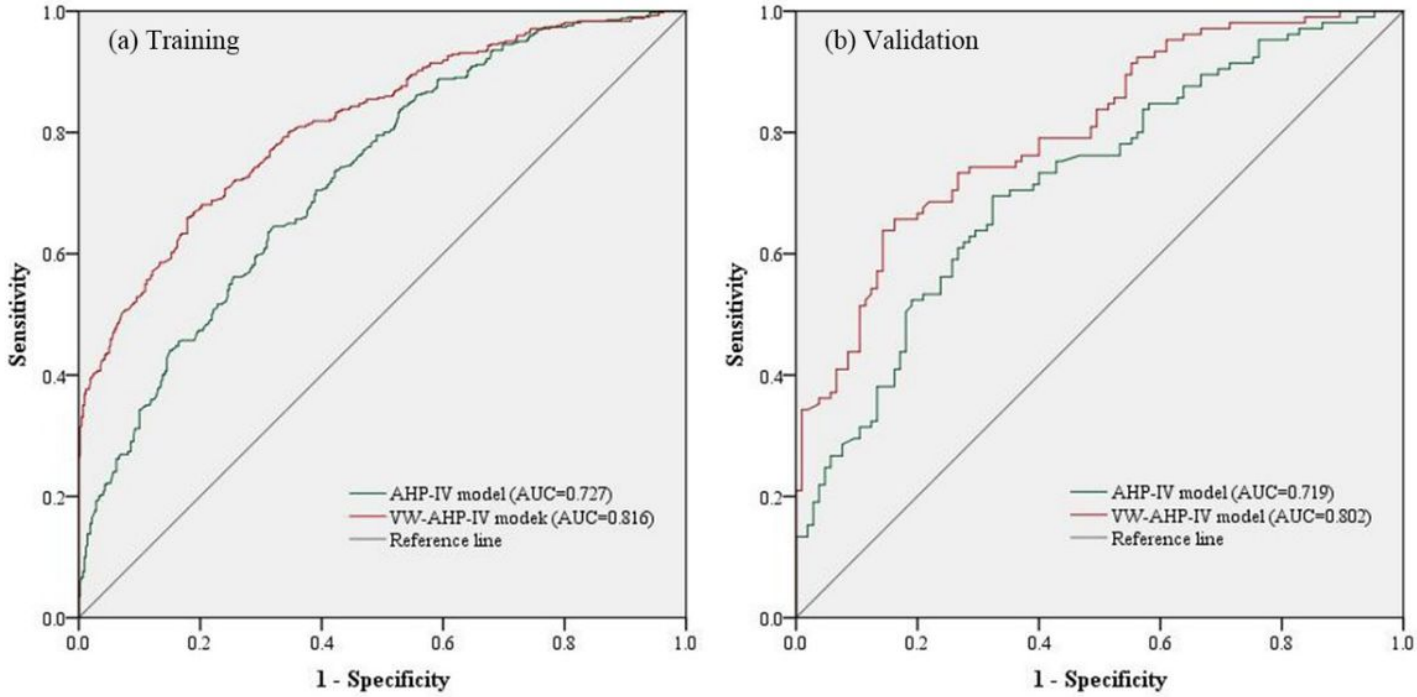

Figure 10

ROC curves of the model: (a) training; (b) validation