

Article

Coupling FR-AHP with Information Value Model for Landslide Susceptibility Assessment in the Yanhe River Basin, China

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Abstract

The Yanhe River Basin on the Loess Plateau suffers frequent landslides, threatening sustainable development and ecological security. This study employs correlation and multicollinearity analyses to select evaluation factors and construct an index system. The information value (IV) model determines indicator values, while the Analytic Hierarchy Process (AHP), frequency ratio (FR), and their combination, FR-AHP, establish relative weights of influencing factors, thereby constructing weighted IV models validated by Receiver Operating Characteristic (ROC) curves. Results demonstrate that: (1) slope, aspect, curvature, lithology, average annual precipitation, NDVI, distance from rivers, distance from roads, and land use type are key influencing factors; (2) compared with IV, AHP-IV, and FR-IV models, the FR-AHP-IV model achieves the highest prediction accuracy with an AUC = 0.818; and (3) areas of low, moderate, high, and very high susceptibility account for 32.01%, 40.69%, 18.49%, and 8.80%, respectively, with higher susceptibility along both banks of the middle and lower reaches. The landslide-prone hotspot in the southern Baota District aligns with actual survey conditions. The methodological framework proposed in this study can serve as a reference for basins with similar geographic settings and hazard backgrounds, yet the specific zoning results should be adapted and validated in accordance with the actual conditions of individual basins.

Keywords: landslides; susceptibility assessment; FR-AHP; weighed information quality model; hotspot analysis

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1. Introduction

The Loess Plateau, the world's largest loess deposit, is situated in north-central China. It is characterized by severe soil erosion, a fragile ecological environment, and widespread landslides [1–4]. The formation of loess landslides is closely linked to topography, lithology, vegetation, meteorological conditions, and human activities [5,6]. Furthermore, climate change and economic development have intensified the impacts of extreme rainfall and engineering activities, resulting in increased landslide frequency [7–9]. These events pose substantial threats to human life and property and significantly affect the social, economic, and ecological environment [10,11]. Landslide susceptibility assessment reflects the likelihood of landslide occurrence and their distribution characteristics

in the study area, and is one of the key factors in assessing and predicting landslide risk [12,13]. Therefore, conducting a landslide susceptibility assessment of the study area can effectively reduce losses and casualties, and is of great significance for the prevention and mitigation of landslides. [14–17]. The Yanhe River Basin is rich in mineral and culture resources and is a key region for the sustainable development of the Yellow River Basin [18]. However, frequent landslides have become a major factor hindering its socio-economic sustainable development. Therefore, there is an urgent need to accurately reveal the spatial distribution pattern of landslides in the Yanhe River Basin and explore the main factors causing them. Conducting a basin-scale susceptibility assessment, analyzing influencing factors, and pinpointing areas prone to landslides along river systems—particularly in support of China’s “River Chief System”—facilitates more effective landslide prevention and mitigation [19,20]. Consequently, landslide susceptibility assessment and factor analysis in the Yanhe River Basin hold considerable theoretical and practical importance.

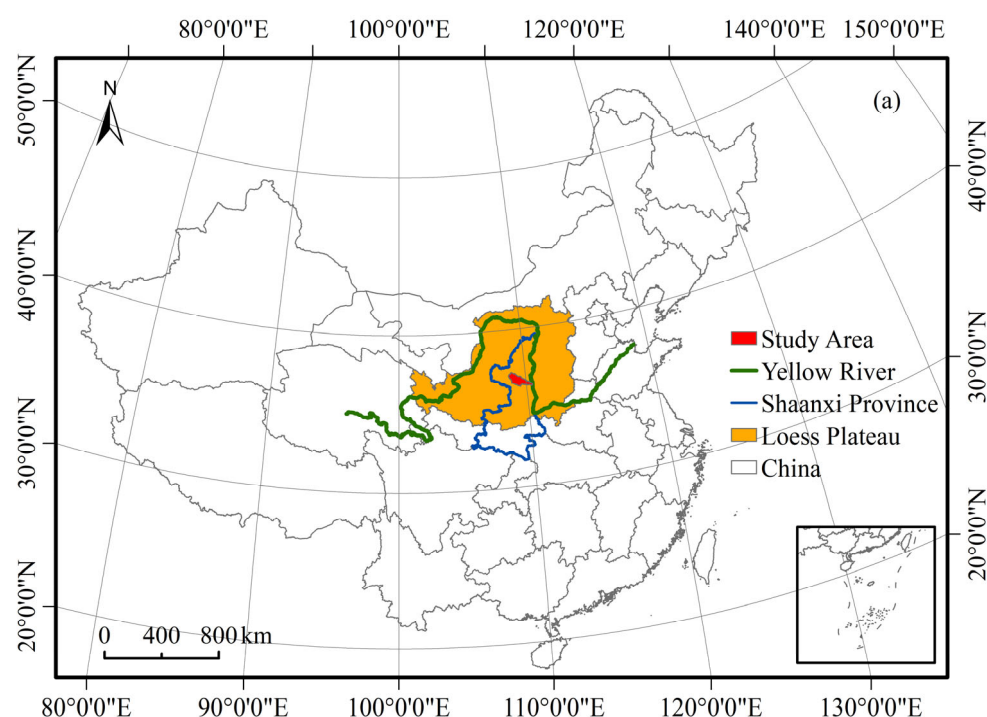
With the rapid development of computer technology and geographic information system (GIS) technology, many scholars have conducted research on the assessment of landslide susceptibility [21–23]. Commonly used models for susceptibility assessment can be categorized into empirical, mathematical–statistical and machine learning models [24]. Empirical models, such as AHP [25,26], the expert marking scheme [27], and the fuzzy integrated evaluation method [28], are simple to compute but are highly influenced by subjective factors. Mathematical and statistical models, such as the deterministic coefficient method [29], principal component analysis [30], FR [31], and IV [32], can determine quantitative relationships between landslides and intervals of a single influence factor. Still, it is difficult to characterize the associations between combinations of factors. Machine learning models, such as the artificial neural network model [33], logistic regression model [34], and decision tree model [35], which have a high prediction accuracy, are challenging to apply on a large scale because of the complexity of the modeling process and the difficulty of obtaining data [36–38]. Collectively, these methodologies exhibit inherent limitations regarding objectivity, interpretability, or operational scalability. This study innovates in two aspects. Methodologically, an integrated FR-AHP-IV assessment framework is constructed, achieving an organic integration of subjective and objective weighting that effectively overcomes the limitations of single statistical models (strong subjectivity) and machine learning models (high data dependency and difficulty in large-scale application) [39,40]. In application, responding to the “River Chief System” management requirements, this study adopts the basin geomorphic system as the analytical unit and spatially couples susceptibility assessment results with the basin river network. On the basis of revealing the controlling effects of key factors on landslide development along river systems, it accurately identifies high-risk river reaches and proposes a zoned basin management strategy for disaster prevention and mitigation, offering a referable technical pathway for territorial spatial planning and ecological governance in similar basins on the Loess Plateau.

Therefore, to accurately delineate the spatial distribution of landslide susceptibility and identify its driving factors in the Yanhe River Basin, this study first employed correlation and multicollinearity analyses to ensure the rationality of the selected evaluation factors. Subsequently, the AHP, FR and the FR-AHP hybrid method were utilized to determine factor weights. By integrating these weights with the IV model, a landslide susceptibility map was generated and validated using ROC curves. Furthermore, a comprehensive analysis was conducted on the spatial patterns of landslides across the basin and the underlying influencing factors. The findings provide a scientific basis for landslide prevention and mitigation management in the Yanhe River Basin and offer a valuable reference for similar basins.

2. Materials and Methods

2.1. Study Area

The Yanhe River, a major first-order tributary of the Yellow River, is situated in the hill-and-gully region of the Loess Plateau in Shaanxi Province, 108°40′–110°29′ E, 36°21′–37°20′ N; the specific geographic location is shown in Figure 1. The Yanhe River originates in Jingbian County, Yulin City. It trends from northwest to southeast, flowing through Zhidan County, Ansai County, and the Baota District of Yanan City, and merges into the Yellow River in Yanchang County. The river extends 286.90 km in length, draining a basin area of 7725.00 km², with an average channel gradient of 3.26‰ and a mean annual runoff of 2.93×10^8 m³. The region experiences a continental monsoon climate, with a mean annual temperature of approximately 9.00 °C. The towns of Huaziping and Ganguyi divide the Yanhe River into upper, middle and lower reaches. The structure of the water system of the Yanhe River Basin as a whole is dendritic, distributed on both sides of the main-stream. The larger tributaries are in the middle and upper basin. The downstream area tributaries are short and small, and have a feather's structure. In this study, landslides primarily refer to landslides and collapses, both of which are driven by gravity and topographic relief. To maintain the consistency of the failure mechanism, other disaster types (e.g., gully type debris flows, ground fissures) were excluded from the susceptibility assessment. Landslides are frequent in the Yanhe River Basin, with a total of 198 historical hazards collected, as shown in Figure 1.



