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# EVALUATION OF REGIONAL LANDSLIDE DISASTER SUSCEPTIBILITY BASED ON GEODETECTOR - ANALYTIC HIERARCHY PROCESS

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## EXTENDED ABSTRACT

La Cina si trova nella parte orientale del continente asiatico ed è caratterizzata da un vasto territorio, strutture geologiche attive, un clima mutevole, forti piogge durante tutto l'anno, un'elevata densità di popolazione e un'intensa attività antropica. Questi fattori, nell'insieme, determinano frequenti frane con ampia distribuzione di disastri. Di conseguenza, un'efficace valutazione della suscettibilità al rischio frane in una regione può migliorare la tempestività e l'accuratezza dei sistemi di monitoraggio e di allerta precoce. Tuttavia, la ricerca esistente è stata criticata per la sua incapacità di tenere conto delle differenze regionali e per l'elevato grado di soggettività nel processo di valutazione. Questo articolo ha come oggetto di ricerca l'area di Xiong'ershan dei Monti Qinling nella provincia occidentale dell'Henan e impiega una combinazione del Geodetector (GD) e dell'Analytic Hierarchy Process (AHP). Il valore *q* nel GD è un indicatore per misurare il grado di interpretazione dell'eterogeneità spaziale per ciascun fattore ambientale soggetto a frane. I valori *q* ottenuti dal Geodetector vengono quindi utilizzati per calcolare il potere esplicativo di ciascun fattore ambientale soggetto a frane proponendo un nuovo metodo di valutazione della suscettibilità ai disastri da frane che rende il processo di analisi più oggettivo, realistico e riproducibile, compensando così le carenze degli studi precedenti, come la forte soggettività e l'elevata richiesta di campioni di dati.

Nello specifico, questo studio ha selezionato due categorie e un totale di 13 fattori ambientali inclini a disastri, ha elaborato i dati in modo coerente e ha utilizzato la tecnologia del Geographical Detector. Successivamente, è stata costruita una matrice di giudizio sulla base dei risultati del rilevamento al fine di ottenere i pesi di valutazione e calcolare l'Indice di Suscettibilità alle Frane (LSI), un valore numerico calcolato moltiplicando ciascuno dei fattori ambientali inclini al rischio per i corrispondenti pesi di valutazione ottenuti dall'analisi basata sul Geographical Detector e quindi sommandoli. Infine, i risultati sono stati analizzati quantitativamente utilizzando metodi quali la riclassificazione, l'analisi di autocorrelazione spaziale e la statistica matematica al fine di fornire un riferimento per la formulazione di politiche scientifiche di prevenzione e mitigazione dei disastri. I risultati dimostrano che diversi fattori inclini al rischio spiegano i disastri da frana in misura diversa. Tra questi fattori, la densità stradale, la densità del sistema idrico, i tagli e le precipitazioni hanno un alto grado di spiegazione per i disastri da frana regionali, in particolare la densità stradale e la densità del sistema idrico, che presentano valori di *q* elevati, rispettivamente di 0.361 e 0.242. Il grado di spiegazione della connettività del sistema idrico, della copertura vegetale, della distanza dalle strade e dell'uso del suolo è inferiore, in particolare per quanto riguarda la connettività del sistema idrico, che ha il valore *q* più basso, pari a solo 0.012. Il valore medio dell'indice di suscettibilità ai disastri da frana nell'area di studio è pari a 0.402 e l'area complessiva è considerata a media suscettibilità. Spazialmente, le aree ad alto valore sono prevalentemente situate lungo corsi d'acqua e strade, mentre le aree a basso valore sono situate principalmente nelle regioni di media e bassa montagna. In termini di livelli di distribuzione, il numero di punti di disastri da frana nelle aree moderatamente e altamente soggette a frana è 100, pari al 98.04% della percentuale complessiva. Di particolare rilievo è l'area altamente soggetta a frana, che rappresenta il 32.35% della percentuale complessiva, con 33 punti di disastri da frana. L'area di studio mostra una significativa correlazione spaziale positiva per quanto riguarda la suscettibilità ai disastri da frana, come indicato da un indice di autocorrelazione spaziale globale pari a 0.9673. I valori LSI nell'area di studio sono caratterizzati principalmente da agglomerati alto-alto e basso-basso, che rappresentano il 65.93% della quota complessiva. Le aree di agglomerazione alto-alto sono prevalentemente localizzate in valli fluviali, valli intermontane e colline pedemontane, mentre le aree di agglomerazione basso-basso sono distribuite principalmente nella media e bassa montagna dell'area di studio.

I risultati della valutazione completa indicano che le aree con elevata suscettibilità alle frane nell'area di studio sono prevalentemente concentrate intorno a strutture, reti idriche e strade. La creazione di strutture crea, inoltre, condizioni topografiche e geomorfologiche predisponenti alle frane a causa dell'erosione, della degradazione meteorica e della pressione dinamica dell'acqua sui pendii che riducono significativamente la resistenza della roccia e del terreno, facendo si che i pendii su entrambi i lati della valle del fiume diventino più ripidi e ondulati, aumentando così la suscettibilità alle frane.