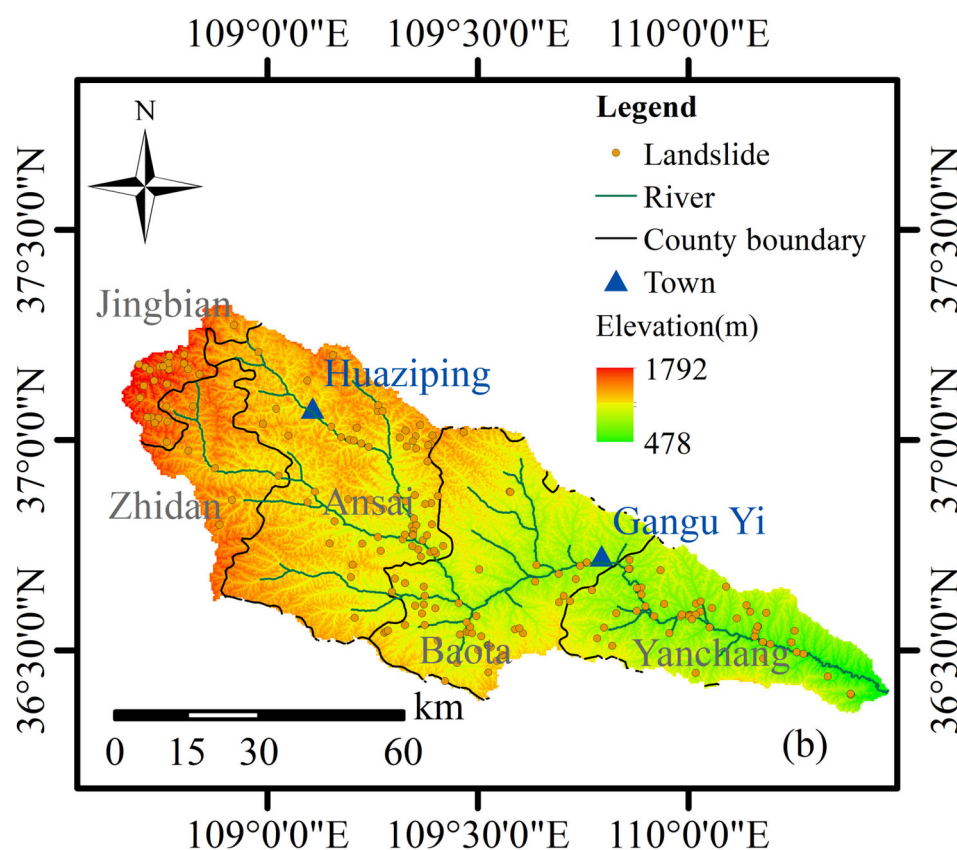


Figure 1. Overview of the study area. (a) Geographical location; (b) distribution of river, counties and landslides.

2.2. Data Type and Source

The types and sources of basic data required for the landslide susceptibility assessment are shown in Table 1. After unifying the projections, these data can be used for spatial overlay and model manipulation.

Table 1. Data types and sources.

Data Type	Data Format	Source	Statistical Time	Resolution
Landslides points	Vector	Geographic Remote Sensing Ecological Network Platform http://www.gisrs.cn/	1960–2020	-
DEM	Raster	Geospatial data cloud http://www.gscloud.cn/	2020	30 m
Remote sensing image (NDVI)	Raster	Geospatial data cloud http://www.gscloud.cn/	2020	-
Lithology	Vector	Shaanxi Provincial Meteorological Bureau	2010–2020	-
Precipitation	Vector	Shaanxi Provincial Meteorological Bureau	2010–2020	-
Precipitation	Vector	RESDC https://www.resdc.cn/	2020	30 m
Land use type	Raster			

The landslide location data were extracted from the Geographic Remote Sensing Ecological Network Platform (<https://www.gisrs.cn>). This dataset compiles inventory records from provincial geological surveys and geo-environmental monitoring agencies, with point locations accumulated from approximately the late 1960s to around 2020, although exact occurrence dates are not consistently documented for all entries. The 30 m resolution Digital Elevation Model (DEM) was obtained from the geospatial data cloud

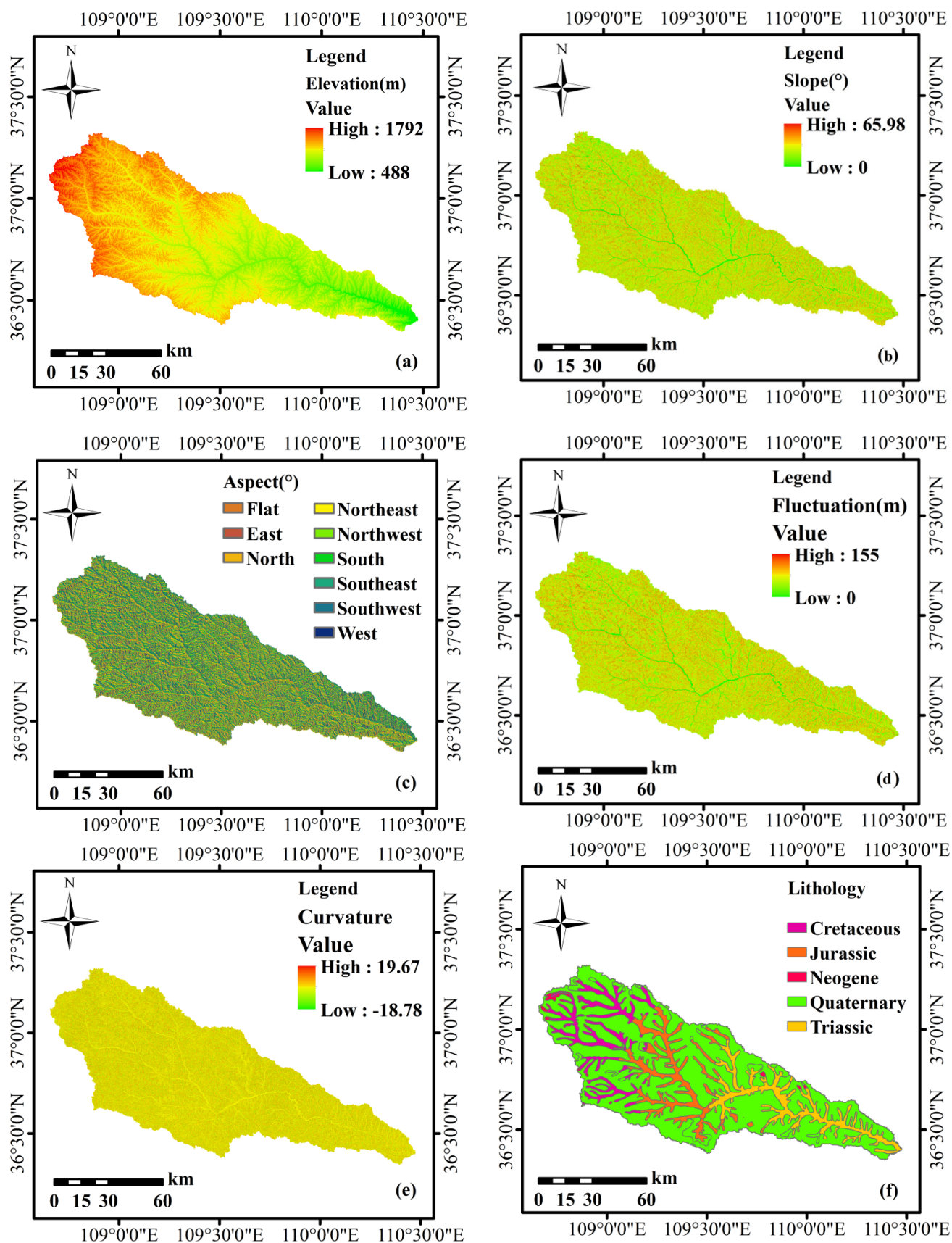
(<https://www.gscloud.cn>). Based on this DEM, terrain factors including slope, aspect, curvature, elevation, and river networks were extracted using the ArcGIS10.8 platform. The 2020 lithology data were obtained from the basic geological map vector products published by the China Geological Survey (CGS) and accessed via the geospatial data cloud. The 2020 vegetation coverage (NDVI) data were obtained by interpreting the Landsat 8 remote sensing data from the geospatial data cloud. The precipitation data were sourced from the Shaanxi Provincial Meteorological Bureau and cover daily precipitation data from 2000 to 2020, which are used to calculate the annual average rainfall. The road data and residential point data for 2020 were sourced from OpenStreetMap (<https://openstreetmap.org>). The 2020 China land use type with a spatial resolution of 30 m was acquired from the Resource and Environment Science Data Center of the Chinese Academy of Sciences (RESDC, <https://www.resdc.cn/>).

All spatial datasets were unified to the WGS84 datum, projected to UTM Zone 49N, resampled to a uniform 30 m × 30 m resolution, and clipped to the Yanhe River Basin boundary for subsequent spatial analyses.

2.3. Selecting Evaluation Indicators

2.3.1. Preliminary Selection of Influencing Factors

The occurrence of geological hazards is influenced by the combined effects of multiple internal and external factors, and the accuracy of their prediction depends heavily on the scientific rigor of factor selection; however, no unified selection criteria have yet been established. Based on the regional geological environment and hazard-inducing mechanisms, the 12 assessment factors initially selected for this study are elevation, slope, aspect, fluctuation, curvature, lithology, average annual precipitation, NDVI, distance from river, distance from settlement, distance from road, and land use type, as shown in Figure 2. Slope, aspect, fluctuation, and curvature are extracted directly from the DEM data. Lithology is obtained by lithological classification and consolidation according to “Engineering Rock Classification Standard GB/T50218-2014” [41]. The study area mainly exposes Mesozoic strata, including Triassic, Jurassic, Cretaceous, Neogene, and Quaternary. Primarily controlled by the regional valley topography and river erosion, the watercourses in the study area are deeply incised, with bedrock exposed in strip-like patterns along the watercourses; consequently, the lithology exhibits a dendritic spatial pattern. The first three are mainly sandstone and mudstone strata of the river and lake facies; the last two are mainly wind-formed clay and loess. Average annual precipitation is obtained by kriging interpolation. NDVI-interpreted remote sensing images are obtained. The distances from river, settlement, and road are obtained using the Euclidean distance analysis tool of ArcGIS10.8.



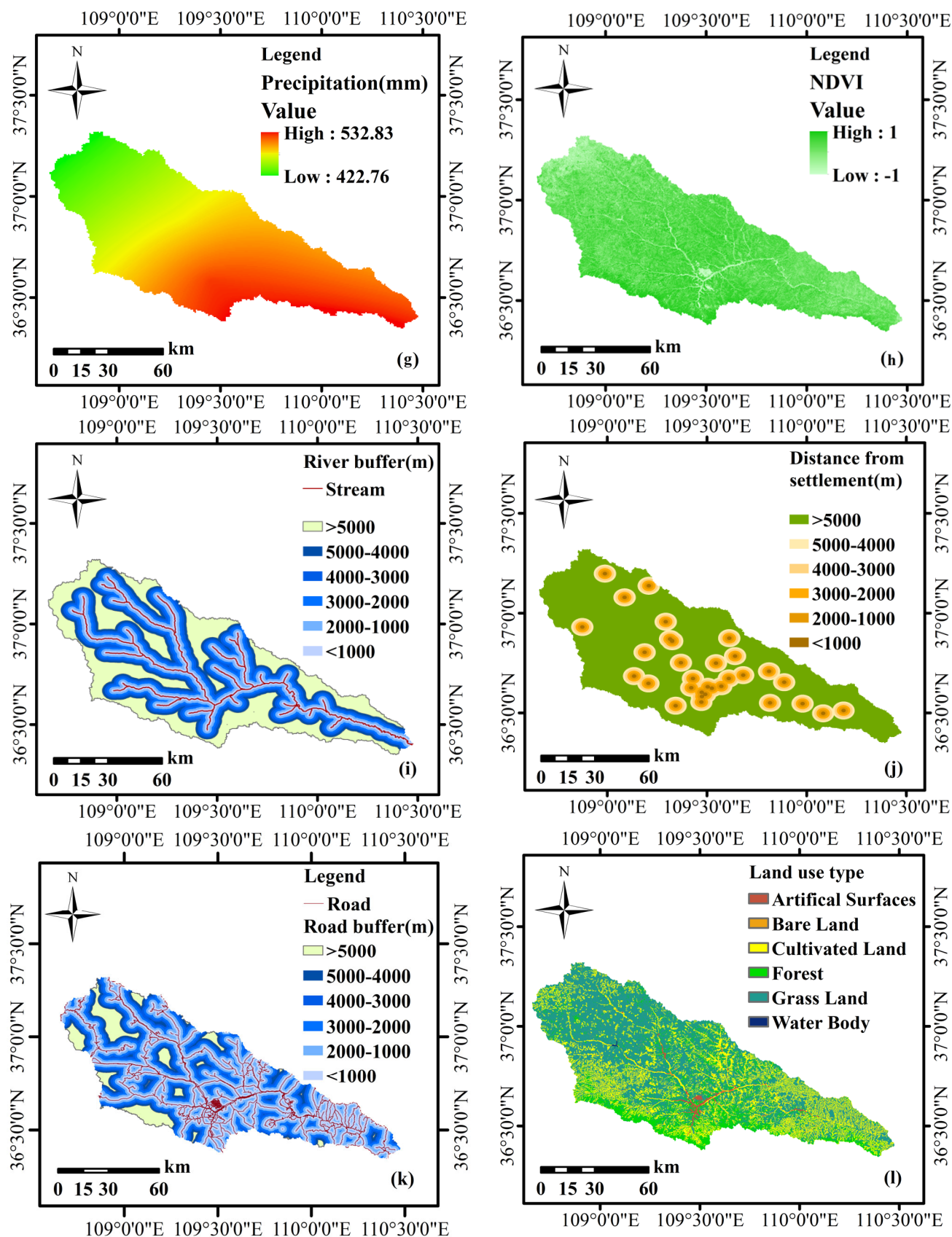


Figure 2. Assessment factors for landslides. (a) Elevation, (b) slope, (c) aspect, (d) fluctuation, (e) curvature, (f) lithology, (g) average annual precipitation, (h) NDVI, (i) distance from river, (j) distance from settlement, (k) distance from road, (l) land use type.

2.3.2. Correlation Analysis and Multicollinearity Analysis

Correlation and multiple covariance analyses were performed to ensure that the factors are independent of each other and to improve the accuracy of model prediction. The Pearson product–moment correlation coefficient (PCC) measures the degree of correlation between the factors. At $|PCCs| > 0.50$, it is considered that there is a high degree of correlation between the factors, and it should be excluded. In the multicollinearity analysis, at $TOL (tolerance) > 0.1$ and $VIF (variance\ inflation\ factor) > 10$, it is considered that there is a strong covariance of the factor, and it should be eliminated. It is reasonable if the selected factor can simultaneously satisfy $|PCCs| > 0.50$, $TOL > 0.1$, and $VIF > 10$ [42,43]. It is worth noting that for categorical variables, IV scores—serving as continuous effect sizes—were used to replace the original category labels. Consequently, all datasets entering the PCC and VIF analyses consist entirely of continuous numerical variables, thereby satisfying the statistical assumptions.

Correlation analysis is performed for all assessment factors and the results of the calculations are shown in Table 2. $|PCCs| > 0.50$ indicates that there is a strong correlation between the evaluation factors and that some of the factors should be excluded. Elevation and precipitation show strong correlation. Precipitation is the direct water condition inducing landslide infiltration and softening sliding mass, which is a direct triggering factor. Elevation itself only reflects spatial location, and its influence on landslides is mostly indirectly manifested through precipitation, vegetation and topography, so precipitation is reserved and elevation is eliminated. Relief amplitude and slope are closely correlated. Slope gradient directly controls shear stress of slope rock–soil mass, which is the core terrain condition of slope stability with clearer physical geological meaning. Relief amplitude is an integrated topographic index; its effect is indirect and overlapping with slope, so slope is retained. Given the pattern of settlement distribution along rivers in the Yanhe River Basin, distance from river, as the hydro-geomorphic controlling factor governing landslides/erosion, holds higher physical mechanistic priority compared to the secondary anthropogenic distribution factor (distance from settlement), and was therefore retained.

Based on this, elevation, fluctuation, and distance from settlements are eliminated, while slope, aspect, curvature, lithology, average annual precipitation, NDVI, distance from the river, distance from the road, and land use type are selected as the main influencing factors.

Table 2. Results of the factor correlation calculation.

Factor	a	b	c	d	e	f	g	h	i	j	k	l
a	1.00											
b	0.10	1.00										
c	0.09	0.18	1.00									
d	0.10	0.97	0.15	1.00								
e	0.01	0.05	−0.02	0.09	1.00							
f	−0.40	−0.10	−0.05	−0.10	0.03	1.00						
g	−0.83	−0.06	−0.09	−0.06	0.08	0.40	1.00					
h	0.13	0.24	−0.01	0.26	0.07	−0.12	−0.01	1.00				
i	0.57	−0.11	0.00	−0.11	0.02	0.00	−0.27	0.06	1.00			
j	0.49	−0.12	0.10	−0.11	−0.06	−0.03	−0.41	−0.07	0.55	1.00		
k	0.36	−0.02	0.06	−0.04	−0.05	−0.07	−0.32	−0.03	0.24	0.27	1.00	
l	−0.11	0.01	−0.08	0.03	0.04	0.06	0.12	−0.01	−0.08	−0.14	−0.12	1.00

Utilizing the multicollinearity analysis test for linear correlations between the final selection of nine influencing factors, the calculation results are shown in Table 3. $TOL >$

0.1 and $VIF < 10$ for each factor indicate no multicollinearity, and the selection of influencing factors is reasonable.

Table 3. Results of the factor multicollinearity calculation.

Factors	TOL	VIF
Slope	0.882	1.134
Aspect	0.951	1.051
Curvature	0.982	1.018
Lithology	0.812	1.231
Average annual precipitation	0.703	1.423
NDVI	0.911	1.098
Distance from river	0.861	1.163
Distance from road	0.86	1.163
Land use type	0.97	1.031

2.4. Determination of Weight Values

After determining the influencing factors by calculating the relative frequency ratio of landslides for each factor, it can be concluded that the grading factors of each factor have different degrees of influence on the development of landslides [44]. To compare the influential degree of each influencing factor on landslides, it is necessary to determine the relative weights of each factor. In this study, both AHP and FR-AHP were employed to determine the weights of the influencing factors.