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## ABSTRACT

Effective evaluation of regional landslide geologic disaster susceptibility can improve the timeliness and accuracy of monitoring and early warning. However, existing studies have problems such as indicator selection without considering regional variability and strong subjectivity in evaluation. In this paper, a new evaluation method of landslide disaster susceptibility is proposed by combining geodetector and hierarchical analysis method; taking the eastern part of Qinling Mountain System in Henan Province as the study area, spatial analysis, reclassification, autocorrelation analysis and statistical methods are used for quantitative analysis and evaluation. The results show that: road density and water system density are the main influencing factors, with *q*-values of 0.361 and 0.242, respectively; the mean value of Landslide Susceptibility Index (LSI) in the study area is 0.402, which belongs to the moderate susceptibility class as a whole, with the high-value zones mainly located in the valley and rivers and along the roads, the LSI values show significant positive spatial correlation. Therefore, this method can more accurately quantitatively evaluate the regional landslide disaster susceptibility.

*Keywords: landslide, geohazard, geodetector, hierarchical analysis method, susceptibility evaluation*

## INTRODUCTION

With the development of economy, climate change and human engineering activities have increased significantly, resulting in frequent occurrence of landslides and other disasters. China is located in the eastern part of the Asian continent, with a vast area, active geological structure, variable climate, high annual rainfall, high population density, and intense human engineering activities, which together lead to the frequent occurrence of landslide disasters and their wide distribution.

The evaluation of landslide disaster susceptibility or sensitivity is a field of research that originated in the 1960s. Currently, the methods of landslide susceptibility evaluation mainly include statistical analysis method and mathematical modeling method (Ibrokhimov *et alii*, 2024). Statistical analysis methods, such as the weight of evidence (WoE) and statistical index (SI), have demonstrated effectiveness in natural hazard assessments. For instance, (Gentilucci *et alii*, 2024) applied WoE to wildfire susceptibility mapping in Central Italy, integrating geomorphological and environmental factors, and achieved an AUC value of 0.72. Similarly, (Salavati *et alii*, 2022) compared WoE and SI models for wildfire risk forecasting, reporting AUC values of 0.741 and 0.739, respectively, highlighting their utility in data-constrained regions.The statistical analysis method includes hierarchical analysis method (Damiani *et alii*, 2024), frequency ratio method (Matsui *et alii*, 2023), the weight of evidence method (Ling *et alii*, 2021; Gentilucci *et alii*, 2024; Salavati *et alii*, 2022), and logistic regression method (Chowdhury *et alii*, 2024), etc. The mathematical modeling method includes neural network method (Taye, 2023), fuzzy comprehensive determination method (Pei & Zhao, 2024), informativeness modeling (Micu *et alii*, 2023), support vector machine modeling method, and advanced ensemble techniques such as the random subspace-based functional tree (RSFT) classifier. (Peng *et alii*, 2022) developed an RSFT model for landslide susceptibility mapping, achieving superior predictive performance (AUC =0.838) compared to traditional methods, showcasing the potential of hybrid machine learning approaches.The existing stage of research mainly utilizes more subjective methods such as hierarchical analysis to evaluate the landslide susceptibility status. Although recent studies emphasize the advantages of machine learning models (e.g., RSFT) in improving accuracy (Peng *et alii*, 2022), with the continuous development of artificial intelligence technology, many scholars have begun to utilize deep learning methods to evaluate regional landslide disaster susceptibility. However, due to the large number of data samples required by such methods, it is difficult to meet the requirements in most regional studies. This limitation underscores the ongoing relevance of statistically driven models (e.g., WoE, SI) in scenarios with constrained data availability (Gentilucci *et alii*, 2024; Salavati *et alii*, 2022).

This paper takes the Xiong'ershan area of the Qinling Mountains in western Henan Province as the research object, and combines the Geodetector (GD) (Han & Dalaibaatar, 2023) and the Analytic Hierarchy Process (AHP) (Kumar & Pant, 2023). The q-values of the explanatory degree of each landslide disaster-prone environmental factor are used to obtain the degree of explanation of each landslide hazard environment factor q value. The proposed methodology is intended to enhance the objectivity, realism and reproducibility of the analysis process, thereby addressing the limitations of previous studies, which were characterised by subjectivity and the requirement for extensive data sets.

Existing studies on regional landslide geological hazard susceptibility assessment have limitations:

1. the selection of indicators does not fully consider regional differences, making it difficult to accurately reflect the actual situation in different areas;
2. the assessment process is highly subjective-traditional methods such as the Analytic Hierarchy Process (AHP) are strongly influenced by human factors when determining weights, leading to doubts about the reliability of results.

This study proposes a GD-AHP landslide evaluation method. Based on 13 disaster-causing environmental factors in 2 categories within the study area, it clarifies the explanatory degree of different factors for landslides, accurately assesses the landslide susceptibility of the study area, and reveals the spatial distribution characteristics of landslide hazard susceptibility.

## MATERIALS AND METHODS

### *Study area*

The study area is located in the western part of Henan Province, on the south slope of Xiong'er Mountain in the eastern part of the Qinling Mountain System, with an average elevation of 715 m , an average annual temperature of 14.5°C, and an annual precipitation of 689.3 millimeters. The area is characterized by mountainous terrain, with the intermittent traps and basins in the middle and low mountains, see Fig. 1, and the exposed stratigraphic layers mainly consist of the Paleoproterozoic Taihuashua Group Shuidigou Formation (Pt1s), the Middle Paleoproterozoic Changcheng Group (Pt2X), the Cretaceous Qubu Formation (K1q), and the Paleoproterozoic GaoYuGou Formation (E1g) and Luoyang Formation (N1l).

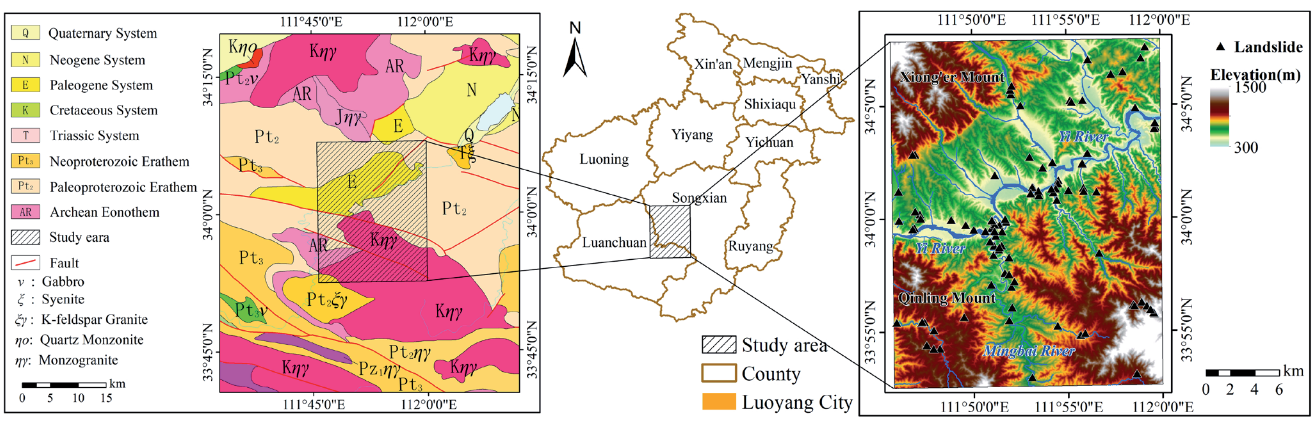



*Fig. 1 - Location of the study area with elevation and geological maps*

### *Geodetector method*

The Geodetector (GD for short) is mainly used to detect the degree of explanation of different factors on the dependent variable in the region, analyze the driving force and influencing factors of various phenomena, and is a powerful tool for exploratory analysis of spatial data. Geodetector gives quantitative correlation results according to the degree of influence of different factors on the dependent variable, which is calculated as equation (1) (Zhang *et alii*, 2022; Wang *et alii*, 2016):

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} \tag{1}$$

In the formula, $q$ value is the degree of spatial heterogeneity interpretation, its value is between 0~1, and the larger the $q$ value is, the higher the degree of interpretation of the factor on the dependent variable, and the higher the degree of correlation between the two; $N$ is the number of units of the whole study area; $N_h$ is the number of units in the hth layer; h is the number of stratification of the continuous factor; $L$ is the total number of layers for the stratification of the continuous factor; $\sigma_h^2$ is the variance value of the hth layer; $\sigma^2$ is the variance value of the factor of the whole study area.

### *GD-AHP method Evaluation steps*

The construction method of judgment matrix in hierarchical analysis is improved based on the geodetector model, and the degree of explanation $q$ of landslide disaster density by each landslide breeding factor is calculated by geodetector, and the relative importance coefficient between factors is determined by the ratio of q of each factor, which is calculated as in Equation (2).

$$a_{ij} = \frac{q_i}{q_j} \tag{2}$$

where $q_i$ and $q_j$ are the degree of spatial heterogeneity explained by the landslide-breeding environmental factors $i$ and $j$, respectively, as calculated by the geodetector, and $a_{ij}$ is the significance coefficient of the landslide-breeding environmental factor $i$ with respect to $j$.

### *Evaluation steps*

*Evaluation system construction*

This paper selects 13 disaster-inducing environmental factors of 2 categories (controlling factors and triggering factors) as indicators to evaluate the susceptibility to landslide disaster. The linear normalization function (Hoque *et alii*, 2024) was used to standardize the factors, and the calculation formula is shown in equation (3):