The AHP calculates w_{AHPj} (the weights calculated using AHP) based on the judgment matrix and employs Equations (1) and (2) to conduct consistency tests on the results [45]. If the test result is qualified, the weights of the indicators are allocated reasonably. Otherwise, the comparison is redone, and final evaluation results are obtained.

$$CR = CI / RI \quad (1)$$

$$CI = \frac{\lambda_{\max} - n_{\text{matrix}}}{n_{\text{matrix}} - 1} \quad (2)$$

where CR is the consistency index. If $CR < 0.10$, it is considered that the matrix passes the consistency test; otherwise, the judgment matrix needs to be corrected. CI is an indicator of coherence. $\lambda_{\max}$ is the largest eigenvalue of the judgment matrix; n_{matrix} is the order of the judgment matrix.

FR is a bivariate model widely used in several studies, in different contexts and regions. It is used to characterize the magnitude of the degree of correlation between the graded factors of each influencing factor and the occurrence of landslides. Equation (3) calculates the relative frequency ratio of landslides. At $FR < 1.00$, the occurrence of landslides is weakly correlated with the weights of the factor classes and vice versa.

FR_i can be calculated as follows:

$$FR_i = \frac{N_i / N}{A_i / A} \quad (3)$$

where FR_i is the relative frequency ratio of landslides for each factor of the grading factor; N_i and N are the number of landslides within each classification for each influencing factor and the total number of landslides; A_i and A are the area of each grading for each influencing factor and the total area of each influencing factor; and i is the number of grading levels corresponding to each influencing factor.

Based on the density distribution of landslides, the density-weighted average of the relative frequencies of each influencing factor is $\overline{FR}_j$, $\overline{FR}_j$ and $\overline{FR}_{gj}$ (normalize $\overline{FR}_j$) can be calculated by

$$\overline{FR}_j = \sum_{i=1}^m FR_i / m \quad (4)$$

$$\overline{FR}_{gj} = \frac{\overline{FR}_j}{\sum_{j=1}^n \overline{FR}_j} \quad (5)$$

where $\overline{FR}_j$ and $\overline{FR}_{gj}$ are the relative frequency ratio and normalize $\overline{FR}_j$ of each influencing factor; i is the number of classifications, $i = 1, 2, \dots, m$. j is the number of factors, $j = 1, 2, \dots, n$.

$$w_j = (\overline{FR}_{gj} + w_{AHPj}) / 2 \quad (6)$$

where w_j is the relative weight value of the j th factor.

FR weights are objective statistical weights derived from measured data on landslide distribution, while AHP weights are subjective, experience-based weights constructed based on the mechanisms underlying landslides and geological experience. The equal integration of these two approaches aims to balance subjective geological understanding with objective data characteristics. Compared with the traditional AHP, the FR-AHP effectively reduces the influence of subjectivity and provides a more accurate assessment of the relative importance of the influencing factors.

Based on expert experience, the influence of slope, lithology, distance from river, average annual precipitation, land use type, distance from road, NDVI, aspect, and curvature on landslides in loess regions decreases in that order. Using this information, a judgment matrix was constructed using the AHP to calculate weights, as shown in Table 4. The results of the weight assignment of the influencing factors were tested for consistency using Equations (1) and (2). At $n_{\text{matrix}} = 9$, $RI = 1.45$. After calculation, $CR = 0.028$ in this paper, which is much less than 0.10; the weights of each influence factor are allocated reasonably.

Table 4. Judgment matrix and weight calculation of the AHP.

Factor	b	f	i	g	l	k	h	c	e	w_{AHPj}
b	1.000	2.000	3.000	3.000	3.000	4.000	4.000	5.000	6.000	0.267
f	0.500	1.000	2.000	2.000	3.000	3.000	4.000	5.000	5.000	0.198
i	0.333	0.500	1.000	2.000	2.000	3.000	3.000	5.000	5.000	0.151
g	0.333	0.500	0.500	1.000	2.000	2.000	3.000	4.000	4.000	0.117
l	0.333	0.333	0.500	0.500	1.000	2.000	2.000	3.000	4.000	0.089
k	0.250	0.333	0.333	0.500	0.500	1.000	2.000	2.000	3.000	0.065
h	0.250	0.250	0.333	0.333	0.500	0.500	1.000	2.000	2.000	0.050
c	0.200	0.200	0.200	0.250	0.333	0.500	0.500	1.000	2.000	0.035
e	0.167	0.200	0.200	0.250	0.250	0.333	0.500	0.500	1.000	0.028

At the sample construction stage, 198 disaster sites were used as positive samples, and an equal number of negative samples were randomly generated from non-disaster areas; the training set and test set were then randomly split in a 7:3 ratio. We calculated w_j according to Equations (3)–(6) (Table 5). Analysis of w_j shows that slope, lithology,

and distance from rivers exert a significant influence on landslides, with respective weight proportions of 0.184, 0.172, and 0.124.

Table 5. Frequency ratio, weight, and the value of information quality of evaluation factors.

Factor	Class	N_i	A_i (km ²)	FR_i	$\overline{FR}_{gj}$	w_{AHPj}	w_j	I_i
Slope (°)	<7	22	1035.54	1.172	0.100	0.267	0.184	0.158
	7–15	32	1904.69	0.926				−0.076
	15–20	22	1410.23	0.860				−0.151
	20–25	24	1284.44	1.030				0.030
	25–30	15	968.18	0.854				−0.157
	30–35	16	599.83	1.471				0.386
	35–40	4	303.30	0.727				−0.318
	>40	4	158.87	1.388				0.328
Aspect	Flat	3	142.47	1.161	0.098	0.035	0.067	0.149
	North	9	759.20	0.654				−0.425
	Northeast	15	948.01	0.873				−0.136
	East	13	1164.07	0.616				−0.485
	Southeast	22	889.74	1.364				0.310
	South	20	795.47	1.386				0.327
	Southwest	28	933.94	1.653				0.503
	West	18	1119.80	0.886				−0.121
Curvature	Northwest	11	912.41	0.665	0.097	0.028	0.062	−0.408
	<−6	0	18.63	0.000				−0.52
	−6−−3	4	311.72	0.709				−0.344
	−3−−1	33	1609.32	1.133				0.125
	−1−1	72	3951.54	1.007				0.007
	1−3	24	1487.26	0.892				−0.114
	3−5	4	260.61	0.848				−0.164
	>5	2	43.83	2.522				0.925
Lithology	Cretaceous	11	646.04	0.931	0.147	0.198	0.172	−0.071
	Jurassic	36	732.25	2.688				0.989
	Neogene	2	73.69	1.484				0.395
	Quaternary	65	5445.60	0.653				−0.427
	Triassic	25	703.29	1.944				0.665
Average annual precipitation (mm)	<460	20	1726.56	0.641	0.092	0.117	0.105	−0.445
	460–490	30	1907.28	0.870				−0.139
	490–510	30	1671.48	0.993				−0.007
	>510	59	2381.40	1.370				0.315
NDVI	−1−0	2	23.53	4.698	0.166	0.050	0.108	1.547
	0−0.3	2	146.05	0.757				−0.279
	0.3−0.5	26	686.67	2.093				0.739
	0.5−0.65	32	1424.73	1.241				0.216
	0.65−0.8	49	2369.12	1.143				0.134
	0.8−1	28	3032.93	0.510				−0.673
Distance from river (m)	>5000	37	2648.21	0.764	0.097	0.151	0.124	−0.269
	5000–4000	8	819.55	0.534				−0.628
	4000–3000	18	906.36	1.086				0.082
	3000–2000	15	996.13	0.823				−0.194
	2000–1000	10	1066.08	0.513				−0.668
	<1000	51	1164.53	2.395				0.873
Distance from road (m)	>5000	8	692.33	0.632	0.075	0.065	0.070	−0.459
	5000–4000	4	473.44	0.462				−0.772
	4000–3000	12	726.50	0.903				−0.102
	3000–2000	11	1085.36	0.554				−0.590
	2000–1000	19	1638.50	0.634				−0.456
	<1000	85	2984.75	1.557				0.443
Land Use type	Artificial surfaces	10	102.62	5.386	0.128	0.089	0.108	1.684

Bare land	0	12.15	0.000	−1.139
Cultivated land	47	1997.71	1.300	0.263
Forest	10	1180.33	0.468	−0.759
Grass Land	72	4381.13	0.908	−0.096
Water Body	0	9.04	0.000	−1.139

Classes with $N_i = 0$ were assigned an IV slightly lower than the observed minimum to maintain numerical continuity.

2.5. The IV and the Weighted IV

The information value model is based on the sample statistics approach to complete a classified information value calculation for all impact factors. Finally, the probability of the occurrence of landslides is assessed by summing up the amount of information values [46]. Both the FR and IV are derived from the ratio of landslide frequency to areal proportion within factor intervals. The FR uses the direct ratio for weight determination, whereas IV applies a logarithmic transformation to quantify information contribution for susceptibility indexing.

It can be calculated as follows:

$$I = \sum_{j=1}^n I_i = \sum_{j=1}^n \ln \frac{N_i / N}{A_i / A} \quad (7)$$

where I is the total information value. At $I > 0$, the greater the likelihood that landslides will occur; at $I < 0$, the likelihood of landslides is relatively low; and at $I = 0$, no landslides occur in the study area. The rest of the symbols have the same meaning as above.

Since the weighted information value model considers the importance of different influencing factors, it is more reasonable than the general information value model.

The AHP-IV, FR-IV and FR-AHP-IV models are shown in Equations (8)–(10), respectively:

$$I_{AHP} = \sum_{j=1}^n I_{AHPj} = \sum_{j=1}^n w_{AHPj} * \ln \frac{N_i / N}{S_i / S} \quad (8)$$

$$I_{FR} = \sum_{j=1}^n I_{FRj} = \sum_{j=1}^n w_{FRj} * \ln \frac{N_i / N}{S_i / S} \quad (9)$$

$$I_w = \sum_{j=1}^n I_{wj} = \sum_{j=1}^n w_j * \ln \frac{N_i / N}{S_i / S} \quad (10)$$

where I_{AHP} is the AHP-IV model, I_{FR} is the FR-IV model, and I_w is the FR-AHP-IV model.

2.6. ROC Curve

The test of the landslide susceptibility result obtained based on the weighted information value model is as important as the construction of the model. If the model is not accurate enough, it cannot be used for susceptibility evaluation in the study area. Model susceptibility prediction results are quantitatively evaluated using ROC curves. The ROC curve is a curve based on a series of different dichotomous classifications (cut-off values or decision thresholds), with the rate of true positives (sensitivity) as the vertical coordinate and the rate of false positives (1-specificity) as the horizontal coordinate. The accuracy of the model is then measured by calculating the AUC. The closer the AUC is to 1.00, the more accurate the model is. At $0.50 < \text{AUC} \leq 0.70$, $0.70 < \text{AUC} \leq 0.90$, and $\text{AUC} > 0.90$; they indicate that the model has low, high and very high accuracy, respectively [47].

3. Results

3.1. Analysis of Susceptibility

Using the information value model to evaluate the nine influencing factors, the resulting information quantity values are presented in Table 5. Slope (30–35°), aspect (south-west), curvature (>5), lithology (Jurassic), annual average precipitation (>510 mm), NDVI (−1–0), distance from rivers (<1000 m), distance to roads (<1000 m), and land use type (artificial surfaces) are prone to inducing landslides in the Yanhe River Basin.

Based on this, the IV, AHP-IV, FR-IV, and FR-AHP-IV models were constructed according to Equations (7)–(10). Using the ArcGIS10.8 raster calculator function to obtain susceptibility results, the susceptibility index values were finally classified into four categories from low to high according to the natural break method (Jenks) (Figure 3, Table 6). The four models exhibit generally consistent spatial distribution patterns of landslide susceptibility, all showing a prominent feature of higher susceptibility in river valleys and lower susceptibility in elevated terrain (Figure 3). The very-high-susceptibility zones are distributed in strip-like patterns along the main river and its tributaries, forming continuous high-value clusters in the south-central part of the study area (Ansai–Baota–Yanchang), which is highly consistent with the regional settings characterized by intense fluvial erosion, concentrated human engineering activities, and favorable topographic conditions for slope instability. The high-susceptibility zones appear as patchy mosaics surrounding the very high zones, mainly distributed on slopes adjacent to river networks. Very-high- and high-susceptibility areas have fragile geological environments, with Jurassic and Triassic strata and high rock exposure, forming a loess–mudstone (bedrock) slippery structural surface with the overlying loess, which is one of the fundamental causes of landslides [48]. Moreover, the region has a strong erosion effect on loess scouring due to the high intensity of rainfall; it is densely populated, with rapid urbanization and construction, and human activities are strong, destroying the stability of the original valley slopes, which are prone to cause landslides. In addition, the existing landslides and other landslides are large in number and high in density, and are prone to recur under the combined effects of climate and human activities, causing mass landslides. The moderate- and low-susceptibility areas are located in most of the upper and lower Yanhe River region and in the middle reaches of the river where human engineering activities are weak. The valleys in this area are narrow, landslides are not developed, and although small avalanches are frequent, they do not cause landslides. As shown in Table 6, the IV and FR-IV models share highly similar spatial patterns, whereas the FR-IV model identifies high- and very-high-susceptibility zones with finer granularity. The AHP-IV model shows relatively dispersed very-high-susceptibility zones (10.29%) with the smallest proportion of high-susceptibility zones (16.98%), indicating slightly inferior spatial aggregation compared to other models. In comparison, the FR-AHP-IV model demonstrates optimal spatial continuity in very-high-susceptibility zones, the highest spatial overlay accuracy with known landslide points, and clearer boundary delineation in the low-susceptibility areas of northern Jingbian–Zhidan.

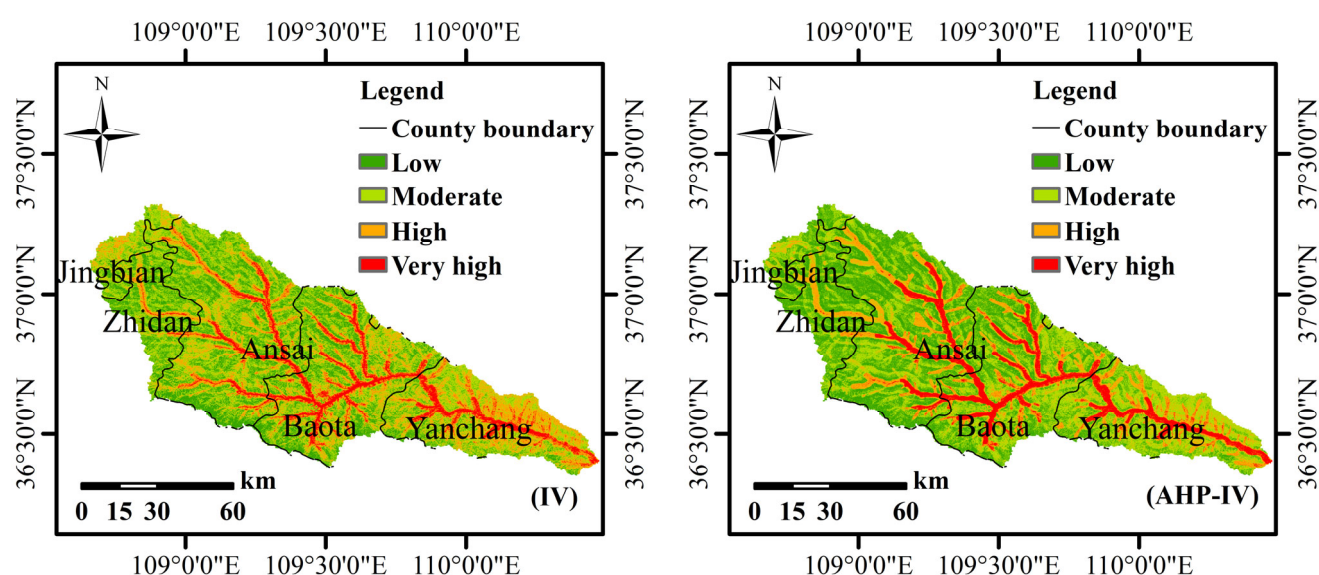
Table 6. Landslide susceptibility zoning results of different models.

Model	Susceptibility Level	<i>N_i</i>	<i>N_i/N (%)</i>	<i>A_i/A (%)</i>	<i>FR</i>
IV	Low	13	9.35	27.95	0.335
	Moderate	35	25.18	38.95	0.647
	High	45	32.37	23.91	1.354
	Very high	46	33.09	9.19	3.602
AHP-IV	Low	16	11.51	35.67	0.323
	Moderate	43	30.94	37.07	0.835

FR-IV	High	30	21.58	16.98	1.271
	Very high	50	35.97	10.29	3.497
	Low	10	7.19	26.03	0.276
	Moderate	35	25.18	40.23	0.626
	High	51	36.69	25.18	1.457
FR-AHP-IV	Very high	43	30.94	8.55	3.619
	Low	15	10.79	32.01	0.337
	Moderate	43	30.94	40.69	0.760
	High	36	25.90	18.49	1.400
	Very high	45	32.37	8.80	3.680

The FR method was used for analysis, with the following criteria: an $FR < 1$ indicates that the area is not prone to landslides, while an $FR > 1$ indicates that it is prone to landslides. The higher the susceptibility level, the greater the relative frequency of landslides; that is, the frequency of landslide occurrence gradually increases from low-susceptibility areas to extremely high-susceptibility areas. The FR values exhibit a strictly ascending trend (low < moderate < high < very high), with $FR < 1$ in low- and moderate-susceptibility zones and $FR > 1$ in high- and very-high-susceptibility zones; the majority of landslides are concentrated in the high- and very-high-susceptibility zones (Table 6). This indicates that the thresholds determined by this method can effectively distinguish between different levels of landslide susceptibility.

To further evaluate the comprehensive performance of the different coupled models, this study conducted a comparative analysis focusing on the dynamic range of FR values, landslide concentration, and spatial distribution consistency (Table 6). Regarding the FR dynamic range, the FR-AHP-IV model exhibits the largest range (3.343), indicating the strongest capacity to characterize susceptibility variations. For landslide concentration, the FR-IV model achieves the highest value (67.63%), followed by the IV model (65.47%), with the FR-AHP-IV model at 58.27%. However, the FR-AHP-IV model attains a relatively high landslide concentration with the smallest combined area proportion of very-high- and high-susceptibility zones (27.29%), demonstrating the precise identification advantage of “less area, more disasters”. Integrating the three indicators of the FR dynamic range, landslide concentration, and spatial distribution conformity, the FR-AHP-IV model achieves optimal identification and spatially precise localization of very-high-susceptibility zones while maintaining rational grading.