$$x_{nor} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{3}$$

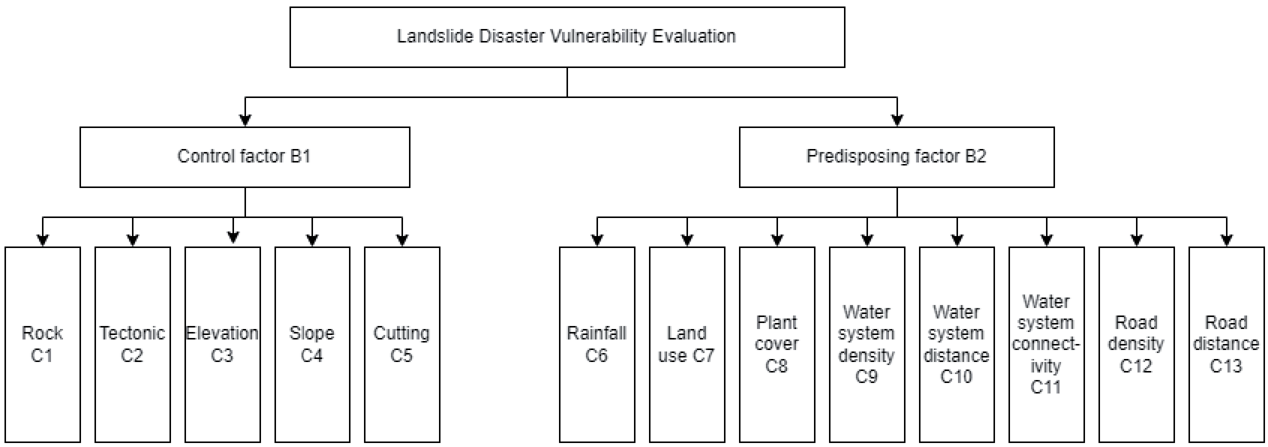



*Fig. 2 - Hierarchical model for landslide hazard susceptibility evaluation*

Where, $x_{nor}$ is the result of normalization of a factor, $x$ is the value of the image element of a factor; $x_{min}$ is the minimum value of a factor, and $x_{max}$ is the maximum value of a factor.

### *Construction of hierarchical analysis model based on GD*

By analyzing the evaluation indexes of the study area, the landslide susceptibility evaluation is hierarchized and structured, and the hierarchical structure model of landslide susceptibility evaluation in the study area is constructed (Fig. 2).

### *Evaluation method*

The landslide susceptibility evaluation model is constructed with the environmental factors of landslide geohazard breeding in the study area, and the evaluation weights of each factor obtained by GD-AHP method are applied to obtain the landslide geohazard susceptibility index LSI of the study area by applying the product of each factor and its weight, as in equation (4):

$$\mathrm{LSI} = \sum_{i=1}^{n} C_i \times W_i \qquad (4)$$

In the formula, LSI is the landslide geohazard susceptibility index, $C_i$ and $W_i$ are the results of the normalization of landslide hazard-preventing environmental factors and the corresponding weight values, respectively. Finally, in order to more intuitively reflect the spatial distribution of landslide susceptibility in the study area, the LSI is graded, as shown in Table 1.

| Level | Level Name | Corresponding Index Range |
|---|---|---|
| Level I | Low-prone area | 0~0.3 |
| Level II | Medium-prone area | 0.3~0.6 |
| Level III | High-prone area | 0.6~1 |

*Tab. 1 - Classification of landslide susceptibility*

## RESULTS AND DISCUSSIONS

### *Analysis of the contribution degree of pregnant environmental factors based on geodetector*

Table 2 shows the $q$-value of the degree of explanation of the distribution of landslide hazards by using geo-detector to detect the 13 pregnant environmental factors, which shows that each pregnant environmental factor plays a certain role in the distribution of landslide geohazards, and the influence of different factors on the landslide geohazards has a differentiated effect, among which the influence of the road density factor is the largest, 36.1%; the influence of the water system connectivity factor is the weakest, 1.2%.

| Contingency Environmental Factor | | q-value |
|---|---|---|
| Controlling factor | Lithology | 0.051 |
| | Tectonics | 0.079 |
| | Elevation | 0.058 |
| | Slope | 0.052 |
| | Cutting | 0.096 |
| triggering factor | Rainfall | 0.089 |
| | Land use | 0.047 |
| triggering factor | Vegetation cover | 0.017 |
| | Water system density | 0.242 |
| | Water system distance | 0.068 |
| | Water system connectivity | 0.012 |
| | Road density | 0.361 |
| | Road distance | 0.036 |

*Tab. 2 - Geodetector detection results*

By analyzing the weights (i.e., $q$-values) of the factors and the consistency test results, it can be found that (Table 3) in general, the induced factors have a higher intensity of explaining landslide hazards in the study area than the controlling factors, in which the induced factors are ranked as road density is the highest and water system connectivity is the lowest, while the controlling factors are ranked as cutting > tectonics > elevation > slope > rockiness. Specifically, road density and water system density had the highest