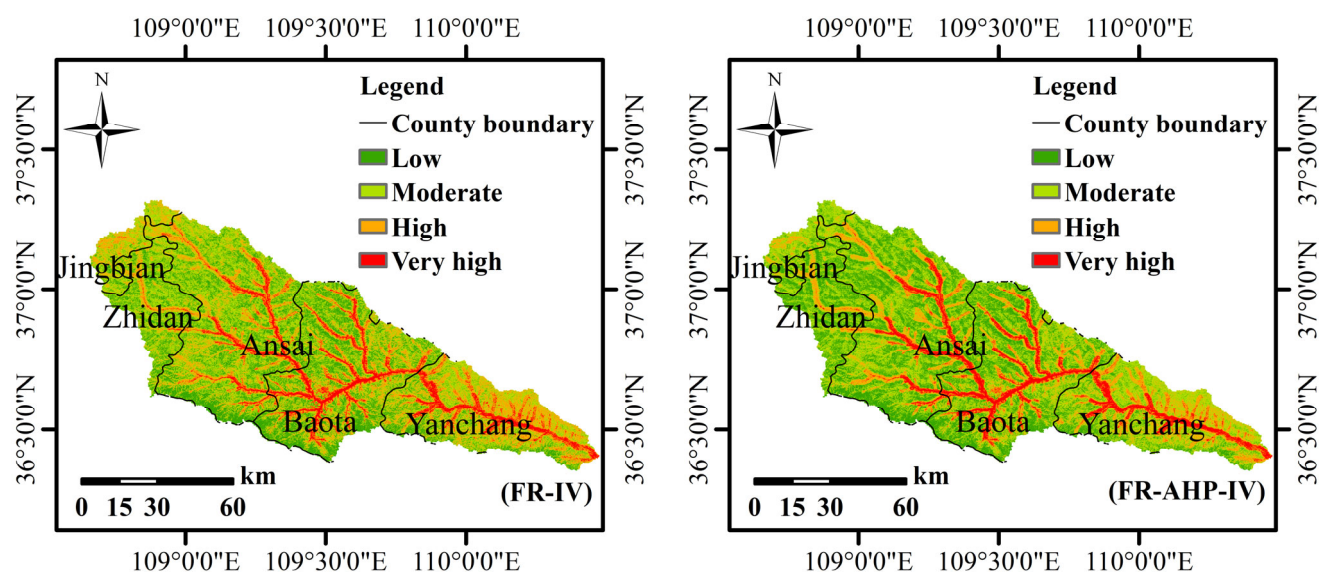


Figure 3. Landslide susceptibility zoning in the Yanhe River Basin.

For the FR-AHP-IV model, the low-, moderate-, high-, and very-high-susceptibility zones accounted for 32.01%, 40.69%, 18.49%, and 8.80% of the study area, respectively, presenting a pattern of “moderate > low > high > very high”. This ranking reflects the geological and geomorphological setting of the Yanhe River Basin as a typical loess hilly region: the moderate zone exceeds the low zone in area primarily because the loess-bed-rock dual structure is extensively exposed along both banks of the middle and lower reaches. Coupled with deep valley incision and anthropogenic disturbances (e.g., cave dwellings, road-cut slopes, terraces), “potentially unstable slopes” form contiguous patches across the basin, making it difficult to form extensive, truly “low-susceptibility” continuous blocks. The relative frequency ratios increased monotonically at 0.337, 0.760, 1.400, and 3.680, respectively, confirming the rationality of the classification. The closer to the river system, the greater the value of landslide susceptibility index. The high value of the susceptibility index is distributed as midstream > downstream > upstream. Analyzed in conjunction with Figure 1, there is a good spatial match between the susceptibility class and the distribution of landslides, indicating that the categorization is reasonable.

3.2. Examination of Evaluation Results

The ROC analysis based on the test sample is shown in Figure 4. Among the four models compared by ROC analysis, the IV model (AUC = 0.755) yields the lowest accuracy. The FR-IV (AUC = 0.791) and AHP-IV (AUC = 0.760) models achieve comparable and suboptimal accuracy. The FR-AHP-IV model (AUC = 0.818) attains the highest accuracy. Analysis indicates that the IV model is a data-driven approach that calculates the contribution of each factor class to landslide occurrence based on the statistical information value, with the advantage of strong objectivity. The AHP-IV model integrates the AHP with the IV, incorporating expert knowledge and offering strong interpretability; nevertheless, it is relatively subjective and exhibits insufficient characterization of extreme values. The FR-IV model couples the FR with the IV, but its results are sensitive to weight allocation. The FR-AHP-IV model synthesizes statistical regularities, expert experience, and information value contributions. While maintaining the strengths of each individual model and reducing the uncertainty associated with single models, it performs relatively well. Therefore, it was selected as the optimal model for subsequent spatial pattern analysis (hotspot analysis) in this study.

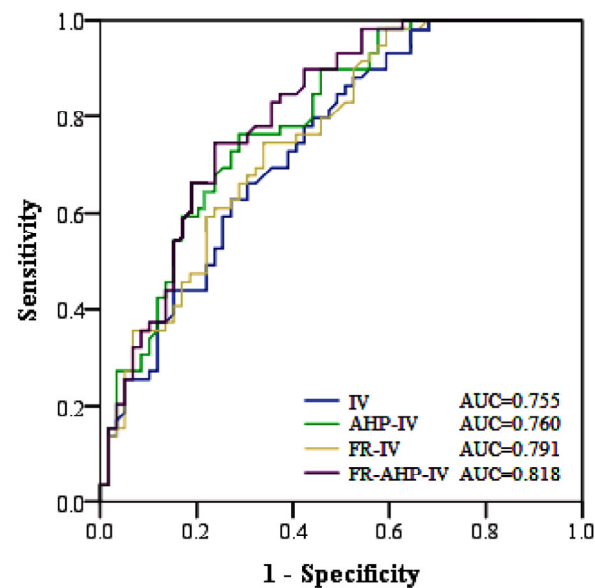


Figure 4. ROC curve.

3.3. Spatial Patterns Identification and Analysis of Landslides

The sub-basin division of the Yanhe River Basin was carried out using WHIST software (2022) with the following parameter settings, resolution set to 30, type set to acc (flow accumulation), and Aro limit set to 500 km², which means that the sub-basin area is limited to no more than 500 km². Based on this, the Yanhe River Basin was divided into 45 sub-basins, as shown in Figure 5. Based on the sub-basin division combined with the results of weighted information quality calculation, the spatial pattern of cold spots and hotspots of landslides in the Yanhe River Basin was identified based on regional and spatial statistics using the Getis-Ord Gi* tool.

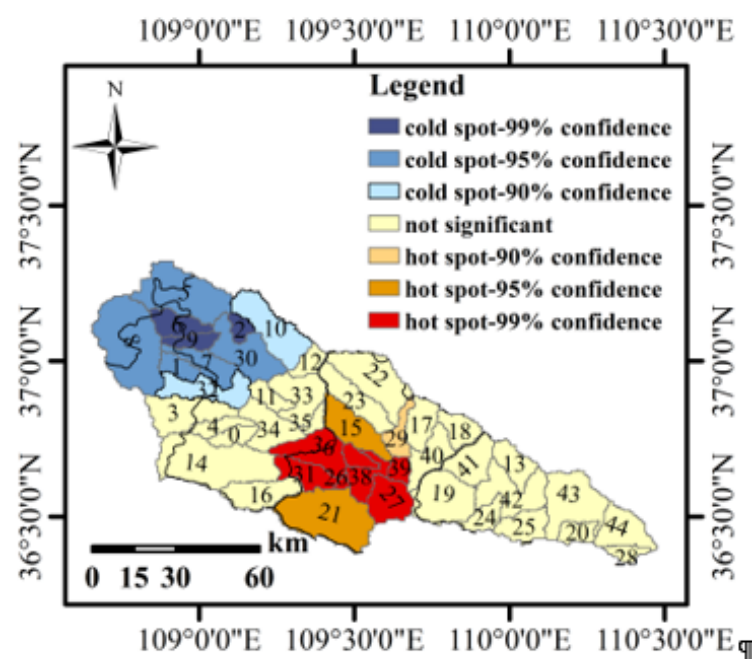


Figure 5. Hotspot analysis of landslides in the Yanhe River Basin.

Cold spots and hotspots reflect the spatial clustering of high and low values of landslide susceptibility, respectively. The results of the FR-AHP-IV model's susceptibility zoning and hotspot analysis show a high degree of consistency at the macroscopic scale, but exhibit significant similarities and differences at the local scale (Figure 5). Overall, the very-high- and high-susceptibility zones (accounting for 27.29% of the study area) show good spatial overlap with the clusters of high-value hotspots, while the low-susceptibility zones (32.01%) clearly correspond to the low-value cold spots, jointly revealing the general pattern of "high risk in the middle-reach valleys and low risk in the upstream plateau" across the Yanhe River Basin. Together, these findings reveal the overall pattern of the Yanhe River Basin, characterized by "high susceptibility in the middle-reaches valley and low susceptibility in the upper-reaches of the plateau." Specifically, the hotspots concentrated in the middle-reach sub-basins (Nos. 26, 27, 31, 36, 38, and 39) overlap highly with the very-high-high-susceptibility zones in southern Baota District. These areas are jointly controlled by the Jurassic weak strata, deeply incised valley landforms, relatively abundant precipitation, and intensive human engineering activities (road-cut slopes, cave-dwelling construction, and terrace reclamation), resulting in not only prominent high susceptibility but also significant spatial autocorrelation and clustering characteristics.