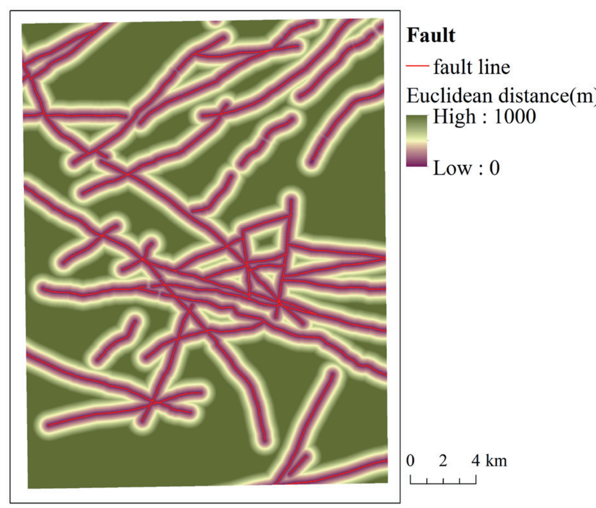
| standardized layer | Criteria layer weights relative to target layer | Criterion level versus target level judgment matrix consistency | indicator layer | Indicator level to guideline level weights | Consistency of judgment matrices at the indicator level relative to the criterion level | Consistency of judgment matrices at the indicator level relative to the criterion level |
|---|---|---|---|---|---|---|
| Controlling factors (B1) | 0.278 | 0.000 | Rock C1 | 0.152 | 0.000 | 0.043 |
| | | | Tectonic C2 | 0.235 | | 0.065 |
| | | | Elevation C3 | 0.173 | | 0.048 |
| | | | Slope C4 | 0.154 | | 0.043 |
| | | | Cutting C5 | 0.286 | | 0.079 |
| Triggering factors (B2) | 0.722 | | Rainfall C6 | 0.102 | 0.000 | 0.074 |
| | | | Land use C7 | 0.054 | | 0.039 |
| | | | plant cover C8 | 0.019 | | 0.014 |
| | | | Water system density C9 | 0.278 | | 0.200 |
| | | | Water system distance C10 | 0.078 | | 0.056 |
| | | | Water system connectivity C11 | 0.014 | | 0.010 |
| | | | Road density C12 | 0.414 | | 0.299 |
| | | | Road distance C13 | 0.041 | | 0.030 |

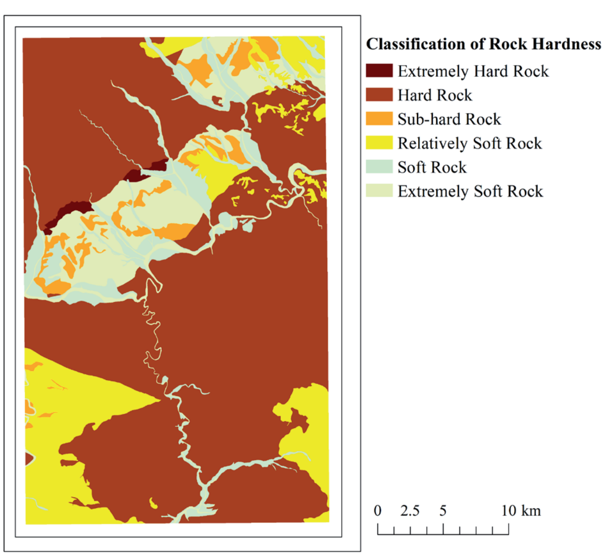
*Tab. 3 - List of the weights of each disaster-preventing environmental factor for landslide susceptibility*

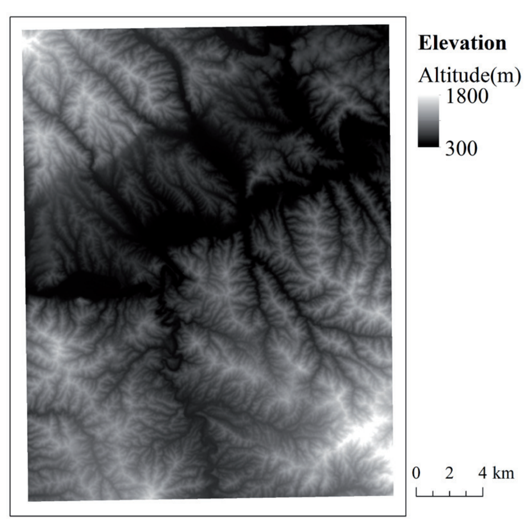
$q$-value of 0.361 and 0.242, respectively, indicating that road and water system density were the most important influencing factors of landslide hazard in the study area, followed by cutting and rainfall, with q-values of 0.096 and 0.089, respectively, compared to vegetation cover and water system connectivity, which had the lowest degree of influence.

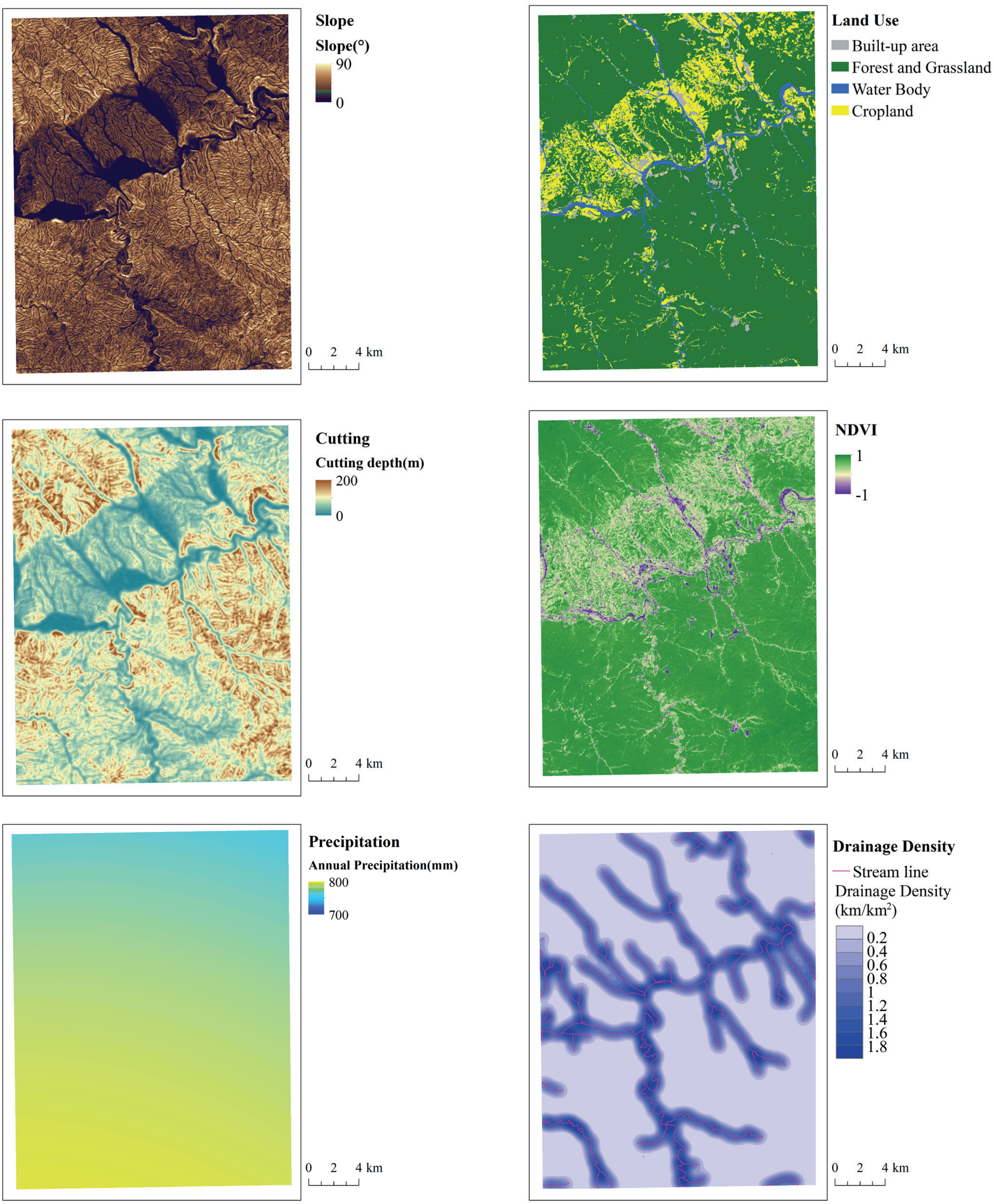
### *Analysis of landslide disaster susceptibility evaluation results*

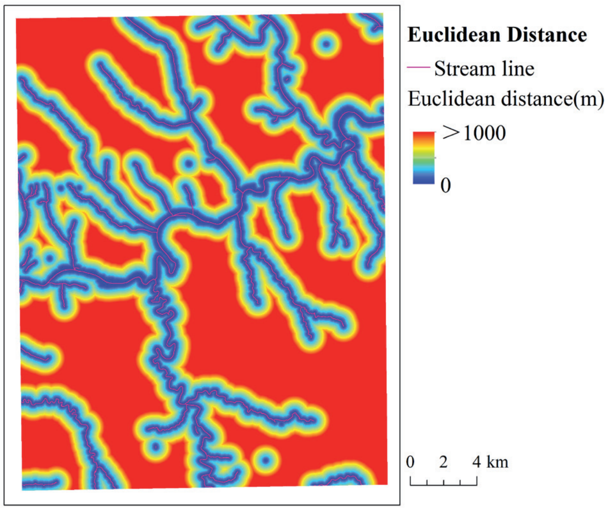
Figure 3 shows the results of each landslide geohazard breeding environment factor. The study area is characterized by a middle-low mountain intermittent trap basin landform with significant topographic undulation, complex geological structures, strong topographic dissection, and developed drainage systems. Rainfall decreases from south to north, vegetation coverage in mountainous areas is significantly higher