The differential features between the two approaches also reveal their methodological complementarity. The hotspot analysis further characterizes local clustering effects at the sub-basin scale: certain sub-basins classified as "moderate susceptibility" in the zoning evaluation (e.g., Nos. 15 and 21) show significant hotspot clustering, indicating that although these areas do not reach the threshold for very high susceptibility, they exhibit locally strong spatial associations of landslide clusters, likely related to micro-topographic mutations or localized human activity aggregation. Conversely, some patchy "high-susceptibility" areas on the susceptibility map fail the significance test in the hotspot analysis, suggesting that their high susceptibility may stem from isolated topographic or lithological conditions rather than regional clustered controlling factors. This discrepancy indicates that the susceptibility evaluation reflects the continuous planar distribution of landslide occurrence conditions, whereas the hotspot analysis portrays the spatial statistical significance of disaster clustering. The complementary integration of both methods enables more precise identification of priority prevention and control areas featuring both "high susceptibility and high clustering," such as sub-basins Nos. 26, 27, 31, 36, 38, and 39. These areas are not only designated as very-high-susceptibility zones by the FR-AHP-IV model but also identified as hotspots at the 99% confidence level, and should therefore serve as the core target areas for landslide prevention and control in the basin.

Analyzed in conjunction with Figure 2, the hotspots are mainly concentrated in the southern part of the Baota District. This is mainly due to the high average annual precipitation in these areas (>480 mm), the fragile geological environment (Jurassic), the high density of the river network of 3.15 km/km², the low level of vegetation cover, and the high intensity of human engineering activities. Cold spot areas are mainly concentrated in Jingbian County, Zhidan County and the northern part of Ansai County. This is mainly due to the low average annual precipitation (<480 mm) in these areas, the relatively solid geology (Cretaceous), the low density of the river network, and the low intensity of human engineering activities.

4. Discussion

The empirical results derived from the Yanhe River Basin elucidate the complex interplay between geophysical predispositions and anthropogenic perturbations in shaping landslide susceptibility across the Loess Plateau. The FR-AHP-IV model outperformed the

standalone IV, AHP-IV and FR-IV models, underscoring that integrating data-driven relative frequencies with expert judgment effectively mitigates the subjectivity inherent in traditional weighting systems. The hierarchical structure of factor weights further clarifies region-specific failure mechanisms: the predominance of lithology and slope confirms that landslide occurrence is fundamentally governed by bedrock integrity and gravitational terrain stress, while the significant contribution of distance to river highlights the pivotal role of fluvial erosion in destabilizing valley flanks—a process exacerbated by the incised topography characteristic of the Loess Plateau. Furthermore, the influence of NDVI and land use indicates that surface ecological conditions act as a secondary yet vital regulatory layer mediating the impact of hydrological triggers on slope resilience. Spatially, the concentration of high- and very-high-susceptibility zones along the middle and lower reaches and within the southern Baota District reveals a dangerous overlap between high landslide potential and dense socioeconomic exposure, posing direct threats to ecological restoration achievements and infrastructure viability.

Nevertheless, several limitations warrant critical acknowledgment. The AUC value of 0.818, while indicating acceptable predictive capability, falls within the “good” range rather than the “excellent” range ($AUC > 0.90$). This moderate precision likely stems from the limited sample size of 198 landslide points, which constrains the statistical representativeness of factor interval frequencies for rare lithological units or extreme slope gradients; the absence of soil type data, which exerts significant control on loess slope stability through infiltration and shear strength; and the spatial resolution of input data, which may smooth local topographic variations critical for site-specific landslide initiation. Additionally, like other statistical approaches, this model assumes stationarity in the factor–landslide relationship across the entire basin, yet geomorphic processes in the gully region may exhibit spatial non-stationarity that localized calibration could better capture. Moving forward, sustainable development strategies in the basin must adopt a risk-informed approach that respects these geo-environmental thresholds. Priority research directions include integrating high-resolution soil property and loess thickness data, exploring machine learning algorithms to capture non-linear factor interactions, and developing dynamic susceptibility models that incorporate rainfall thresholds and land use change scenarios—advancing landslide assessment from static mapping toward actionable, adaptive governance.

5. Conclusion

In this paper, the FR-AHP, combined with the information quality methodology, was used to partition and evaluate the susceptibility of landslides in the Yanhe River Basin and to analyze the degree of susceptibility of landslides in different sub-watersheds under the joint action of multiple factors. It is necessary to carry out landslide susceptibility assessments when planning and building large-scale engineering projects. The conclusions are summarized as follows:

(1) Compared to the four models (IV, AHP-IV, FR-IV, FR-AHP-IV), the FR-AHP-IV model achieved the highest accuracy, $AUC = 0.818$. This indicates that the relative weights of influencing factors determined by the FR-AHP method are more accurate. This is because it compensates for the relatively strong subjectivity inherent in the traditional AHP method. The relative weights of the influencing factors were determined using FR-AHP, with slope > lithology > distance from river > NDVI = land use type > average annual precipitation > distance from road > aspect > curvature.

(2) The susceptibility zoning results indicate that low-, moderate-, high-, and very-high-susceptibility zones account for 32.01%, 40.69%, 18.49%, and 8.80% of the basin area, respectively. High- and very-high-susceptibility zones are predominantly concentrated

along both banks of the middle and lower reaches. In total, 8.80% of very-high-susceptibility zones, particularly in the southern part of the Baota District, should be designated as priority control zones in land use planning, with restrictions on high-sensitivity development activities. The concentration of 18.49% high-susceptibility zones along riverbanks underscores the need for prioritized engineering interventions and early warning systems, aligning with the “River Chief System” management requirements.

(3) Landslide susceptibility exhibits a pronounced “block” spatial agglomeration pattern, with hotspots concentrated in southern Baota District and cold spots in northern Jingbian, Zhidan, and Ansai Counties. This spatial heterogeneity provides a scientific basis for zoned and differentiated governance: hotspot areas should serve as the core focus for enhanced monitoring and ecological restoration, while cold spot regions may adopt relaxed prevention standards, enabling limited resources to be concentrated where risk is highest and ensuring that socio-economic development respects geo-environmental thresholds.

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References

1. Li, S.; Li, C.; Yao, D.; Liu, C.; Zhang, Y. Multiscale nonlinear analysis of failure mechanism of loess-mudstone landslide. *Catena* **2022**, *213*, 106188.
2. Jing, J.; Hou, J.; Sun, W.; Chen, G.; Ma, Y.; Ji, G. Study on influencing factors of unsaturated loess slope stability under dry-wet cycle conditions. *J. Hydrol.* **2022**, *612*, 128187.
3. Zhou, S.; Tian, Z.; Di, H.; Guo, P.; Fu, L. Investigation of a loess-mudstone landslide and the induced structural damage in a high-speed railway tunnel. *Bull. Eng. Geol. Environ.* **2020**, *79*, 2201–2212.
4. Peng, J.; Wang, S.; Wang, Q.; Zhuang, J.; Huang, W.; Zhu, X.; Leng, Y.; Ma, P. Distribution and genetic types of loess landslides in China. *J. Asian Earth Sci.* **2019**, *170*, 329–350.
5. Luo, L.; Guo, W.; Tian, P.; Liu, Y.; Wang, S.; Luo, J. Unique landslides (loess slide-flows) induced by an extreme rainstorm in 2018 on the Loess Plateau: A new geological hazard and erosion process. *Int. J. Sediment Res.* **2023**, *38*, 228–239.
6. Yang, H.; Xie, W.; Liu, Q.; Zhu, R.; Liu, Y. Three-stage collapsibility evolution of Malan loess in the Loess Plateau. *Catena* **2022**, *217*, 106482.
7. Kristo, C.; Rahardjo, H.; Satyanaga, A. Effect of variations in rainfall intensity on slope stability in Singapore. *Int. Soil Water Conserv. Res.* **2017**, *5*, 258–264.
8. Pan, Y.; Wu, G.; Zhao, Z.; He, L. Analysis of rock slope stability under rainfall conditions considering the water-induced weakening of rock. *Comput. Geotech.* **2020**, *128*, 103806.
9. Andrea, A.; Monica, P.; Laura, L. Analysis of meteorological parameters triggering rainfall-induced landslide: A review of 70 years in Valtellina. *Nat. Hazard. Earth. Sys.* **2021**, *21*, 2041–2058.