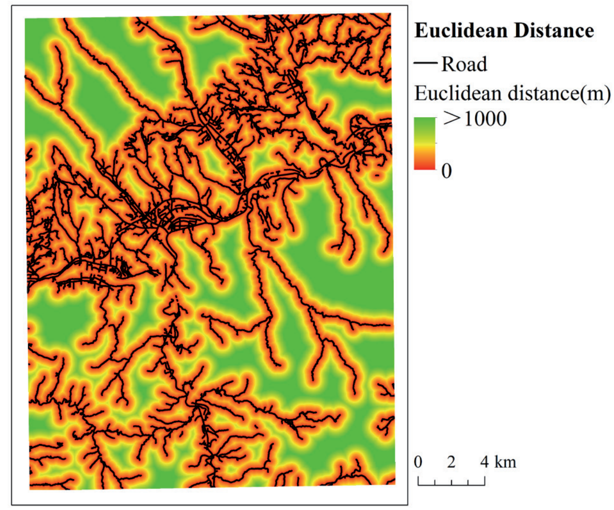


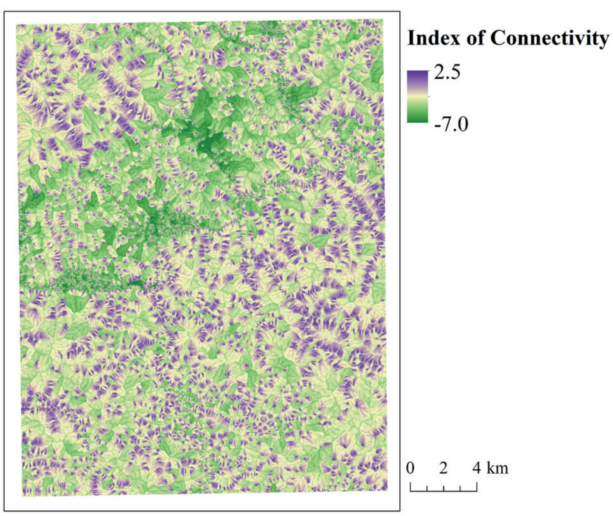




Slope
Slope(°)
90
0
0 2 4 km
Land Use
Built-up area
Forest and Grassland
Water Body
Cropland
0 2 4 km
Cutting
Cutting depth(m)
200
0
0 2 4 km
NDVI
1
-1
0 2 4 km
Precipitation
Annual Precipitation(mm)
800
700
0 2 4 km
Drainage Density
Stream line
Drainage Density
(km/km2)
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
0 2 4 km



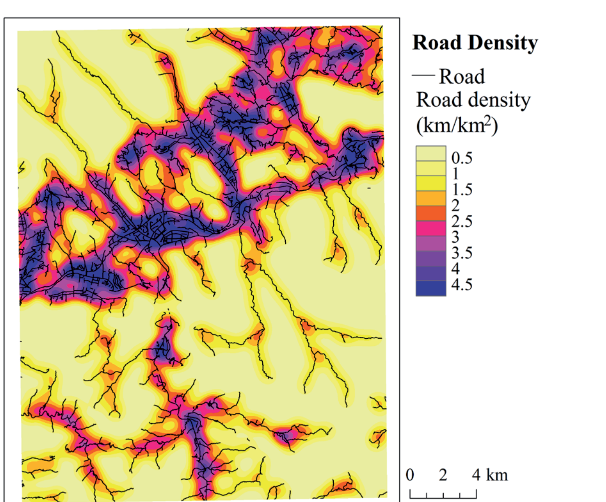




*Fig. 3 - Normalised results of environmental factors for landslide geohazard breeding*

than in the central region, and human activities are mostly concentrated in the basin area.

According to Fig. 4, it can be obtained that the average value of LSI in the study area is 0.402, which belongs to the medium susceptibility area. From the spatial point of view, the LSI of the study area is characterized by obvious geomorphic distribution, the high value area is mainly distributed along the gully, and the mountainous part, the LSI value is lower, comparing with the data of the investigated landslide geohazard points, it can be seen that landslides are concentrated in the gully and rivers and roads along the coast, and seldom occur in the mountainous area, so it can be seen that the calculation results are consistent with the actual situation.

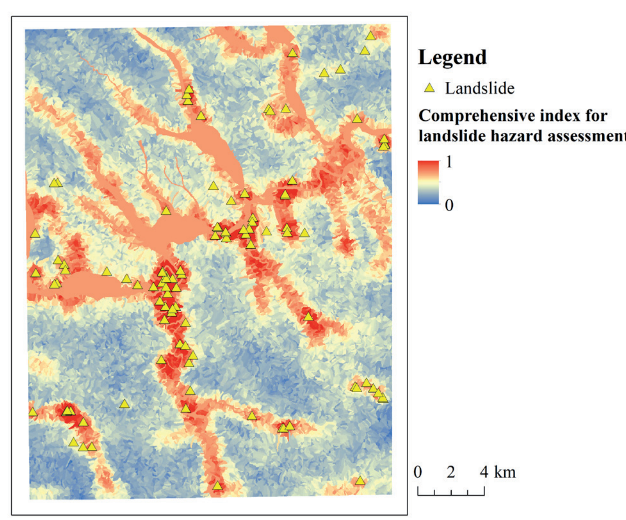



*Fig. 4 - Distribution of landslide susceptibility index in the study area*

According to Table 2, the reclassification, clustering and filtering processing to get the landslide susceptibility zoning in the study area (Fig. 5), it can be seen that the low susceptibility zone is mainly distributed in the middle and low mountainous areas of the study area, the high susceptibility zone is mainly distributed in the periphery of the rivers and along the transportation routes. By counting the area of landslide susceptibility zoning in the study area, it can be seen (Table 4) that the whole area is dominated by medium and low susceptibility zones, with less high susceptibility zones. Combined with Fig. 4, it can be obtained by counting the number of landslide hazards within each grade area, the proportion of the number of landslide hazard sites within different susceptibility zones is in the order of medium susceptibility zone (65.69%) > high susceptibility zone (32.35%) > low susceptibility zone (1.96%), which indicates that the grade of susceptibility of landslide disasters obtained from the present study and the location of landslide hazards have a better spatial consistency.

| Vulnerability classification | Area | Area proportion | Number of landslides | Number of landslides as a percentage |
|---|---|---|---|---|
| low susceptibility area | 314.32 | 52.39% | 2 | 1.96% |
| medium susceptibility area | 279.37 | 46.56% | 67 | 65.69% |
| high susceptibility area | 6.31 | 1.05% | 33 | 32.35% |

*Tab. 4 - Statistical table of landslide susceptibility zoning (unit: km²)*

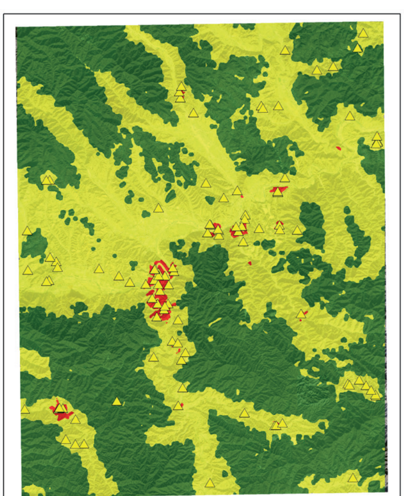



*Fig. 5 - Zoning map of landslide susceptibility in the study area*

In order to understand the spatial autocorrelation distribution of LSI index in the study area, this study calculated the global and local spatial autocorrelation index of landslide geohazards in the study area, and the $I_g$ value of the LSI value in the study area was 0.9673, which passed the test of significance at the 0.01 level (*Z*-value of 1135.9480, *P*-value of 0.0000), indicating that the LSI value showed extremely strong spatial positive correlation, that is, the LSI values show significant spatial aggregation characteristics. Fig. 6 shows the spatial aggregation of the local spatial autocorrelation index of LSI values.

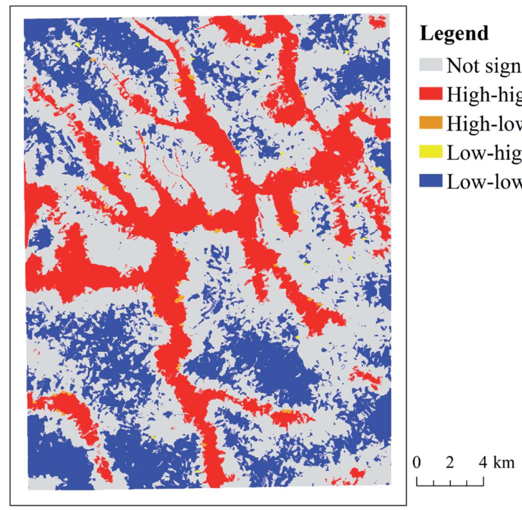



*Fig. 6 - Spatial clustering of landslide susceptibility index in the study area*

According to Fig. 6, it can be obtained that the LSI aggregation types are mainly high-high aggregation and low-low aggregation. Among them, the high-high aggregation area is mainly distributed in the river valley area, intermountain valleys and pre-mountain hills in the study area, accounting for about 31.42% of the whole study area; and the low-low aggregation area is mainly distributed in the middle and low mountains in the study area, accounting for about 34.51% of the whole study area. The high-low aggregation and low-high aggregation areas are lower, the proportion of the two is only 1.22%, and the remaining are insignificant areas, which are mainly distributed in the transition area between high - high aggregation and low - low aggregation areas.

## CONCLUSIONS

(1) In this paper, a landslide disaster hazard susceptibility evaluation method is proposed by combining geo-detector and hierarchical analysis method with the Qinling Xiong'er Mountain area in the western part of Henan Province as the research object. Compared with the traditional hierarchical analysis method, this evaluation method adopts the q-value of the degree of explanation of each landslide disaster-inducing environmental factor obtained by the geodetector when constructing the judgment matrix, which makes the analysis process more objective and real, and the reproducibility is higher.

(2) Different hazard-preventing factors have different degrees of explanation for landslide hazards, among which road density, water system density, cutting, and rainfall have higher degrees of explanation for regional landslide hazards; whereas the degrees of explanation for water system connectivity,

vegetation cover, road distance, and land use are lower.

(3) The mean value of landslide hazard susceptibility index in the study area is 0.402, which is a medium susceptibility zone overall. In terms of distribution grade, the number of landslide disaster sites in the medium-prone and high-prone zones is 100, accounting for 98.04% of the overall proportion, especially in the high-prone zone, the number of its landslide disaster sites is 33, accounting for 32.35% of the overall proportion.

(4) The susceptibility to landslide hazards in the study area shows significant positive spatial correlation, with a global spatial autocorrelation index of 0.9673. Spatially, the LSI values in the study area are mainly characterized by high-high aggregation and low-low aggregation.

(5) This study has certain limitations. The selected disaster-causing environmental factors are limited, failing to cover factors such as seismic activities and details of human engineering activities. Meanwhile, the accuracy of the model may also be limited when facing complex geological conditions and interactions of multiple factors.

(6) For future research, it is recommended to collect more detailed multi-source data and incorporate additional influencing factors such as seismic activities and human engineering details that were not fully addressed in the current study, while also exploring the integration of advanced methods like deep learning to improve the model, thereby enhancing the accuracy, comprehensiveness, and adaptability of landslide susceptibility assessments.

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