10. Sun, Y.; Zhang, J.; Wang, H.; Lu, D. Probabilistic thresholds for regional rainfall induced landslides. *Comput. Geotech.* **2024**, *166*, 106040.
11. Ma, J.; Zeng R., Meng, X.; Zhang, Z.; Zhao, S.; Wei, Z. Field Research on preferential infiltration in rainfall-induced loess landslides. *Eng. Geol.* **2025**, *354*, 108184.
12. Cigna, F.; Tapete, D.; Lee, K. Geological hazards in the UNESCO world heritage sites of the UK: From the global to the local scale perspective. *Earth Sci. Rev.* **2018**, *176*, 166–194.
13. Zou, F.; Che, E.; Long, M. Quantitative assessment of geological hazard risk with different hazard indexes in mountainous areas. *J. Clean. Prod.* **2023**, *413*, 137467.
14. Bourenane, H.; Meziani, A.A.; Benamar, D.A. Application of GIS-based statistical modeling for landslide susceptibility mapping in the city of Azazga, Northern Algeria. *Bull. Eng. Geol. Environ.* **2021**, *80*, 7333–7359.
15. Navdeep, A.; Jagabandhu, D. GIS-based landslide susceptibility mapping of the Meghalaya- Shillong Plateau region using machine learning algorithms. *Bull. Eng. Geol. Environ.* **2023**, *82*, 170.
16. Pavlova, I.; Makarigakis, A.; Depret, T.; Jomelli, V. Global overview of the geological hazard exposure and disaster risk awareness at world heritage sites. *J. Cult. Herit.* **2017**, *28*, 151–157.
17. Lu, Z.; Yang, H.; Zeng, W.; Liu, P.; Wang, Y.D. Geological hazard identification and Susceptibility Assessment Based on MT-InSAR. *Remote Sens.* **2023**, *15*, 5316.
18. He, Z.; Yue, T.; Chen, Y.; Mu, W.; Xi, M.; Qin, F. Analysis of spatial and temporal changes in vegetation cover and driving forces in the Yanhe River Basin, Loess Plateau. *Remote. Sens.* **2023**, *15*, 4240.
19. Zhang, Z.; Xiong, C.; Yang, Y.; Liang, C.; Jiang, S. What makes the River Chief System in China viable? Examples from the Huaihe River Basin. *Sustainability* **2022**, *14*, 6329–6329.
20. Wu, C.; Ju, M.; Wang, L.; Gu, X.; Jiang, C. Public participation of the River Chief System in China: Current trends, problems, and perspectives. *Water* **2020**, *12*, 3496–3496.
21. Bhagyaraj, U.; Sreevalsa, K. Seismic hazard assessment and landslide vulnerability mapping for Ladakh, and Jammu Kashmir using GIS technique. *J. Geol. Soc. India.* **2023**, *99*, 377–382.
22. Wang, X.; Zhang, C.; Wang, C.; Liu, G.; Wang, H. GIS-based for prediction and prevention of environmental geological disaster susceptibility: From a perspective of sustainable development. *Ecotoxicol. Environ. Saf.* **2021**, *226*, 112881.
23. Jam, A.S.; Mosaffaie, J.; Sarfaraz, F.; Shadfar, S.; Akhtari, R. GIS-based landslide susceptibility mapping using hybrid MCDM models. *Nat. Hazards.* **2021**, *108*, 1–22.
24. Hilal, A.; Chen, N.; Mahfuzur, R.; Monirul, M.; Reza, P.; Fahad, H.; Maurice, H.; Enlong, L.; Zheng, H.; Ni, H.; et al. Geohazards susceptibility assessment along the upper Indus Basin Using four machine learning and statistical models. *ISPRS. Int. J. Geo-Inf.* **2021**, *10*, 315–315.
25. Jena, R.; Pradhan, B.; Beydoun, G.; Nizamuddin, A.; Sofyan, H.; Affan, M. Integrated model for earthquake risk assessment using neural network and analytic hierarchy process: Aceh province, Indonesia. *Geosci. Front.* **2020**, *11*, 613–634.
26. Stanley, T.; Kirschbaum, B.D. A heuristic approach to global landslide susceptibility mapping. *Nat. Hazards.* **2017**, *87*, 145–164.
27. Raghuvanshi, T.K. Plane failure in rock slopes—A review on stability analysis techniques. *J. King. Saud. Univ.-Sci.* **2019**, *31*, 101–109.
28. Chen, W.; Han, H.; Huang, B.; Huang, Q.; Fu, X. A data-driven approach for landslide susceptibility mapping: a case study of Shennongjia Forestry District, China. *Geomat. Nat. Haz. Risk.* **2018**, *9*, 720–736.
29. Rehman, F.; El-Hady, M.S.; Atef, H.A.; Harbi, H.M. Seismic hazard assessment of Western Coastal Province of Saudi Arabia: Deterministic approach. *Earthq. Sci.* **2016**, *29*, 299–309.
30. Basu, T.; Das, A.; Pal, S. Application of geographically weighted principal component analysis and fuzzy approach for unsupervised landslide susceptibility mapping on Gish River Basin, India. *Geocarto Int.* **2020**, *37*, 1–24.
31. Youssef, B.; Bouskri, I.; Brahim, B.; Kader, S.; Brahim, I.; Abdelkrim, B.; Spalević, V. The contribution of the frequency ratio model and the prediction rate for the analysis of landslide risk in the Tizi N'tichka area on the national road (RN9) linking Marrakech and Ouarzazate. *Catena* **2023**, *232*, 107464.
32. Niu, H.; Shao, S.; Gao, J.; Jing, H. Research on GIS-based information value model for landslide geological hazards prediction in soil-rock contact zone in southern Shaanxi. *Phys. Chem. Earth.* **2024**, *133*, 103515.
33. Zhou, J.; Tan, S.; Li, J.; Xu, J.; Wang, C.; Ye, H. Landslide susceptibility assessment using the Analytic Hierarchy Process (AHP): A case study of a construction site for photovoltaic power generation in Yunxian County, Southwest China. *Sustainability* **2023**, *15*, 5281.

34. Nhu, V.-H.; Shirzadi, A.; Shahabi, H.; Singh, S.K.; Al-Ansari, N.; Clague, J.J.; Jaafari, A.; Chen, W.; Miraki, S.; Dou, J.; et al. Shallow Landslide susceptibility mapping: A comparison between logistic model tree, logistic regression, naïve bayes tree, artificial neural network, and support vector machine algorithms. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2749.
35. Pham, T.B.; Prakash, I. Evaluation and comparison of LogitBoost ensemble, Fisher's linear discriminant analysis, logistic regression and support vector machines methods for landslide susceptibility mapping. *Geocarto. Int.* **2019**, *34*, 316–333.
36. Yuan, R.; Chen, J. A novel method based on deep learning model for national-scale landslide hazard assessment. *Landslides* **2023**, *20*, 2379–2403.
37. Kong, C.; Li, Y.; Dong, K.; Tian, Y.; Xu, K. Landslide susceptibility assessment in Qinzhou based on rough set and semi-supervised support vector machine. *Earth Sci. Inform.* **2023**, *16*, 3163–3177.
38. Huang, S.; Dou, H.; Jian, W.; Guo, C.; Sun, Y. Spatial prediction of the geological hazard vulnerability of mountain road network using machine learning algorithms. *Geomat. Nat. Haz. Risk.* **2023**, *14*, 2170832.
39. Dipika, K.; Kripamoy, S.; Lal, S.C. Landslide susceptibility mapping in parts of Aglar watershed, Lesser Himalaya based on frequency ratio method in GIS environment. *J. Earth. Syst. Sci.* **2023**, *133*, 100146.
40. Lin, J.; Chen, W.; Qi, X.; Hou, H. Risk assessment and its influencing factors analysis of geological hazards in typical mountain environment. *J. Clean. Prod.* **2021**, *309*, 127077.
41. GB/T 50218-2014; Standard for engineering Classification of Rock Mass. China Planning Press: Beijing, China, 2015.
42. Pourghasemi, H.R.; Pradhan, B.; Gokceoglu, C. Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Nat. Hazards.* **2012**, *63*, 965–996.
43. Linghu, C.; Qian, Z.; Chen, W.; Li, J.; Zou, S.; Yang, L.; Gao, Y.; Zhu, Z.; Gao, Q. Assessment of landslide susceptibility and risk in Tengchong City, southwestern China using machine learning and the Analytic Hierarchy Process. *Land* **2025**, *14*, 1966–1966.
44. Ahmad, M.S.; Khan, S. Comparative analysis of analytical hierarchy process (AHP) and frequency ratio (FR) models for landslide susceptibility mapping in Reshun, NW Pakistan. *Kuwait J. Sci.* **2023**, *50*, 387–398.
45. Nefeslioglu, H.A.; Sezer, E.A.; Gokceoglu, C.; Ayas, Z. A modified analytical hierarchy process (M-AHP) approach for decision support systems in natural hazard assessments. *Comput. Geosci.* **2013**, *59*, 1–8.
46. Ma, J.; Wang, X.; Yuan, G. Evaluation of geological hazard susceptibility based on the regional division information value method. *ISPRS. Int. J. Geo-Inf.* **2023**, *12*, 17–17. <https://doi.org/10.3390/IJGI12010017>.
47. Cabral, V.; Reis, F.; Veloso, V.; Ogura, A.; Zarfl, C. A multi-step hazard assessment for debris-flow prone areas influenced by hydroclimatic events. *Eng. Geol.* **2023**, *313*, 106961.
48. Zhang, Z.; Qi, W.; Zhao, Z.; Zheng, T. Influence of loess-mudstone strata structure on slope seismic stability of Loess Plateau in China. *Appl. Sci.* **2023**, *13*, 12854.

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